Edited by
Bart L. MacCarthy | Dmitry Ivanov

THE DIGITAL SUPPLY CHAIN

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The Digital Supply Chain

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Preface

Digitalization is one of the most dramatic and impactful megatrends occurring across business, industry, and commerce. Digital technologies, systems, and platforms are affecting how we collaborate and exchange information across a supply chain, and how we integrate, manage, and control supply chain operations. Digitalization potentially enables a strong digital thread connecting an entire physical supply chain. The **Digital Supply Chain** examines and analyzes in depth the impact of digitalization on the design, management, and control of contemporary and future supply chains.

In Chapter 1, MacCarthy and Ivanov provide an overview of the principal technologies and systems that offer the most promise in linking the virtual and physical worlds to improve supply chain performance. These include smart factories, smart warehouses, smart logistics, cloud-based systems, and digital platforms, as well as the computational engines powered by Analytics, Data Science and Artificial Intelligence. Emerging technologies likely to influence future supply chains are also discussed, including Blockchain, Digital Twins, Internet of Things, 5G, Edge, and Fog computing. The chapter describes an evolving spectrum from digitally immature to digitally enabled and digitally transformed supply chains. The transformative effects of the digitalization of supply chains will affect supply systems in diverse ways providing not only many new opportunities but also giving rise to many challenges in data rich supply chain ecosystems. The remaining chapters of the book develop, expand, and critically analyze all of the themes discussed in the introductory chapter.

In the second part of the book, Chapters 2—8 describe, analyze, and critically appraise the building blocks and enabling technologies for the digital supply chain. In Chapter 3, Mourtzis, Angelopoulos, and Panopoulos chart the evolution of digital manufacturing from the early applications of computers in industry to today's digitally rich Smart Manufacturing ecosystems. They highlight the key components, frameworks, and architectures of the Smart Factory, a cornerstone for Industry 4.0 (I4.0), and the interoperability challenges it presents. In Chapter 4, Winkelhaus and Grosse apply a socio-technical lens to understand and analyze the combination of human and technology components needed in contemporary Smart Warehousing systems. In Chapter 5, Baziyad, Kayvanfar, and Kinra examine the emerging IoT paradigm and its supporting technologies that have the potential to facilitate smart manufacturing and enable future Digital Supply Chains. In Chapter 6, Zhang, MacCarthy and Ivanov review key computing advances that underpin and enable the Digital Supply Chain and have the potential to transform future supply chains, namely, the Cloud, Platforms, and Digital Twins. In Chapter 7, Brusset, La Torre and Broekaert introduce the computational approaches, algorithms, analytics, and AI that can be harnessed to underpin data-driven supply chain decision-making. In Chapter 7, Pettit, Wang, and Beresford trace the impact of digitalization on the logistics sector and discuss how digitally enabled logistics can improve supply chain transparency, operational efficiency, and responsiveness. In Chapter 8, Treiblmaier, Rejeb, and Ahmed review the drivers, inhibitors, and industrial applications of one of the most iconic digital technologies that is set to influence the management and control of future supply chains—the Blockchain.

The third part of the book, Chapters 9—13, addresses opportunities and challenges in the management of the Digital Supply Chain. In Chapter 9, Spanaki, Karafili, and Despoudi analyze the significant challenges in ensuring data quality and achieving effective data governance in the shared data architectures that accompany the digitalization of the supply chain. In Chapter 10, Chan considers one of the most dominant supply chain management challenges—traceability—and discusses how to design robust digital systems to ensure products can be traced and tracked across the supply chain. In Chapter 11, Cox examines the evolution of digital support for both routine and strategic activities in purchasing and procurement, one of the most critical supply chain management functions. In Chapter 12, Jha, Verma, and Bose use an information processing perspective to examine opportunities and approaches for measuring and managing performance in the Digital Supply Chain. In Chapter 13, Cha reviews the state of knowledge on Supply Chain Cyber Security from both practitioner and academic perspectives, providing guidance for detection and defense against the many potential vulnerabilities at the interface of the digital and physical worlds.

Many chapters throughout the book provide detailed examples of practice. Part 4, encompassing Chapters 14−20, examines digitalization of the supply chain in six important business and industrial sectors. In Chapter 14, Zhang and Hänninen focus on retailing, examining how digitalization has affected retail strategy, front-end retail operations and fulfilment systems, and the back-end logistics that support contemporary omnichannel retailing. In Chapter 15, Pal and Jayarathne examine the impact of digitalization in the globally dispersed textiles and clothing industry. They examine the impact of digitalization across the whole product lifecycle from design through manufacturing, retailing, and the reverse circular economy. In Chapter 16, Sgarbossa, Romsdal, Oluyisola, and Strandhagen look at the impact and challenges of digitalization on production and warehousing in food supply chains through four live cases. In Chapter 17, Fabbe-Costes and Lechaptois look at the automotive sector, a critical industry in the global economy that is undergoing disruptive change. They examine the evolving history of digitalization by tracing the "digital journey" of a major car manufacturer. In Chapter 18, Ahmed and Rios critically assess one of the most prominent current Blockchain-based logistics platforms, developed by a major shipping organization and a major IT provider for shipping documentation. They examine its effects on the international shipping ecosystem. In Chapter 19, Benitez, Ayala, and Frank examine the opportunities for SMEs to develop their digital capabilities through engagement with technology providers on I4.0 initiatives using extensive case evidence from Brazil.

The final part of the book, Chapters 20−24, presents studies at the frontiers of research in the analysis, design, and management of the Digital Supply Chain. In Chapter 20, Demirel discusses the application of network science to analyze the structure and dynamics of supply chains. He surveys the state of knowledge on data sources, methods, and results for advanced supply network analysis. In Chapter 21, Liotine analyzes the computational challenges of scaling a Blockchain solution for product traceability in the pharmaceutical industry, proposing viable solutions for tracking exceptional transactions. In Chapter 22, Brintrup, Kosasih, MacCarthy, and Demirel examine both the opportunities and challenges in conducting digital surveillance of supply networks. They present digital surveillance frameworks that can adapt and apply AI methods and algorithms. In Chapter 23, Beltagui, Nunes, and Gold consider the sustainability of digitally enabled supply chains, showing where digitalization can be beneficial but also noting the potential for negative consequences from digitalization in the context of two contrasting supply chains—electric vehicles and the beef industry. In Chapter 24, the concluding chapter, Lambourdiere, Corbin, and Verny examine what digitalization means for the strategic management of supply chains. They argue for a dynamic capabilities perspective that can achieve digital ambidexterity to enhance value creation in supply chains and drive competitive advantage.

Transforming business, industry, and supply chains to adopt and utilize digital technologies will result in disruptive change across many sectors. The transformation presents formidable challenges, but digital technologies are already having very significant effects in reengineering and rearchitecting supply chains. The studies reported in this book provide insights and analysis on the impact of digitalization across the supply chain landscapes of many sectors, citing the latest and most seminal work throughout. The digitalization of business, commerce, and industry will affect supply chains, supply networks, and business ecosystems in diverse ways across different industries and sectors. The book provides the essential groundwork for further exploration, analysis, and evaluation of the Digital Supply Chain by both researchers and practitioners.

Bart L. MacCarthy
Dmitry Ivanov

Part I

Introduction

Chapter 1

The Digital Supply Chain—emergence, concepts, definitions, and technologies

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Abstract

Advances in technology, rapid globalization, trade liberalization, and increased regulation have shaped supply chains in the last four decades. We examine the impact of digitalization on contemporary and future supply chains. Digitalization potentially enables a strong digital thread connecting and mirroring an entire physical supply chain. We provide an overview of the principal technologies and systems enabling the Digital Supply Chain, including Smart Factories, Smart Warehouses, Smart Logistics, Cloud-based systems, and digital platforms. We discuss the computational engines enabled by Analytics, Data Science, and Artificial Intelligence and the emerging technologies likely to influence future supply chains—Blockchain, Digital Twins, Internet of Things, 5G, Edge, and Fog computing. The technologies offering the most promise in linking the virtual and physical worlds to improve supply chain performance are noted. We describe an evolving spectrum from digitally immature to digitally enabled and digitally transformed supply chains. We provide both narrow and broad definitions for future Digital Supply Chains. The transformative effects of the digitalization of supply chains will affect supply systems in diverse ways. Data-rich supply chain ecosystems will provide many new opportunities but will also give rise to many challenges that require continued analysis and evaluation by researchers and practitioners.

Keywords: Blockchain; Digital supply chain; Digital twins; Internet of things; Smart factory; Supply chain analytics; Cloud computing.

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1. A transformative decade

The Covid-19 pandemic has brought wide attention to supply chains, stimulating strong media interest in their design and operation (Bown & Irwin, 2021). It has highlighted the global nature of supply chains, their diversity and complexity. The public is now aware of society's critical reliance on the manufacturing, transportation and logistics networks that provide the essential plumbing for the global economy (IFG, 2022a). Business and industry emphasize supply chain design, management and control more strongly than ever (Alicke et al., 2021). Policy makers, regulators, and governments have taken note (IFG, 2022b; The White House, 2021). Supply chains are truly in the spotlight.

Supply chain management seeks to connect, coordinate, and manage all of the value-adding stages in manufacturing a product (Ivanov et al., 2021). Technological advances, rapid growth in global sourcing and global markets, trade liberalization, and increased regulation have shaped supply chains over the last four decades (MacCarthy et al., 2016). The pandemic and other disasters have heightened the emphasis on guaranteeing security and resilience of supply (Handfield et al., 2020). The urgent need for sustainability in supply systems is evident across society and governments. Sustainability reporting has risen strongly in corporate agendas (Elalfy et al., 2021). Technological advancements continue to shape the operational landscape (Dosi & Nelson, 2010)—what we produce, how and where we produce, and how we source and supply. We focus on one of the most dramatic and impactful megatrends—the continued and rapid digitalization of commerce, which has had a profound effect on the modern world, not least on supply chains and all aspects of their management (Hoe, 2019; Stank et al., 2019).

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The last decade has been transformative in terms of advances in communication and computing technologies—the connected decade in which the world has moved from analog to digital. Mobile access to information and services has become ubiquitous, and mobile commerce continues to grow (Mordor Intelligence, 2021). Utilization of the Cloud, not only for data storage but also for computing infrastructure, software, and services, has accelerated rapidly, providing new architectures for corporate Information Technology (IT) and enabling enterprises to scale up rapidly (Attaran & Woods, 2019). Digital and communication technologies are all pervasive (Porter & Heppelmann, 2014), e.g., in products, in factories and warehouses, and in retail outlets. Potentially, all objects can now interact digitally across the Internet (Tran-Dang et al., 2020). It is not just the purely digital realm that has seen technological advances. Industry 4.0 (I4.0) initiatives have brought together many "tech ingredients" to enable new industrial and manufacturing systems (Culot et al., 2020). There have been significant developments in flexible and smart automation and warehousing (Boysen et al., 2019), providing the physical infrastructure that is essential to support the platform economy (Parker et al., 2016).

Digitalization has had major transformative effects on many sectors. It is redefining the morphology of the Information Systems (IS) landscape within organizations that participate in supply chains and horizontally across supply chains. Digital technologies, systems, platforms, and algorithms are affecting how we collaborate, exchange, integrate, manage, and control across the supply chain. Transforming industry and supply chains to adopt and utilize digital technologies presents formidable challenges (Hoe, 2019; Preindl et al., 2020), but the technologies are already having an effect. We highlight two examples here—one reflects incremental but significant digital change, the other a transformative sectoral change.

Robotic Process Automation (RPA), sometimes called Intelligent Process Automation, refers to the replacement of routine business activities with software (Czarnecki and Fettke, 2021, Chapter 1; Siderska, 2020). In RPA, a robot refers to software (a "bot"), which typically automates an activity or process previously carried out by a person. As noted by Czarnecki and Fettke (2021, p12), RPA is an umbrella term covering "a broad range of concepts that enable processes to be executed automatically." The underlying tasks are usually routine, repetitive, and rule-based, allowing autonomous execution. RPA implementations should not require fundamental changes to an organization's IT architecture and should be deployable with minimum coding effort. Clearly, RPA is aimed at productivity enhancements and reduction in costs but may also drive quality improvements by reducing errors and by providing standardized, repeatable, and reliable execution of processes.

RPA is applied widely in service and administrative contexts in sectors such as finance, banking, and insurance and may allow "quick wins" (Berruti et al., 2017; Hartley & Sawaya, 2019). However, there is much potential for wider deployment for repetitive tasks in design, manufacturing and supply chain operations such as Purchase-to-Pay (P2P) systems (Hartley & Sawaya, 2019; Pfeiffer & Fettke, 2021, chap. 16; Cox, 2022). Many developments may be expected, including further incorporation of AI, machine learning (ML), and natural language processing (Rizk et al., 2021), as is happening with the rapidly developing "chatbot" applications that respond to online customer enquiries through text or speech in sectors such as retail (Kalkum et al., 2020). Although incremental, the effects of these technologies may be significant when deployed at scale, with strategic implications for organizations deploying RPA in the context of a digital transformation (Berruti et al., 2017; Lacity & Willcocks, 2021).

The impact of digitalization on the retail sector has been strongly disruptive over the last two decades (McKinsey & Company, 2020). Traditional store-based retailing dominated in the postwar era with customers fulfilled from store inventories replenished from the retailer's distribution center (DC) (see the top route shown in green in Fig. 1.1). The retail

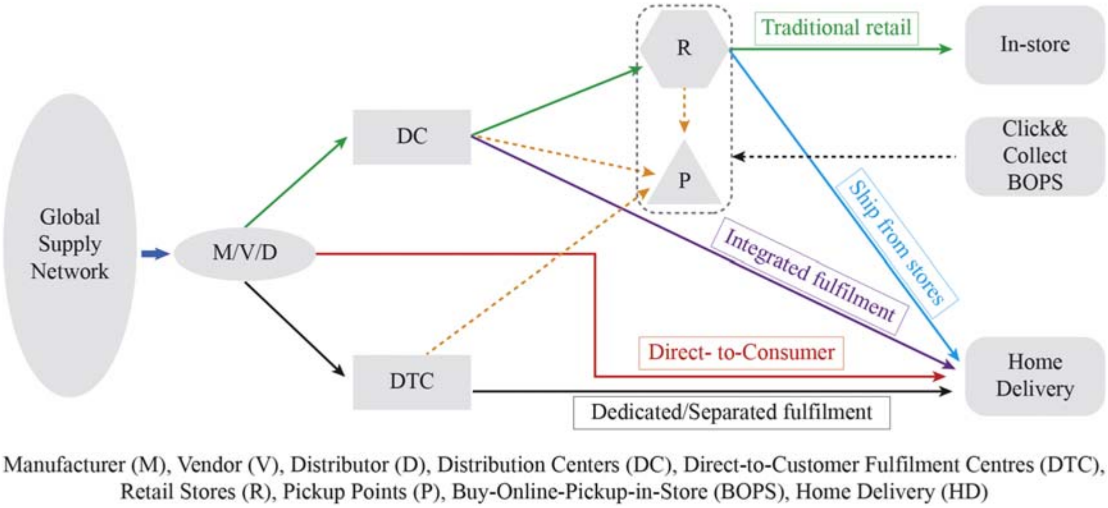

FIGURE 1.1 A multitude of digitally enabled omnichannel retail fulfilment options. *Adapted from Ishfaq, R., & Raja, U. (2018). Evaluation of order fulfillment options in retail supply chains.* Decision Sciences, 49*(3), 487−521.*

sector was one of the first to be affected by the growth and use of the Internet in the 1990s. Many traditional retailers introduced separate online channels, but this was also the era of the birth of pure platform retailers including Amazon. Fast forward to today's omnichannel retailing—customers can place orders through a variety of virtual and physical channels, including smart home technologies such as Google Assistant and Amazon Alexa (Roggeveen & Sethuraman, 2020). The retailer seeks to exploit flexibility in its distribution and supply network to satisfy a heterogeneous customer base with a diverse range of fulfilment options, illustrated in Fig. 1.1. These include in-store fulfilment, click and collect services, and home delivery (Ishfaq & Raja, 2018).

A click and collect customer ordering online could be fulfilled using inventory from the store from which they collect the order, from another store in the retailer's network, from a central DC that also fulfills the store, or from a dedicated Direct-to-Consumer (DTC) fulfilment center (Marchet et al., 2018). Similarly, home delivery customers can be fulfilled in different ways. Many other variants and options are possible, including pick up and return kiosks and fulfilment through third party premises. A customer that finds their desired product is out of stock in store may also avail of the multiple fulfilment options offered by the retailer if the product is available somewhere in the retailer's network.

The retailer manages the complexity arising from multiple ordering and fulfilment options through digitalization at every level across the network, from order placement to order receipt. The retailer and its partners in logistics require strong digitally enabled operational processes that perform accurately at scale to ensure a high level of customer service at a much finer level of granularity than traditional store replenishment.

The retail example throws up further features of digitally enabled supply networks—competition and new entrants. Platform-based retailers such as Amazon have had a very significant effect on the retail market. However, by utilizing their store networks, warehousing and distribution infrastructure, and their supply chain management skills, traditional retailers have valuable resources that enable them to compete in this landscape (Brynjolfsson et al., 2013). The traditional retailer must decide which fulfilment services to offer to be competitive. They may use manufacturers or other distributors and vendors to satisfy orders placed online, particularly for big ticket and/or slow-moving items—so-called 'drop shipping' (Yu et al., 2017). However, the manufacturer may also see this as an opportunity to market and sell directly to customers, as is shown by the rise in direct selling and supply in some sectors that is further intensifying the competitive landscape (Rangan et al., 2021).

The impact of digitalization on the supply chain has been long predicted by consultancies (IBM, 2010; Accenture, 2014; Mussomeli et al., 2016). Some have predicted the dawn of autonomous and 'self-thinking' supply chains (Alicke et al., 2022; Calatayud et al., 2019)—visionary perhaps, but an indicator of potential changes to come. In this opening chapter, we examine the antecedents and emergence of the Digital Supply Chain, showing how and where the virtual and physical supply chain worlds interact. We describe the building blocks for the Digital Supply Chain, outlining the major technologies, systems, and subsystems, both existing and emerging, that are engendering change and enabling digitalization across the supply chain. We describe an evolving spectrum spanning digitally immature, digitally enabled, and digitally transformed supply chains and provide both a narrow and a broad definition for future Digital Supply Chains. We note the opportunities, implications, and the many challenges in supply chain digitalization and conclude with a brief overview of the book.

2. Emergence of the Digital Supply Chain

A supply chain encompasses all the value-adding stages in producing and delivering a product. In general, no one party owns the supply chain, although there are dominant and powerful players such as retailers, brand owners, and original equipment manufacturers (OEMs) present in most chains. The information flowing back through the supply chain results in orders being placed and deliveries being made with appropriate lead times and stocking levels to ensure high customer service levels (Ivanov et al., 2021).

Although the importance of securing supply has been evident throughout history, the term supply chain management did not emerge until the 1980s (Ellram & Cooper, 2014). The importance of integrating the links in the supply chain goes back to the work of Jay Forrester at MIT in the late 1950s and his identification of dynamic effects and distortions in uncoordinated supply systems (Geary et al., 2006). The operational world witnessed major changes in the last two decades of the 20th century as the pace of globalization accelerated. Global sourcing and global markets began to emerge, assisted by the expansion of international transportation networks, containerization, and the growth of China that changed the configuration and geography of many supply systems (Guerrero & Rodrigue, 2014). New approaches to the design, management, and control of supply chains mirrored these changes.

In the 1980s, lessons began to be learned from Japan about the design and management of effective and efficient production systems and supply chains (Schonberger, 2007). Kanban and Just-in-Time (JIT) approaches emphasized that high levels of stationary inventory indicated inefficiencies and highlighted the benefits of production systems responding directly to downstream demand signals. These are key concepts in Japanese inspired Lean thinking that also stresses the importance of strong value-adding business processes and the elimination of waste (Womack & Jones, 1994). From its emergence in the auto-sector, Lean has become a dominant paradigm in the design of operational and supply systems of all types (Janoski & Lepadatu, 2021; Rossiter et al., 2011). Additionally, pioneers such as Deming and Juran highlighted the importance of quality management as a bedrock for high-performing operations (Ehigie & McAndrew, 2005). Japanese approaches, in particular the Toyota Production System, established the ground rules for quality management practices in industrial operations (Liker, 2004). In the 21st century, there has been much greater appreciation of the risks and vulnerabilities in globally dispersed supply chains. Supply chain risk management has developed strongly in academic research and as a practitioner discipline (Ho et al., 2015; WEF, 2021a), as has sustainability. Increased consumer and societal awareness of the environmental and social impacts of production and consumption, more stringent regulatory and reporting requirements, and the overriding global concerns of climate change have highlighted the importance of sustainability (Elalfy et al., 2021). Supply chains are central to many of the core questions in sustainable development (Pyykkö et al., 2021).

The discipline of supply chain management has coevolved with IT over the last three decades. Enterprise Resource Planning (ERP) systems emerged as integrated business software solutions in the 1990s, providing the backbone of corporate IT systems since then (Nazemi et al., 2012) and the core systems used by enterprises to plan, manage, and control their supply chains (Grabski et al., 2011). However, ERP implementation and deployment resulted in many problems and challenges (Chen et al., 2009).

The digitalization of the supply chain promises new digital architectures, new capabilities, and more effective ISs and IT for supply chain integration, planning, management and control.

2.1 The digitalization of supply chains

The digitalization of supply chains has been discussed widely in the academic literature in recent years. Terms such as Smart Supply Chain (Wu et al., 2016), Digital Supply Chain (Buyukozkan and Gocer, 2018; Nasiri et al., 2020), Supply Chain 4.0 (Frederico et al., 2019), and the Self-thinking Supply Chain (Calatayud et al. 2019) have been put forward to describe the phenomenon. The strongly related domains of the digitalization of manufacturing, particularly I4.0 (Hofmann and Rüsch, 2017; Ghobakhloo, 2018; Culot et al., 2020) and Smart Manufacturing (Kusiak, 2018), have also added to the debates on the impact of digital technologies on business operations, industry, and supply chains.

As noted by Wu in 2016, “The deep integration of the digital world with the physical world holds the potential to bring a profound transformation to global supply chains” (Wu et al., 2016, p. 396). However, much of the subsequent academic research has been primarily literature based, proposing concepts and frameworks to capture the effects of digitalization on supply chains and their management. The wider practitioner literature, consultancy studies, and policy reports have also strongly emphasized the phenomenon for more than a decade and offer more examples of practice. These include early reports on digital trends and initiatives (e.g., Accenture, 2014; IBM, 2010; Kagermann et al., 2013) succeeded by numerous reports on opportunities, challenges, and imperatives of adopting appropriate digital technologies and developing digital strategies for the supply chain (e.g., ATK, 2015; BCG, 2016; WEF, 2017). The trend continues at pace (e.g., ASCM, 2021; Bhargava & Mahto, 2021; EY, 2020; WEF, 2021b). We summarize the arguments typically made on the potential for digital transformation of the supply chain.

There is general agreement across the academic and practitioner literatures that application of digital technologies has the potential to improve and automate many aspects of supply chain management, internally within organizations and externally across the supply chain. Digital technologies may replace or obviate the need for some activities and processes through disintermediation, enable the redesign of supply chain configurations, and allow new business opportunities in wider digital ecosystems. In combination, their effects are expected to be disruptive, changing the supply chain landscape fundamentally. Change will occur from greater connectivity between entities across the supply chain, enabling better and more effective communication and greater visibility and transparency of supply chain operations in real time. Such information will reduce uncertainty and facilitate productive use of available supply chain resources to achieve high service levels in customer-focused supply chains.

Effective use of data and information will enable synchronous, frictionless, and responsive supply chain operations, allowing more demand-driven operations than in traditional supply chains. Control will be achieved through the application of algorithms powered by Advanced Analytics, Business Intelligence, and Artificial Intelligence (AI). This will generate clear and timely information, and improve analysis and decision-making, with opportunities for some autonomous decision-making. Data availability is expected to be “big” in terms of volume, variety, and velocity. Data sources will be at different levels of granularity, e.g., data generated internally from machines in factories may indicate the need for maintenance, external data may provide indicators of changes in consumer sentiments affecting demand, or signal potential disruptions and vulnerabilities in a supply chain. Such data, combined with effective decision-making, may enable a greater ability to orchestrate and utilize supply chain resources at speed to generate competitive advantage. There is also general appreciation that data-rich supply chain systems may generate more vulnerabilities to cyber risks.

Some argue that digitalization will enable leaner operations and may support sustainability at many levels (De Felice & Petrillo, 2021; Li et al., 2020; McGrath et al., 2021). There is general acknowledgment that there are significant challenges in digital adoption at a company level. However, the academic literature shows limited appreciation of the challenges of adopting and integrating digital technologies across globally dispersed supply networks composed of multiple supply chain actors with different interests and perspectives. Issues such as data ownership, security, digital complexity across multiple systems, and governance of data ecosystems at the supply chain level are less well explored in the research literature but are highlighted by practitioners (WEF, 2021b).

Although there is wide agreement that digital and communication technologies allow enterprises to become more connected, there is less agreement on which digital technologies, existing or emerging, offer the greatest promise, or on the precise mechanisms by which different technologies, alone or in combination, will engender change and enable improved supply chain performance. We discuss next the range of technologies that are contributing to providing a strong digital thread connecting the entire supply chain, both those technologies that are firmly established and those that are emerging.

3. Building blocks for the Digital Supply Chain

Product design and manufacturing processes have developed enormously over the last half century. Manufacturing systems have undergone changes in structure, organization, and operation. There have been step changes in automation across most sectors, facilitating productivity improvements and higher levels of product variety and differentiation. Computers have been at the heart of these changes, from the emergence of early Computer-Aided Design and Manufacturing technology to today's Product Lifecycle Management systems (MacCarthy & Pasley, 2021). Similarly, technology, systems, and software have contributed to improving the management of supply chains and logistics.

We distinguish here between digitization and digitalization, using the former term to reflect the digital encoding of something physical (e.g., a product model captured digitally in a design system). We use the latter to reflect an application that uses a digital encoding in an organizational or business context to perform a business process digitally (e.g., an invoicing process initiated automatically on dispatch of an order to a customer). Many of the technologies, systems, and subsystems enabling the Digital Supply Chain are given the label “smart,” which we discuss below.

3.1 Smart Factories, Smart Warehouses, and Smart Logistics

The term smart is applied widely to describe devices, consumer appliances, and products (Porter and Heppelmann, 2014, 2015), as well as machines and technologies across a diverse range of contexts. It is also applied to describe buildings, homes, factories, business processes, and many other domains such as medicine. The “smart city” has garnered a strong research interest (Pan et al., 2021). However, there is a lack of precision in the definition and use of the term ‘smart’, although some of its properties were predicted three decades ago (Weiser, 1991).

“Smartness” of an object, system, process, or environment typically implies at least three attributes. First, a smart object has embedded (or has access to) technologies and software that allow it to sense aspects of its environment in some way to assess its current state. Second, it can make autonomous decisions on appropriate courses of action depending on the current state, or can provide indicators, directions, instructions, or options for users (or decision makers) to choose a course of action, particularly in warning about or taking action on the prediction or occurrence of undesirable or critical states. Decisions or instructions may be optimal in some sense, giving the object intelligent characteristics. Third, smart objects are connected to the Internet and/or other digital networks, possibly mediated through Cloud technologies. This enables external communication and facilitates remote monitoring, supervision, analysis, diagnosis, and control. Products that possess these attributes are sometimes called smart, connected products (Porter & Heppelmann, 2014). The smart descriptor is applied more broadly to environments, systems, processes, and organizational structures that possess some of these attributes. However, not all objects, systems, or environments labeled as smart will possess all of the features noted—autonomous behavior for instance may be limited.

The acronym STARA (Smart Technology, Artificial Intelligence, Robotics, and Algorithms) is used in some management disciplines to capture the range of digitally enabled technologies, devices, software, systems, and platforms that are affecting employment (Brougham & Haar, 2018). We discuss first the smart physical systems that feature in the digitally connected supply chain, specifically Smart Factories, Smart Warehouses, and Smart Logistics.

3.1.1 Smart Factories and Industry 4.0

The topic of smart factories and smart manufacturing more generally has gained increasing prominence (Burke et al., 2017; Kang et al., 2016; Mittal et al., 2018; Sjödin et al., 2018; Sajadieh et al., 2022). Smart factories are highly digitally connected production systems. The physical assets that produce, work on, or transport materials are connected to the digital layer of the factory, allowing direction, management and control to meet demand in responsive, flexible, and potentially adaptive ways.

Physical assets such as machines and material handling systems in a smart factory incorporate intelligent automation rather than conventional "hard wired" or fixed automation (Coito et al., 2020). The assets themselves may possess smart properties from the incorporation of intelligent sensors in their design (e.g., advanced machine vision systems). Smart factories are also described as Cyber-Physical Systems (CPS) that link the physical components with the cyber components that compute, control, and communicate (Mourtzis & Vlachou, 2018; Yao et al., 2019). They may also contain advanced robotic systems including Cobots—robots that work collaboratively with human operators (Ferreira et al., 2021). The digital thread across a smart factory enables visibility, remote monitoring, and real-time performance measurement. This supports smart maintenance (Bokrantz et al., 2020), offering alerts and warnings and allowing proactive rather than reactive corrective actions. Smart factories are expected to be highly productive with reduced labor costs, faster setups and changeovers, with diverse applications in different sectors.

The vision for future smart factories includes self-optimization, self-adaptation, and learning (e.g., Tao et al., 2018). However, there are significant challenges in realizing the vision of productions systems that can learn, adapt, and evolve with the changing needs of an organization. These include lack of standards for interoperability and the design of the underlying ontologies that can support intelligent connectivity, communication, and control between the physical and cyber layers. Additionally, as noted by Kusiak (2018), the "cyber part" of the smart factory requires a work force with additional skill sets in addition to traditional manufacturing skills.

Smart factories are a cornerstone of the I4.0 vision, which began as an initiative in Germany (Kagermann et al., 2013). However, it has had very wide resonance across the world, generating extensive research studies (e.g., Culot et al., 2020; Ghobakhloo, 2018; Mittal et al., 2018). As noted by Culot (2020), I4.0 represents a broad evolutionary territory that is affected by the rate of technological development. Rather than being viewed as a hard set of technical components, principles, and standards, it converges on key enabling technologies that combine physical, digital, and analytical elements (Culot, 2020). I4.0 has helped to reestablish the economic importance of manufacturing in some countries, e.g., in the United Kingdom (UK.GOV, 2022) and in the United States of America (Manufacuring.Gov, 2022). In its original conception, I4.0 was not restricted to factory operations but highlighted the network of suppliers and customers in the manufacturing value chain and the connecting logistics systems (Hofmann & Rüsch, 2017). The smart factory concept has been extended to incorporate not just a single production unit but smart manufacturing networks (Bhargava & Mahto, 2021) as well as to the study of smart manufacturing more broadly (Kusiak, 2017, 2018).

3.1.2 Smart Warehouses

The functions performed by warehouses of receiving, storing, and dispatching goods to meet demand have always been essential in supply chains. A number of factors have heightened their importance and driven the design and development of contemporary warehouses, including adoption of JIT principles in the 1990s, the growth of e-commerce in the early 2000s, and the rise of omnichannel retailing in the contemporary era (Boysen et al., 2019; Custodio & Machado, 2019; Kumar et al., 2021). Across the same time span, we have witnessed the growth in global sourcing and the rise of global markets with a concomitant growth in the product variety managed in warehouses. Warehouses have progressed from being a secondary service in business operations to being an integral part of high-performance supply chains because of their impact on responsiveness, service level, and costs.

Warehouses were early targets for automation with the development of Automated Storage and Retrieval Systems in the 1970s. The 1990s saw the widespread adoption of IS/IT in warehouses and the development of warehouse management systems (WMSs) (Custodio & Machado, 2019; Kumar et al., 2021). Warehouse design and management have also been a very active area for research with the development of algorithms and techniques for optimal layout, storage, routing, and picking operations (Kumar et al., 2021). The rise of JIT systems, particularly in the automotive sector, necessitated rapid and precise flow of small batches of products between suppliers and manufacturers. E-commerce has had a major effect on contemporary warehouses, changing the granularity and predictability of demand (Boysen et al., 2019). Omnichannel retailing requires a high level of inventory accuracy and the development of solutions such as microfulfilment systems[1]—highly automated systems deployed close to the concentration of demand.

Many warehouses still involve human-intensive operations, particularly for picking operations, but this is also a rapidly developing technological space[2,3]. Automation and Robotic solutions are being developed to assist human operators (Glock et al., 2021), including wearable technology items. Future developments are likely to allow warehousing units to perform further value-adding services in addition to the bulk breaking, labeling, packaging, and kitting operations typically offered today (Hotze, 2016).

3.1.3 Smart Logistics

Many of the issues noted with respect to warehouses are equally relevant for the logistics sector. Logistics impacts strongly on responsiveness, customer service level, and supply chain costs (Tang & Veelenturf, 2019; Winkelhaus & Grosse, 2020). Logistics is one of the areas in the supply chain where digital intelligence and control have advanced most. Geographical Positioning Systems (GPS) and Geographical Information Systems (GIS) embedded in Transport Management Systems (TMS) have revolutionized the transportation industry (Shahparvari et al., 2020; Suresh & Vasantha, 2018). The Maersk and IBM Tradelens initiative provides one of the most mature applications of Blockchain in the supply chain, offering secure digital control of documentation in the shipping of goods internationally (Ahmed & Rios, 2022). Contemporary Logistics companies (3/4 PL) provide many services in addition to transporting of goods, which include offering warehousing facilities, optimal distribution strategies, and the management of material flows in the supply chain.

Effective logistics has long been recognized as central to successful JIT and Lean supply chains (Fawcett & Birou, 1992), providing the “glue” that links each of the value-adding stages and the “rhythm” that ensures rapid and dependable material flow (Lai & Cheng, 2016). The logistics industry is central to the achievement of sustainability goals, not only because of the environmental concerns associated with conventional transportation but also to support green supply networks and to underpin the emerging circular economy. Smart Logistics is a core capability in the vision of the Digital Supply Chain, acting as an integrator across the supply chain. As with Smart Factories and Smart Warehouses, human−technology interactions are crucially important. The nature of jobs and employment will change, as noted by Winkelhaus and Grosse (2020) in their vision for Logistics 4.0.

3.2 The Cloud and platforms

Two of the biggest impacts in the digital field have been the adoption of Cloud-based systems for business operations and the growth of platform commerce.

3.2.1 Cloud computing

Cloud computing has a rich history (Van Eyk et al., 2018). Application Service Providers began to emerge in the late 1990s, allowing computing services to be sourced through the Internet (Zhang & Ravishankar, 2019). Technological advancements since then have resulted in organizations moving away from investing in, and maintaining hardware and software “on premises” to utilizing computing resources and services provided by Cloud service providers over the Internet.

Cloud computing resources and services are available “on-demand” using pay per use models (Van Eyk et al., 2018). Infrastructure-as-a-Service offers foundational computing resources, including storage, networks, and data centers. Platform-as-a-Service provides programming and applications environments. Software-as-a-Service (SaaS) is the provision of software applications deployable as services over the Internet (El-Gazzar et al., 2016). SaaS is one of the most important service models in Cloud computing and is a rapidly growing market (Gartner Insights, 2019). Cloud computing’s advantages include easy access to computer resources that can be configured and scaled to meet business needs and accessed remotely (Attaran & Woods, 2019). Cloud resources and services are location independent and more flexible than traditionally installed hardware and software. Software applications can be deployed simultaneously in multiple locations. Clients can utilize and combine software from multiple vendors. Costs to access advanced computing capabilities may reduce, and the speed of deployment may increase. More generally, by lowering entry barriers, the Cloud helps to foster digital innovation, collaboration, and experimentation, leading to new business models (Nambisan, 2017).

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1. https://www.cbinsights.com/research/micro-fulfillment-tech-shipping-retail/ (accessed, 18/3/2022).

2. https://www.bostondynamics.com/solutions/warehouse-automation (accessed, 18/3/2022).

3. https://getfabric.com/ (accessed, 18/3/2022).

Cloud architectures provide a new technological landscape for corporate computing with new data structures, new data storage systems, new file management systems, and new programming models (Weerasiri et al., 2017; Zhang & Ravishankar, 2019). Although migrating business critical systems to the Cloud raises many challenges (Chang, 2020), there are many potential benefits. Conventional "on premises" ERP systems have been the cornerstone of corporate ISs, but ERP services can now be sourced from the Cloud (Capgemini, 2020), offering access to a wider client base, including SMEs. The Cloud facilitates the development of advanced services such as remote monitoring of equipment in the supply chain (Bokrantz et al., 2020). Clients and cloud service providers may contract with different tenancy models in deploying cloud services and resources. The Cloud may offer advantages in terms of cyber security, but successfully exploiting cloud resources requires organizational skills to orchestrate, build, and deploy effective and stable solutions, requiring trust between clients and Cloud vendors (Herbst et al., 2018; Weerasiri et al., 2017; Zhang & Ravishankar, 2019).

Migration to the Cloud will continue to have a major disruptive impact on corporate IT strategies. It signals a "cloud first" principle (Gartner, 2021) that will lead to a transformation from traditional, locally maintained computing infrastructure to cloud-based architectures. These developments will affect digitalization across the supply chain.

3.2.2 Platforms

Digital platforms connect suppliers and customers. The platform's infrastructure provides the digital hub for parties on the supply and demand sides to interact and contract for the delivery of products and services (Cennamo & Santaló, 2015). Platforms lower search and communication costs, enable disintermediation and facilitate "frictionless" commerce. A digital platform can become increasingly attractive for both customers and suppliers when services from a range of providers are available to meet the heterogeneous demands of a diverse customer base. In this way, platforms can generate powerful network effects that result in rapid growth in the user base (Parker et al., 2016). As noted in Section 1, retail commerce has changed in fundamental ways with the emergence of platforms. However, the impact of platforms is broader across business and commerce, for instance, with the emergence of platforms for sourcing in purchasing,[4] supplier integration in supply chain management,[5] and integrated service provision in logistics[6].

Platforms enable rapid matching and connection between customers and appropriate suppliers and service providers. They affect the nature of supply chain communications, information flows, supply chain connectivity, and ultimately product flow in supply chains. For physical products, rapid information flow needs to be matched by fulfilment systems designed and configured to meet demand generated by the platform. By reducing intermediation, platforms support direct supply models, as seen with the continued growth of DTC fulfilment channels for both new market entrants and traditional brands and manufacturers (Rangan et al., 2021). Platforms may act as business ecosystems for product and service development (Gawer & Cusumano, 2014; Kapoor & Agarwal, 2017), generating new business models that restructure firm and industry boundaries, resulting in new organizational forms for value creation (Zhao et al., 2020) such as the emergence of Manufacturing-as-a-Service (Adamson et al., 2017). However, the market dominance and power of platforms also raise concerns with calls for more regulation (e.g., Bourreau & Perrot, 2020).

3.3 Analytics, Data Science, and AI

Operations Research and Management Science (OR/MS) focus on the application of mathematical models, methods, and techniques to improve operational performance and support decision-making in organizations of all types. OR/MS has a rich history dating back to the Second World War when it began to emerge as a distinct discipline (Kirby, 2007; Mortenson et al., 2015). In the following half century, great strides were made in the science of optimization, inventory management, scheduling, queuing theory, and computer simulation, inter alia. However, by the millennium, there was a view that the academic discipline of OR/MS had diverged from practice (Kirby, 2007) and was failing to exploit the growing availability of large volumes of digital data (Kohavi et al., 2002).

The following decade saw the emergence of "Analytics" with strong inputs and interest from practice. There has been much debate about the term (Chiang et al., 2012; Mortenson et al., 2015; Power et al., 2018), but there is now broad consensus that Analytics encompasses all of the OR/MS toolset while also stressing the primacy of data and its effective use to support managerial decision-making. The book by Davenport and Harris (Davenport & Harris, 2007) was influential in arguing that Analytics capabilities could generate competitive advantage for firms. Contemporary Analytics supports

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[4] https://www.findsourcing.com/ (accessed, 18/3/2022).

[5] https://www.supplyon.com/en/platform/ (accessed, 18/3/2022).

[6] https://ware2go.co/ (accessed, 18/3/2022).

and informs decision-making by describing phenomena (Descriptive Analytics), by forecasting and prediction (Predictive Analytics), by generating effective or optimal plans and courses of action (Prescriptive Analytics), and in identifying root causes of problems (Diagnostic Analytics) (Bowers et al., 2018; Wasserkrug et al., 2019).

Data Science has its origins in the interfaces between Statistics, Computer Science, and Information Science (Chiang et al., 2012; Provost & Fawcett, 2013). It has developed in parallel with Analytics. Data Science seeks to interrogate and derive insights from data sets (Chiang et al., 2012; Provost & Fawcett, 2013), providing principles and techniques to "mine" data to determine patterns that can inform decision-making (Provost & Fawcett, 2013). The Cross-Industry Standard Process for Data Mining (CRISP-DM) is a common methodology used in Data Science projects (Martínez-Plumed et al., 2019) to understand the problem context, identify relevant data sets, mine and extract knowledge from the data, and provide insights to inform decision-making. A strong motivator driving Data Science is the realization that organizations may be rich in data but fail to utilize the information and insights attainable from data.

Data Science and Business Analytics are partially overlapping and complementary. The former provides computational approaches to process and extract knowledge from data sets, and the latter provides the models and techniques to discover, utilize, and exploit insights for business problems. Both are frequently associated with "Big Data" (Provost and Fawcett, 2013) and Big Data Analytics. Big Data sets may be heterogeneous, emanating from a multitude of sources within and outside an organization. A 3-V description is commonly used to characterize Big Data—Volume, Variety, and Velocity. Further "V" descriptors have been added, including Value (relevance for organizational decision-making) and Veracity (appropriateness of the data for the task) (Alsaig et al., 2018).

AI is an umbrella term used in many fields. AI brings intelligence to machines, business processes, and computer systems. However, what is considered "intelligent" is debated. A key distinguishing feature of AI is the ability to learn, i.e., products, processes, or systems should develop and improve their performance over time by learning. The automation and optimization of products, processes, and systems may make them more productive, perhaps faster and less costly, but if they fail to learn, their performance may deteriorate over time.

Machine learning (ML) is a critical and rapidly developing area of the AI domain (Jordan & Mitchell, 2015; Shang & You, 2019; Waring et al., 2020) with roots in Statistics and Computer Science. ML models are "trained" on a data set, with the aim of generalizing their learning for "unseen" data. The ability to learn and make inferences enables computers to improve autonomously over time and address new situations (Jordan & Mitchell, 2015). AI approaches have many applications in diverse domains, e.g., spam filtering, online recommender systems, natural language processing, computer vision, customer analytics, and healthcare analytics (Jordan & Mitchell, 2015; Shang & You, 2019; Waring et al., 2020), and the range of applications continues to increase.

The impact of Analytics, Data Science, and AI is being felt at every level of granularity within organizations and across supply chains—from intelligent machines and robots to work flow and business process automation (Iansiti & Lakhani, 2020). Forecasting and demand sensing for supply chain planning have been highly active areas (Gilliland et al., 2021). Being digital and software-based, AI approaches can be scaled easily, particularly for those organizations with strong digital cores. As noted by Iansiti and Lakhani (2020), in such organizations, "AI runs the show," providing the engine that powers digital business, enabling business system innovation, and redefining the boundaries of the firm (Burström et al., 2021).

However, successful adoption of Analytics, Data Science, or AI is challenging (Björkdahl, 2020; Burström et al., 2021). There are many challenges in identifying where to apply and how to exploit these approaches to improve business operations and drive innovative strategies (Björkdahl, 2020; Janssen et al., 2017; Kiron & Schrage, 2019). There are significant concerns on ethicality and trust in AI (Ashoori & Weisz, 2019), and the implications for people in such systems (Brougham & Haar, 2018). These aspects need to be part of broader social, political, and economic debates (Dafoe et al., 2021) as digitalization of the supply chain continues.

3.4 Emerging technologies—Blockchain, Digital Twins, and the Internet of Things

The hardware and software components and the architectures of the Digital Supply Chain will continue to develop, influencing and affecting how future supply chains are designed, configured, managed, and controlled. We provide brief overviews of three technologies that are fast emerging—Blockchain, Digital Twins, and the Internet of Things (IoT)—and in Section 3.4.4, note three others that may have a strong impact in the future—5G, Edge, and Fog computing. Fig. 1.2 illustrates conceptually the range of technologies that can support the supply network of a focal firm, upstream and downstream.

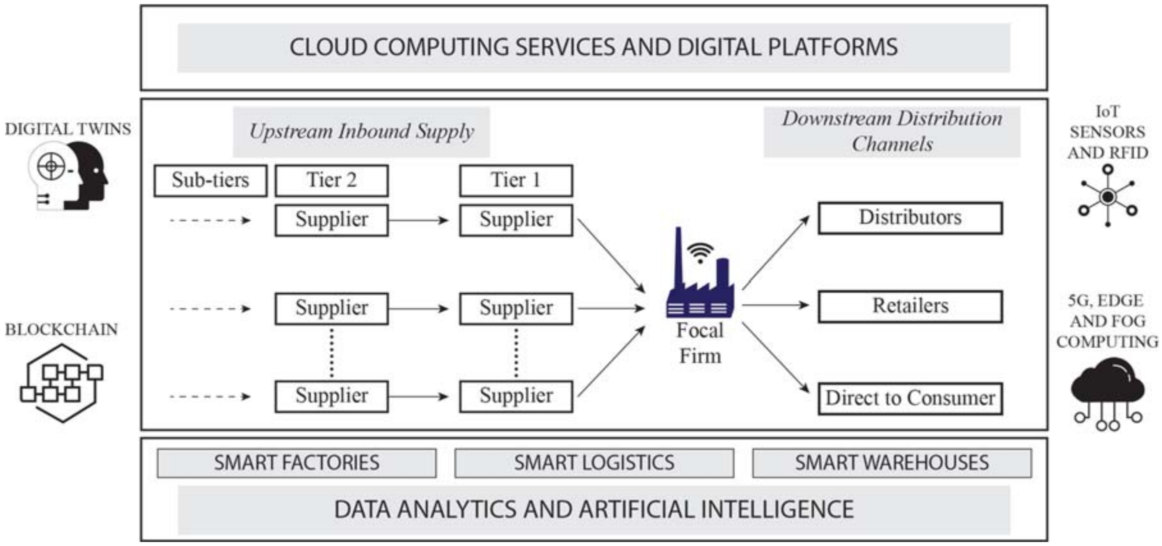

FIGURE 1.2 Digital technologies supporting the supply chain of a focal firm—upstream and downstream.

3.4.1 Blockchain technology

Although Blockchain is strongly associated with crypto currencies, it is important to stress that the technology has a wide range of potential uses, and has particular relevance for applications in supply chain management (Cole et al., 2019). Blockchain technology harnesses the power of the Internet to record data in a decentralized and distributed manner (Treiblmaier, 2020; Viriyasitavat & Hoonsopon, 2019; Wang et al., 2019). Information is captured in a sequence of blocks to form a record of transactions, providing a digital ledger. Each block is time-stamped and connected to the preceding block using cryptographic methods, forming a chain. Blocks can record any kind of digital information or transaction depending on the application domain.

Importantly, Blockchain is a distributed ledger technology in which potentially all nodes in a network have access to and visibility of the chain. To add a block, there must be agreement among network participants—the consensus mechanism. Different types of consensus mechanism may be employed (Lashkari & Musilek, 2021). Together, these characteristics give the Blockchain one of its defining properties—immutability, i.e., the distributed ledger provides a digital trace that is tamper-proof and almost impossible to change. The validation mechanism, governance model, and the degree of accessibility afforded to network participants distinguish different types of Blockchain network. These range from public or open chains, in which any participant can write to the Blockchain, to private or permissioned chains for which access and/or visibility may be limited, depending on the governance mechanisms adopted (Farah, 2018).

Why should Blockchain be relevant for supply chain management? Supply chains comprise a network of independent organizations. Information relating to operations, transactions, and movements along the supply chain is typically fragmented, dispersed, and stored on a myriad of systems with limited access, verifiability, or visibility. Such dispersed digital records may be lost, destroyed, or insecure. Blockchain provides a digital ledger that is immutable, essentially promising a single source of truth for a supply chain. A block may contain information on supply chain products, processes, operations, and transactions. Each block is time-stamped and may contain geolocation information. Such an immutable and verifiable digital record has many potential supply chain applications, including provenance (where has this product come from?), traceability (where has it been?), authenticity (is it a genuine product?), and sustainability (has the product been produced in an appropriate way in conformance with acceptable standards?).

Blockchain is a very active area for supply chain research and practice (Treiblmaier et al., 2022) with the formation of many industrial consortia (Ahmed & MacCarthy, 2022) and prominent commercial platforms reporting interesting and exciting applications (Everledger, 2022; Ahmed & MacCarthy, 2021). Having an immutable digital record should engender trust in the supply chain (Wamba & Queiroz, 2020). Notwithstanding its potential benefits, there are significant challenges in deploying Blockchain in supply chains. These include getting agreement across a wide network of participants on its use, deciding the network type and governance model, the level of transaction granularity needed, as well as systems integration, interoperability, and scalability challenges. Ultimately, to guarantee that the Blockchain provides a trustworthy record of physical operations is an emerging supply chain collaboration challenge (Lacity & Van Hoek, 2021).

3.4.2 Digital Twins

Many computer applications utilize digital models of physical objects, processes, and systems to simulate behavior. Computer simulation has been an important technology for practitioners in operations and supply chain management (Banks et al., 2013), particularly for facility design and layouts, and supply chain design. Simulation allows us to ask, explore, and potentially answer "what if" questions. However, Digital Twins promise more than conventional digital models and computer simulations.

Originally proposed by NASA (Glaessgen & Stargel, 2012), the concept has broadened to describe digital systems that capture the characteristics of a physical system and record its current state digitally with strong bidirectional coupling between the physical system and its digital representation in real-time (Kritzinger et al., 2018; Liu et al., 2021). A Digital Twin is enabled by technologies that connect and transmit information (e.g., sensors and wireless technologies) and may be supported by technologies that enable modeling, exploration, visualization, and optimization in a virtual space (Liu et al., 2021). The current prominence of the concept marks the confluence of a number of technologies that provide what Accenture has described as a "mirrored world" with applications in many domains (Accenture, 2021).

Digital Twins expand the range of applications for simulation and exploration, providing a safe experimental space to answer "what if" questions, make decisions, or obtain insights about a real system. The range of potential applications in the supply chain includes systems evaluation and optimization, managing and maintaining dispersed physical assets, training and education, and strategizing about systems design and operation (Fuller et al., 2020; Liu et al., 2021). The virtual factory, captured as a Digital Twin, is a vision for many manufacturers (GE, 2017). Digital Twins may enable future Supply Chain Control Towers, providing real-time support to enhance supply chain resilience (Ivanov et al., 2019).

Much of the technology exists in isolation at different levels of granularity. Digital Twins have strong links with IoT for the provision of data and 5G for real-time remote viewing (see below). Still, major challenges exist in determining the nature of the links between the real system and its Digital Twin, how information is acquired, and what information flows between them (Uhlemann et al., 2017; van der Valk et al., 2021). The development and applications of Digital Twins may become context-specific, seeking to answer the business and management questions typically posed in a particular environment (van der Valk et al., 2021).

3.4.3 The Internet of Things (IoT)

The IoT may be viewed from different perspectives (Tran-Dang et al., 2020). In its broadest sense, it refers to a networked connection of smart objects. Connected objects bring a physical dimension to the Internet and have origins in the older technology of RFID (Birkel & Hartmann, 2019). The objects or things can be devices, machines, or infrastructure including elements of buildings, people, or some combination, each of which has a unique identifier and the ability to connect with, and transmit data over a network. Harvesting data from a collection of smart objects may allow greater visibility and monitoring, enabling more effective control and optimization at a network level than if smart objects operated independently. In managing a facility, such a localized IoT network has significant attractions. IoT is closely related to Digital Twins as the technology enabling the twin may be IoT based. When IoT relates to logistics systems, the term Physical Internet is often used (Tran-Dang et al., 2020).

At a supply chain level, IoT refers to a connected network of "things" extending beyond the confines of a single organization. Ben-Daya et al. (2019, p. 4721) define IoT in a supply chain context as "a network of physical objects that are digitally connected to sense, monitor and interact within a company and between the company and its supply chain, enabling agility, visibility, tracking and information sharing to facilitate timely planning, control and coordination of the supply chain processes." Some of the potential applications of deploying IoT within and across supply chains include predictive maintenance and condition monitoring (Compare et al., 2019), effective management of cold chain logistics (Tsang et al., 2018), managing energy consumption (Mawson & Hughes, 2019), and addressing sustainability issues (Nižetić et al., 2020).

However, the challenges and risks in IoT can be significant for enterprises (Lee & Lee, 2015; Tuptuk & Hailes, 2018) and these become more acute at a supply chain level in managing and coordinating many digitally connected 'things'. Birkel and Hartmann (2019) discuss issues related to costs and economics, privacy, security, and trust, lack of technical standards on interoperability and compatibility, and lack of regulation. Although, the enabling technologies, technical architectures, protocols, and platforms to support IoT continue to develop, and may be enhanced through 5G technology, achieving agreement to implement and deploy IoT across a supply chain poses significant collaboration challenges between participants in a supply chain ecosystem.

3.4.4 5G, Edge, and Fog Computing

5G wireless digital communication promises dramatic enhancements in terms of data transmission speeds, reduced delay (low latency), and high reliability, along with many other potential benefits (Rao & Prasad, 2018; Taboada & Shee, 2021). As an enabling technology that allows more information to be transmitted at a much faster rate than current 4G technology, 5G can affect many aspects of supply chain operations at every level of granularity. 5G may enable more effective IoT networks within factories, enable high-fidelity remote viewing in real time of production activities conducted deep in a supply network (Rao & Prasad, 2018; Taboada & Shee, 2021), and support Virtual and Augmented Reality (Ericsson, 2020). 5G also has strong relevance in streaming of products and processes to consumers, which may influence demand (Taboada & Shee, 2021; Wongkitrungrueng & Assarut, 2020). Dolgui and Ivanov (2022) discuss the potential impact in terms of supply chain intelligence, visibility, transparency, dynamic networking, and connectivity. Its benefits can be expected to multiply as 5G standards and platforms develop and as global coverage increases and becomes the norm in the next decade.

In contrast to Cloud computing, Edge computing distributes and deploys some computing, data processing, and computational resources close to user devices and sensors, reducing the amount of data sent to the cloud. Fog computing refers to combining Edge resources and the Cloud (Hong & Varghese, 2019). Well-architected Edge and Fog computing may have advantages in terms of increased speed, latency reduction, reduced power consumption, and greater operational flexibility (Hong & Varghese, 2019; Lin et al., 2019). Edge and Fog architectures may find applications in supply chain operations to capture local production operations automatically such as in guaranteeing organic food produce to engender consumer trust (Hu et al., 2021).

4. Defining the Digital Supply Chain

Most organizations have some digital capabilities. Many have acquired numerous systems, technologies, and platforms to support business functions over a period of time—their legacy IT estate (Charette, 2020). In one sense, they may be digitally rich. Some organizations use systems and data well to enable their supply chain operations but may not be aware of the opportunities for greater exploitation of digital technologies or data to enhance supply chain operations and derive competitive advantage. We take an intentionally broad view, acknowledging that the contemporary digital landscape is diverse. We describe a spectrum of digitalized supply chains and then provide definitions for both a narrow and broad view of the future Digital Supply Chain.

In considering the digitalization spectrum, we note (1) the degree of connectivity across the principal actors in the supply chain, and (2) the depth of penetration and deployment of interoperable digital technologies within the operations of the principal actors. The focus is on primary supply chain performance metrics—time compression, productivity enhancement, cost reduction, and high customer service levels—although wider competitive benefits may accrue from the possession of strong digitally enabled processes, including traceability and sustainability. We describe three scenarios.

1. **The digitally immature supply chain**: The principal supply chain players utilize conventional technologies and systems to support business processes and supply chain transactions and interactions. Typically, organizations in the supply chain will deploy conventional IT systems to support design, manufacture, and business operations but with limited interoperability between systems within their internal operations. The degree of connectivity across the supply chain is limited to conventional IT-supported communication with immediate suppliers and customers. Neither the supply chain nor the organizations within it actively seek to exploit data-driven opportunities to achieve higher levels of operational performance or greater supply chain control to improve timeliness, productivity, and service levels, or to reduce costs. Thus, the supply chain is digitally immature and underdeveloped.
   This describes many contemporary supply chains. Organizations use conventional ERP technologies to plan and manage operations and inventory, and utilize conventional WMSs that optimize picking sequences for human pickers based on incoming orders. Supplier audit teams extract information periodically from ERP systems to evaluate supplier performance and may take action based on human judgment when poorly performing suppliers are identified. Such organizations demonstrate a lack of awareness of opportunities to further exploit data or deploy Business Analytics. They fail to realize the opportunities for greater systems interoperability internally, or the benefits that could accrue from deeper and more extensive digital integration with suppliers and customers.

2. **The digitally enabled supply chain:** The principal actors in the supply chain demonstrate strong digital connectivity aimed at achieving agreed customer service goals for the supply chain. Organizations within the supply chain have some interoperable digital technologies within their operations and have relevant automation supporting high productivity operations. However, at a supply chain level, the primary actors do not seek to exploit all opportunities for time

compression, productivity enhancement, and cost reduction that could be derived from fully integrated digital operations and do not appreciate the wider benefits that may derive from stronger digital integration across the supply chain. This describes many contemporary customer-focused supply chains. Examples include organizations using advanced tools to optimize operations and inventory planning at a supply chain level in collaboration with customers and/or suppliers, on top of conventional ERP technologies. Advanced WMSs may be deployed that optimize location placement and picking sequences based on current demand but also analyze projected supply and demand scenarios to prepare for future warehouse use. Suppliers may be audited using Business Intelligence tools to identify poor performance, alerting human decision makers on a need for action. Organizations may seek incremental opportunities to exploit data, systems, and interoperability internally. When a need is identified to improve performance, they may seek more effective digital integration. Thus, they may invest in P2P technology to automate routine purchasing processes or invest in systems to optimize maintenance management.

3. **The digitally transformed supply chain:** The principal actors in the supply chain demonstrate strong digital connectivity aimed at achieving all service-level goals. Supply chain processes have been (re)-designed and (re)-engineered through digitalization and flexible automation, removing unnecessary activities and processes. Key supply chain processes are digitally driven, allowing visibility and traceability to deal with problematic issues at source. Where possible, supply chain processes are executed autonomously. The principal supply chain actors seek every opportunity to exploit and deploy technology to make step changes in performance and to adjust to changes in demand. Gains in time compression, productivity and service levels, and reductions in cost are derived from exploiting strong digital connectivity at every level across the operations of all the principal supply chain actors. Organizations within the supply chain show penetration in depth of interoperable digital technologies. Effective utilization of data across the digital ecosystem enables supply chain participants to offer a wide range of services and support to customers without step changes in costs.

   Organizations within digitally transformed supply chains may augment conventional forecasting techniques with wider market intelligence and Consumer Analytics to anticipate demand changes, allowing inventory to be positioned and deployed more effectively. Warehouse capabilities are fully automated, obviating the need for human pickers, allowing "lights out" operations. Supplier performance monitoring is conducted in real time, alerting suppliers on their performance and automatically invoking penalty clauses if agreed targets are not met. The rich data ecosystem enables tailored services to be implemented for specific customers, for instance, by offering prioritized delivery within a narrow time window. Organizations may invest in Source-to-Pay (S2P) technology, not only automating routine purchasing processes but also allowing intelligent and dynamic supplier categorization and assisting in finding new suppliers. The supply chain data ecosystem allows digital surveillance of the supply network and its wider context, providing intelligence and alerts on potential risks and vulnerabilities.

The spectrum captures the transformative effects of combining technologies, systems, and platforms to gain supply chain performance benefits. It highlights the centricity of data (McKinsey Insights, 2021) in reengineering processes horizontally across supply chain organisations and vertically within organizations to support and operationalize effective, customer-focused business processes. All pervasive digitalization provides a digital core that can act as a supply chain ecosystem, exploited and leveraged for competitive advantage. Against this backdrop, we offer a narrow and a broad view to define a future vision of the Digital Supply Chain. We illustrate the spectrum of digitalized supply chains and the Digital Supply Chain transformation journey in Fig. 1.3.

Narrow view: A Digital Supply Chain is a cyber-network of end-to-end visibility representing a physical supply chain with associated operational data and performance assessments.

Broad view: A Digital Supply Chain is a cyber-physical network of digitally connected, coordinated, and integrated organizations, technological equipment, and data-driven algorithms, with dynamically adaptable material, information, and financial flows, capable of reacting in real time to changes in demand and supply through rapid rearrangement and reallocation of its components and capabilities.

5. Many opportunities, many challenges

"Everything that can be digitized will be digitized"—prophetic words from Angela Merkel in 2015 (AEB, 2015), indicating that no sector or business process is immune from the impact of digitalization. The spectrum outlined above points to an agenda for change to transform supply chains. Digitalization offers opportunities for rearchitecting and reengineering supply chains at every value-adding stage, at every critical supply chain interface, and at every level of operational granularity. Organizations will need to consider their digital maturity on the spectrum, judging their capabilities against

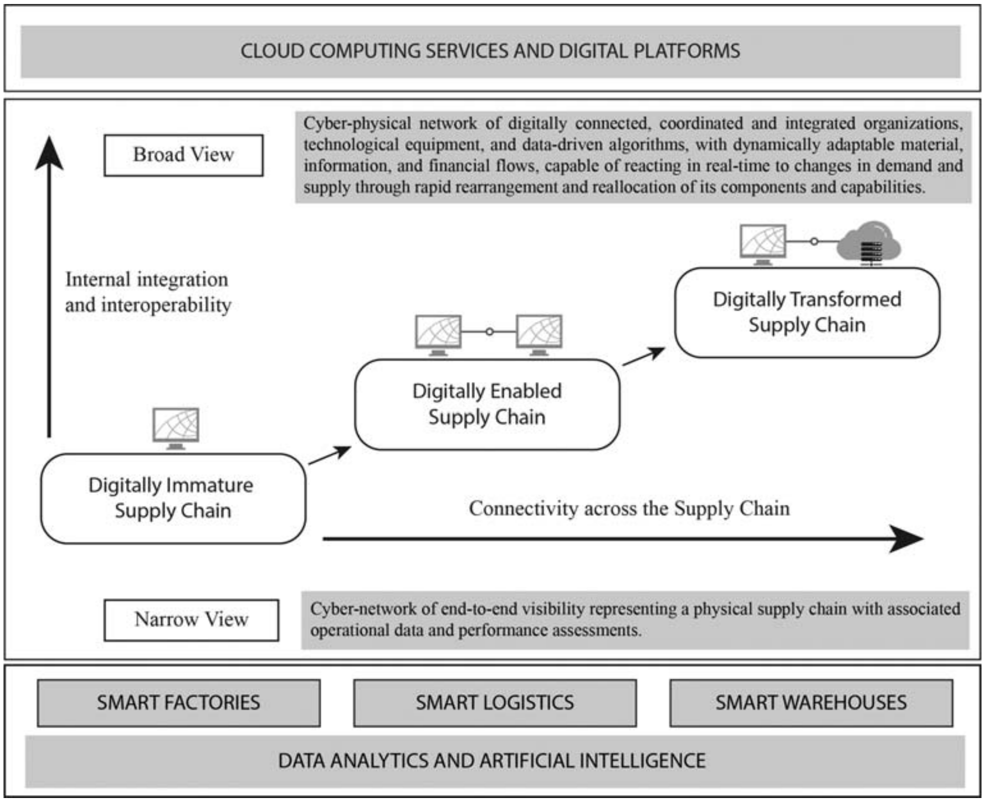

FIGURE 1.3 A spectrum of digitally supported supply chains.

industry peers. In considering supply chain digitalization strategies, organizations need to evaluate digital systems, technologies, and tools carefully, but this should not obscure the potential to develop "smarter" operations that enable better, faster, and more effective operating models.

Opportunities exist to use data more effectively, e.g., utilizing Data Science internally for Six Sigma investigations (Zwetsloot et al., 2018) or for demand sensing using external data sources (Gilliland et al., 2021). The digital ecosystems within which supply chains operate offer new ways of conducting business and potentially new business models. For instance, Blockchain has the potential to provide a verifiable digital trace across an entire global supply chain with strategic implications for supply chain management (Lacity & Van Hoek, 2021). The emergence of "Everything-as-a-Service" (Chimakurthi, 2021) will encompass many Cloud-based supply chain processes as services (Ivanov et al., 2022).

However, we fully acknowledge the myriad challenges in fusing the physical and the digital worlds across diverse supply chain contexts. Transformation journeys are never simple, particularly in a rapidly developing technology landscape where organizations are unsure about technology maturity, impact, or proven use cases. As noted in Section 3, the use of the Cloud is already strongly developed, while other technologies such as the IoT or Digital Twins show promise but are less well developed in terms of the availability of commercial systems, standards, and regulation. How best to harness, implement, and deploy digital technologies in supply chain operations, individually and in combination, is an emerging story.

Industries differ in terms of supply chain configuration, complexity, volume, and variety, presenting different opportunities, challenges, and constraints in digitalizing key stages of supply. The when, where, who, and how questions relating to effective Digital Supply Chain deployment are many. The sheer complexity of many supply chains and the dearth of knowledge on deeper sub-tier supply networks are significant problems. In a relatively simple consumer-product supply chain, primary actors include raw material suppliers, product manufacturers, packaging manufacturers, logistics companies, retailers, and customers. Secondary actors may include product designers, marketers, IT providers, maintenance service providers, financers, and regulators. Each may have legitimate interests in some or all aspects of supply chain operations. Additionally, many physical assets are used across a supply chain—machines that produce products, and the facilities used to store and transport them. The potential for data generation across supply chains is vast, raising many questions about what data can and should be captured—how, why, and by whom. Equally important is identifying the supply chain processes that have the most potential for virtualization (Overby, 2012).

All of these factors underscore that supply chain digitalization initiatives require clear strategic thinking. Organizations need to be cognizant of relationships, responsibilities, ownership, and connectivity between supply chain entities, as well as their geographical spread. The wider societal and sustainability context must be considered as supply chains are at the center of many sustainability challenges. The transition to sustainable supply chains has been described as a "wicked" problem in the sense of complexity and degree of difficulty (Pyykkö et al., 2021). Digital technologies must and do have a part to play in supporting and guaranteeing sustainable operations (McGrath et al., 2021).

Finally, the early visions of Computer-Integrated Manufacturing and to some extent I4.0 missed the critical roles played by people, human knowledge, and expertise. It is clear that future supply chains must address the role of people and the broader role of industry and supply chains in society. Digitalization undoubtedly affects employment and the number and types of jobs that will exist in the future. The central role of people is now being recognized in Industry 5.0, promoted by the European Union, stressing the importance of addressing human–technology interaction as well as the role of technology in society more generally (Breque et al., 2021).

6. Outline of book contents

The remaining chapters of the book develop, expand, and critically analyze all of the themes discussed in this chapter.

In the second part of the book, Chapters 2 to 8 describe, analyze, and critically appraise the digital building blocks and enabling technologies for the digital supply chain. Mourtzis, Angelopoulos, and Panopoulos (Chapter 2) chart the evolution of digital manufacturing from the early applications of computers to today's digitally rich Smart Manufacturing ecosystems. Winkelhaus and Grosse (Chapter 3) apply a sociotechnical lens to understand and analyze the combination of human and technology components needed in contemporary Smart Warehousing systems. Baziyad, Kayvanfar, and Kinra (Chapter 4) examine the emerging IoT paradigm and its supporting technologies that have the potential to facilitate smart manufacturing and enable future Digital Supply Chains. Zhang, MacCarthy, and Ivanov (Chapter 5) review key computing advances that underpin and enable the Digital Supply Chain and have the potential to transform future supply chains, namely, the Cloud, Platforms, and Digital Twins. Brusset, La Torre, and Broekaert (Chapter 6) introduce the computational approaches, algorithms, Analytics, and AI that can be harnessed to underpin data-driven supply chain decision-making. Pettit, Wang, and Beresford (Chapter 7) trace the impact of digitalization on the logistics sector and discuss how digitally enabled logistics can improve supply chain transparency, operational efficiency, and responsiveness. Treiblmaier, Rejeb, and Ahmed (Chapter 8) review the drivers, inhibitors, and industrial applications of one of the most iconic digital technologies that is set to influence the management and control of future supply chains—the Blockchain.

The third part of the book, Chapters 9 to 13, addresses opportunities and challenges in the management of the Digital Supply Chain. Spanaki, Karafili, and Despoudi (Chapter 9) discuss the significant challenges in ensuring data quality and achieving effective data governance in the shared data architectures that accompany the digitalization of the supply chain. Chan (Chapter 10) considers one of the dominant supply chain management challenges—traceability—and discusses how to design robust systems to ensure products can be tracked and traced across the supply chain. Cox (Chapter 11) examines the evolution of digital support for both routine and strategic aspects of purchasing and procurement, one of the most critical supply chain management functions. Jha, Verma, and Bose (Chapter 12) use an information processing perspective to examine opportunities and approaches for measuring and managing performance in the Digital Supply Chain. Cha (Chapter13) reviews the state of knowledge on Supply Chain Cyber Security from both practitioner and academic perspectives, providing guidance for detection and defense against the many potential vulnerabilities at the interface of the digital and physical worlds.

Many chapters throughout the book provide detailed examples of practice. Part 4, encompassing Chapters 14 to 20, examines digitalization of the supply chain in six important business and industrial sectors. Zhang and Hänninen (Chapter 14) focus on retailing, examining how digitalization has affected strategy, front-end retail operations and fulfilment systems, and the back-end logistics supporting omnichannel retailing. Pal and Jayarathne (Chapter 15) examine the impact of digitalization in the globally dispersed textiles and clothing industry, covering the product lifecycle from design through manufacturing, retailing, and the circular economy. Sgarbossa, Romsdal, Oluyisola, and Strandhagen (Chapter 16) look at the impact and challenges of digitalization on production and warehousing in food supply chains through live cases. Fabbe-Costes and Lechaptois (Chapter 17) look at the automotive sector, a critical industry in the global economy undergoing disruptive change, and examine the evolving history of digitalization by tracing the "digital journey" of a major car manufacturer. Ahmed and Rios (Chapter 18) critically assess one of the most prominent current Blockchain-based logistics platforms developed by a major shipping organization and a major IT provider for shipping documentation and examine its effects on the international shipping ecosystem. Benitez, Ayala, and Frank (Chapter 19) examine the opportunities for SMEs to develop their digital capabilities through engagement with technology providers on I4.0 initiatives using extensive case evidence from Brazil.

The final part of the book, Chapters 20 to 24, presents studies at the frontiers of research in the analysis, design, and management of the Digital Supply Chain. Demirel (Chapter 20) discusses the application of network science to analyze the structure and dynamics of supply chains and surveys the state of knowledge on data sources, methods, and results. Liotine (Chapter 21) analyzes the computational challenges of scaling a Blockchain solution for product traceability in the pharmaceutical industry, proposing solutions for tracking exceptional transactions. Brintrup, Kosasih, MacCarthy, and Demirel (Chapter 22) examine both the opportunities and challenges in conducting digital surveillance of supply networks, presenting digital surveillance frameworks that can utilze and apply AI methods and algorithms. Beltagui, Nunes, and Gold (Chapter 23) consider the sustainability of digitally enabled supply chains, showing where digitalization can be beneficial but also noting the potential for negative consequences in the context of two contrasting supply chains—electric vehicles and the beef industry. In the final chapter, Lambourdiere, Corbin, and Verny (Chapter 24) examine what digitalization means for supply chain strategy, arguing for a dynamic capabilities perspective to achieve digital ambidexterity to enhance value creation in supply chains and drive competitive advantage.

The digitalization of business, commerce, and industry means transformative and disruptive changes that will affect supply chains in diverse ways. The studies reported in this book provide insights and analysis on the impact of digitalization across different supply chain landscapes in many sectors, citing the latest and most seminal work throughout. The book provides the essential groundwork for further exploration, analysis, and evaluation of the Digital Supply Chain by researchers and practitioners.

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Part II

Digital building blocks and enabling technologies

Chapter 2

Digital Manufacturing: the evolution of traditional manufacturing toward an automated and interoperable Smart Manufacturing Ecosystem

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Abstract

Manufacturing systems have undergone many changes with regard to their structure, organization, and operation. This chapter charts the technical developments in manufacturing systems over the last 70 years. The basic building blocks of Computer-Aided Manufacturing and their evolution to Computer-Integrated Manufacturing systems are discussed. We describe today's Smart Manufacturing paradigm, which is central to Industry 4.0. We identify the key components of the Smart Factory and highlight its technical challenges through the presentation and discussion of frameworks and architectures. In order to create smart factories capable of autonomous optimization of interconnected processes, disparate computer and communication systems have to operate with many machines, devices, and manufacturing infrastructure, requiring the development of advanced protocols and standards. Interoperability is a major challenge that needs continued research to achieve the integration of many devices in industrial environments and to develop global standards. The harnessing and use of data to create Digital Twins of manufacturing systems shows great promise in diverse applications, including for predictive maintenance. The whole of the product lifecycle from design through to manufacture and use can now be captured digitally in Product Lifecycle Management systems. The vision of interoperable, smart manufacturing ecosystems is slowly becoming a reality.

Keywords: Cloud-based systems; Computer-integrated manufacturing; Digitalization; Industrial Internet of things; Industry 4.0; Interoperability.

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1. Introduction—the evolution of production paradigms

Manufacturing industry has evolved over history through various production paradigms. The manufacturing paradigm shifts and the drivers of change are illustrated conceptually in Fig. 2.1 (Hu et al., 2011; Koren, 2013; Lu, Liu, et al., 2020; Mourtzis, 2016). The first paradigm—craft production—created the product requested by the customer but at a high cost (Chryssolouris, 2006). Through a number of shifts, contemporary manufacturing has evolved to focus on delivering customer solutions and offering product variety that is relevant in the marketplace, efficiently and cost-effectively. Flexible and reconfigurable production systems are needed to create variety tailored to customer needs in final products (Tolio et al., 2010).

Customers in many market segments are requesting unique products tailored to their individual tastes. Thus, manufacturers are seeking for intelligent strategies to transform their infrastructure and resources to accommodate customer and market demands with relevant product variety in an attempt to maintain their competitive edge in a changing market landscape (MacCarthy, 2013; Wan & Sanders, 2017). In the Mass Customization paradigm, a producer must consider end users as integrated entities in the product design and development cycle instead of treating them merely as product buyers.

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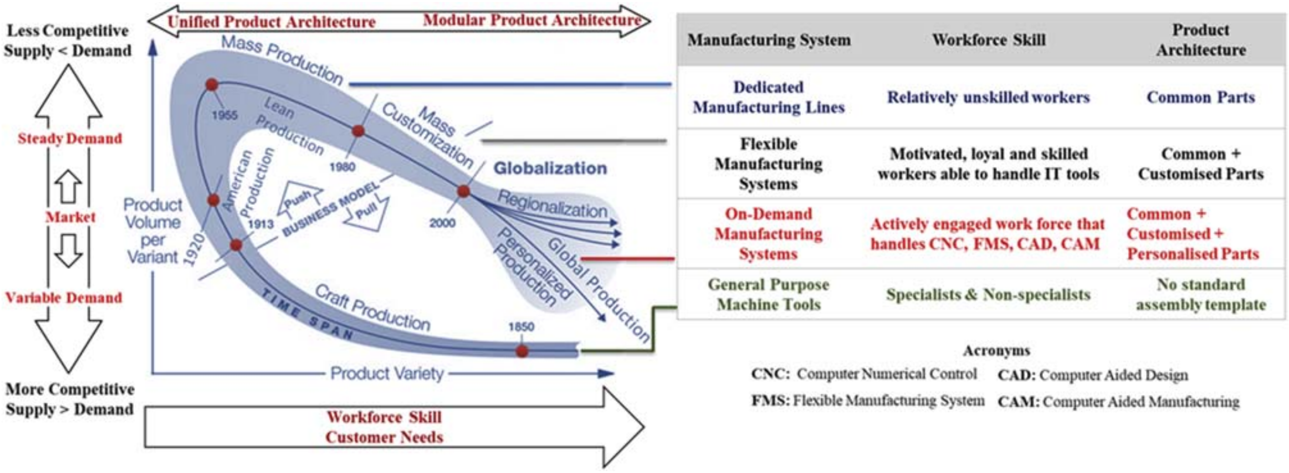
Globalized markets offer opportunities to expand a company's sphere of influence by broadening its customer base and production capacity (Mourtzis, 2016). Additionally, the personalization production paradigm aims to value differentiation where the customer is involved in the design phase of the product. It is characterized by on demand manufacturing systems in which the product structure has common as well as customized or personalized parts (Hu et al., 2011). However, companies must also seek to produce more with less (i.e., maximize output while reducing material use and environmental footprint) while offering relevant product variety in dynamic and uncertain environments (Chryssolouris et al., 2008). Manufacturing systems have continued to evolve to cope with these pressures with the emergence of today's smart factories (Petit et al., 2019) and smart manufacturing concepts (Lu, Xu, & Wang, 2020).

In this chapter, we trace the technical developments in manufacturing systems that have occurred over the last 70 years. We first outline the basic building blocks of Computer-Aided Manufacturing (CAM) and their evolution to become Computer-Integrated Manufacturing (CIM) systems that have led to today's concept of Smart Manufacturing. In Section 2, we discuss one of the biggest challenges in moving towards smart manufacturing—interoperability. This is a challenge between and across different technologies and systems. In Section 3, we discuss generic approaches to implement interoperability in Smart Manufacturing Ecosystems. In Section 4, we briefly discuss Digital Twins in manufacturing and their use in predictive maintenance. In Section 5, a brief overview of technologies that will affect future manufacturing is given, specifically concerning Product Lifecycle Management (PLM) systems and the emergence of 5G communication technologies. Finally, in Section 6, conclusions are drawn and aspects for future research are highlighted. The manufacturing systems domain uses many acronyms—we provide a glossary for those we use at the end of this chapter.

1.1 From Computer-Aided Manufacturing (CAM) to Computer-Integrated Manufacturing (CIM)

CAM uses computer systems to plan, manage, and control manufacturing operations through either a direct or indirect computer interface with the manufacturing resources of the plant (Lazoglu, 2009). The first *numerically controlled* (NC) machines emerged almost 70 years ago. The standards for programming of NC machine tools have remained fundamentally the same since the first NC machine was developed at M.I.T. (Massachusetts Institute of Technology) in the early 1950s. To machine parts with complex shapes in a precise manner, both early NC machines and current CNC (*computer numerical control*) machines use the same standard approach but today's programming interfaces are much more developed (Yusof & Latif, 2015). From the early 1980s, CNC vendors began to develop programming extensions together with 2D *manual data interface* programming capabilities. CNC technology has had a radical effect on the growth of manufacturing across the globe. CNC machine builders have constructed their proprietary versions and brands of controllers based on *programmable logic controllers* and hardware and software designs in parallel with these machine tool and process developments (ISO6983-1, 1982).

Computer-Aided Design (CAD) has developed in parallel with CAM. CAD uses computer systems to create, modify, analyze, and optimize a design. Contemporary CAD frameworks allow intelligent and collaborative design protocols and



Manufacturing System	Workforce Skill	Product Architecture
Dedicated Manufacturing Lines	Relatively unskilled workers	Common Parts
Flexible Manufacturing Systems	Motivated, loyal and skilled workers able to handle IT tools	Common + Customised Parts
On-Demand Manufacturing Systems	Actively engaged work force that handles CNC, FMS, CAD, CAM	Common + Customised + Personalised Parts
General Purpose Machine Tools	Specialists & Non-specialists	No standard assembly template

Acronyms

CNC: Computer Numerical Control

CAD: Computer Aided Design

FMS: Flexible Manufacturing System

CAM: Computer Aided Manufacturing

FIGURE 2.1 Manufacturing Paradigm Shifts and Drivers and differences between PP. *Source: Adapted from Lu, U., Xu, X., & Wang, L. (2020). Smart manufacturing process and system automation – a critical review of the standards and envisioned scenarios. Journal of Manufacturing Systems, 56, 312–325. https://doi.org/10.1016/j.jmsy.2020.06.010.*

records of the design history (Lee et al., 2010). Simulation facilitates the design of systems with the highest probability of satisfying functional requirements (Melvin & Suh, 2002). *Computer-Aided Process Planning* (CAPP) has been a difficult stage in the evolution of integrated CAD-CAM systems. CAPP is a computer application that assists planners in optimally planning the sequence of manufacturing processes. It includes the determination of processes and parameters needed to produce a finished part or product (Yusof & Latif, 2014). The state-of-the-art methodologies for developing systems for integrated assembly simulation, planning, and training from CAD models are described extensively by Leu et al. (2013). Today's commercial CAM suites offer complete integrated PLM solutions (see Section 4.0) to manage multiple stages of production, including conceptualization, design (CAD), manufacturing (CAM), and engineering (CAE).

A further step in development occurred in the late 1980s with the emergence of *Flexible Manufacturing Systems* that have added built-in flexibility to CNC machines for a wide range of discrete-part manufacturing (Feng et al., 2001). The most noticeable effect of CNC machining is a significant increase in production speed, saving employee hours through computerization and preprogrammed actions. During the manufacturing process, human operators are not required, the overall speed of the operation increases, and machines can work 365 days per year (Johnson, 2021). Recent industrial and research approaches in key manufacturing fields, as well as significant historical milestones in the evolution of manufacturing systems simulation technologies are summarized by Mourtzis (2020c).

It is apparent that computers are essential in all of the above-mentioned systems. This led to the concept of using computer technology as the integrating element for a factory with the emergence of CIM systems from the late 1980s. CIM has been defined as the application of computer science technology to the manufacturing enterprise in order to deliver the right information to the right place at the right time, allowing the company to achieve its product, process, and business objectives (Yu et al., 2015). CIM can be considered as comprising three aspects: manufacturing equipment automation, full systems integration, and production planning and control. CIM incorporates all of CAD, CAPP, and CAM functions noted above, as well as the business functions of the company that are related to manufacturing. Starting with order receipt and continuing through design and production to product delivery, a CIM system applies computer and communication technologies to all operational and information processing functions (see Fig. 2.2).

The *Computer-Integrated production system* can be considered as a predecessor of what is known as the "lights-out factory," which refers to highly automated manufacturing environments that can operate entirely independently without human input. Consequently, CIM represents a transition from a human-driven/operated manufacturing plant to a fully digitized/automated manufacturing plant working independently. CIM concepts have laid the basis for Smart Manufacturing Systems (SMS) and the emergence of the Smart Factory.

1.2 Industry 4.0 and the emergence of Smart Manufacturing Systems

By virtue of the technological advances in Information and Communication Technologies (ICT), the fourth industrial revolution has emerged (Rüßmann et al., 2015). The core activities of the current industrial revolution are focused on the complete digitization (Kagermann, 2015) and digitalization (Jakobides et al., 2016) of modern manufacturing systems and networks. In addition, engineers and data scientists are constantly developing innovative solutions and frameworks to utilize the vast amounts of data that may be generated every day in production environments (Mittal et al., 2018). Ultimately, the scope of these frameworks is to enable predictability of manufacturing system status (Fatorachian & Kazemi, 2018), provide meaningful insights as regards the volatility of market demand (Lasi et al., 2014), as well as the provision of "Smart" decision-support tools (Cimini et al., 2019; Frank et al., 2019; Neugebauer et al., 2016). This, practically, forms the new "Smart Manufacturing" paradigm (Kang et al., 2016). The fusion of the advanced digitalization offered by the technologies and the techniques of Industry 4.0 promote the upscaling of current factories to the Smart Factories of the future (Chu et al., 2016).

The vision of the "Smart Factory" is a flexible system that can self-optimize performance across a broader production network, self-adapt to, and learn from new conditions in real or near-real time, and can run entire production processes autonomously (Hozdic, 2015; Chen et al., 2017). However, although there are many exciting developments, the concept of smart factories is in early stages. The three-key enabling digital technologies of a smart factory are (Burke et al., 2017; Sjödin et al., 2018)

- Intelligent automation (e.g., advanced robotics, machine vision, distributed control, drones)
- Extensive connectivity (using the Industrial Internet of Things (IIoT) to collect data from existing equipment and new sensors)
- Data management and Analytics on a large scale in the cloud (e.g., implementing predictive Analytics/AI)

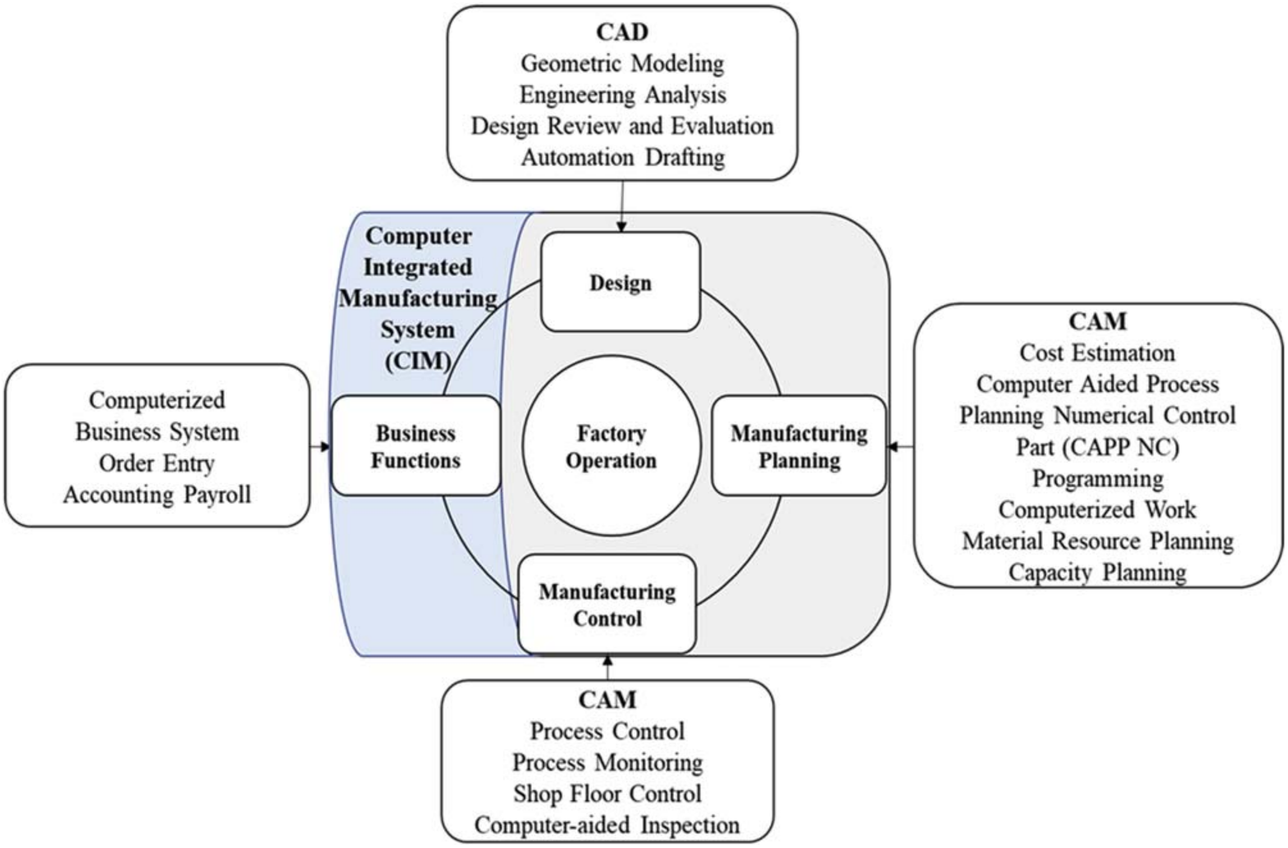


FIGURE 2.2 The role of CAD/CAM in CIM.

Digital technologies are beginning to allow Information Technologies and Operational Technology to converge for end-to-end digital continuity in manufacturing from design to operations. The distinguishing feature of a smart factory is the "closed loop," data-driven optimization of end-to-end operations. Advanced Analytics are initially used for decision support, but the goal is to achieve "self-optimizing operations," in which the factory adapts to demand and supply variations and adapts to process deviations on a continuous basis (Petit et al., 2019). The concept of the Smart Factory is not limited by the physical limits or walls of the factory. Instead, it envisions interconnectivity across a wider production network, which may be globally distributed. By extension, it is highly dependent on other factories connected to the network.

Many of the CIM concepts noted above underpin today's Smart Manufacturing. CIM is used to define the full automation of a manufacturing plant, with all processes operating under computer control and digital information connecting them together (Cheng et al., 2018; Lu et al., 2016, p. 8107). Fig. 2.3 illustrates the Smart Factory concept. In order to achieve the full automation of manufacturing plants, CIM functionalities need to be extended to cover a broader spectrum of manufacturing planning, operations, and control activities.

Historically, manufacturing has always been enabled by the advancement of technology from steam engines to electricity, microprocessors, computers, robotics, and more recently, Cyber-Physical structures, the Internet of Things (IoT), and Artificial Intelligence (AI). The synergistic impact of the emerging technologies and the volatile market needs has led to the development of new production systems and enablers. These are characterized by (1) digitalization and the incorporation of manufacturing tools on cloud-based platforms as adaptive, secure, and on-demand services, and (2) smart and connected objects capable of real-time and autonomous decision-making through embedded electronics and analytical/cognitive capabilities (Moghaddam et al., 2018).

To realize the vision of a data-driven, connected supply network, smart manufacturing combines various concepts and technologies (ElMaraghy et al., 2021). Examples of recent concepts and technologies include smart manufacturing (Lu, Xu, & Wang, 2020), cyber-physical production systems (CPSs) (Li et al., 2018; Mourtzis, Siatras, et al., 2020; Mourtzis & Vlachou, 2018), Industry 4.0 (Mourtzis, Fotia, et al., 2018), cloud production (Xu, 2012; Zhong et al., 2017), and

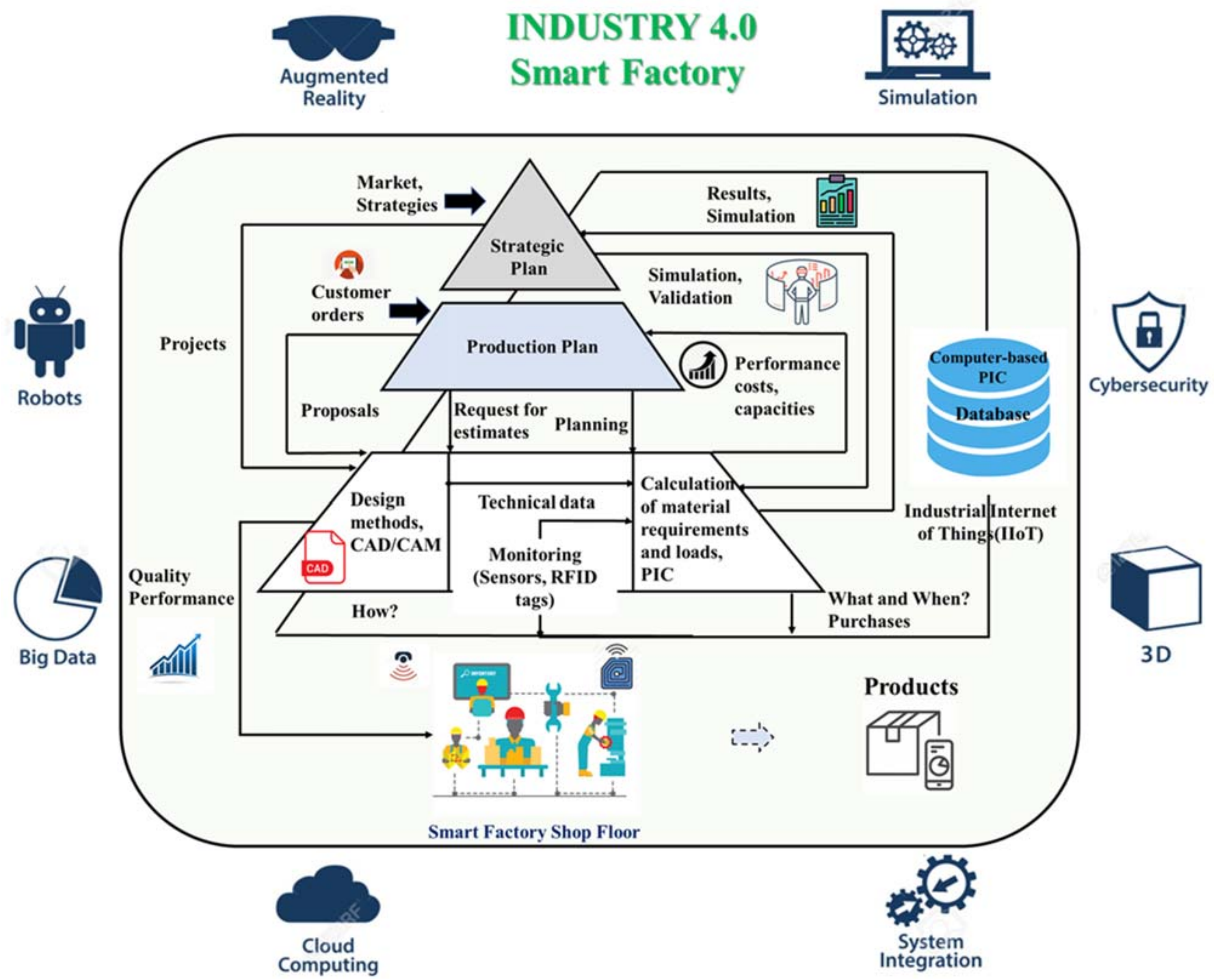


FIGURE 2.3 Computer-Integrated Manufacturing (CIM) and production control system in a Smart Factory.

Simulation and Digital Twins (Mourtzis, 2020b; Thoben et al., 2017). Kusiak (2018) notes that the essence of smart manufacturing is captured in six pillars—manufacturing technology and processes, materials, data, predictive engineering, sustainability and resource sharing, and networking. The cost, delivery, flexibility, and quality capabilities of a manufacturer determine its long-term competitiveness. SMS aim to maximize these capabilities by incorporating advanced technologies that encourage the rapid flow and widespread use of digital data within and between manufacturing systems. SMS is enabling manufacturers to achieve high levels of production agility, quality, and efficiency, boosting their long-term competitiveness. SMS use ICT as well as intelligent software applications (Lu et al., 2016, p. 8107) to

1. Optimize labor, material, and energy use to produce customized, high-quality products on time
2. Quickly respond to shifts in market demand and supply chains.

Several industry studies have highlighted the cost and revenue advantages of digitization in manufacturing (Deloitte, 2017). For instance, an estimated reduction of maintenance costs by 12% has been reported by virtue of the adoption of predictive maintenance adoption (PwC, 2018). Energy consumption and costs, which are predicted to remain high (The World Bank, 2021), may also be moderated using effective digitalization (Lu et al., 2016, p. 8107; Mourtzis, 2021).

Although smart manufacturing is in its early stages, the number of organizations with ongoing smart factory initiatives has increased significantly. Many organizations are investing in relevant technologies to respond to market pressures and achieve new levels of success. Petit et al. (2019) reported that 43% of organizations had ongoing smart factory projects in 2017, increasing to 68% in 2019. Whirlpool can measure how close any factory in its global network is to the zero-waste milestone using IoT and its Analytics platform. Siemens' investment in new technologies includes the MindSphere, their "cloud for industry" that offers global online monitoring of their infrastructure. Hewlett–Packard's 6000-square-feet plant in Singapore is devoted to research and innovative smart applications (Matthews, 2020). The BMW Mini plant at Cowley outside Oxford was identified as the UK's best example of a Smart Factory (The Manufacturer, 2020). Customers are able to select among many car combinations via an online application that offers visualization tools and smart choices depending on the criteria of the customer. Moreover, the assembly line delivers 1000 cars per day in a vast number of possible variations. Some of the most indicative innovations of this smart factory are the digital twin of the assembly line, the fully controlled assistor units, and the collaborative robots used in conjunction with digital monitoring of the production.

2. Interoperability and automation

Industry 4.0 (I4.0) consists of concepts related to business and production services, including production management, product compliance, decision support, and intelligence-based automation of linked processes, as well as system diagnosis. The trend for highly customizable production processes in combination with increasingly complex automation systems that incorporate a wide variety of standards, components, and services poses significant challenges in the development of I4.0 solutions (Nilsson & Sandin, 2018). Interoperability is a necessary critical feature of physical items such as sensors, devices, machines, and other enterprise assets that are interconnected over the Internet in I4.0 production. Devices and sensors need to be context-aware, providing additional process information that improves their performance (Giustozzi et al., 2018). However, despite the existence of interoperability standards, no structured and systematic approach to describing these standards and their relationships exists in the field of manufacturing.

2.1 Interoperability and ontologies

A variety of definitions of interoperability can be found in literature (Barker, 2020; Lu et al., 2016, p. 8107; Wang & Xu, 2013). The goal of I4.0 is to incorporate what is termed *semantic interoperability.* This allows systems to exchange information with unambiguous meaning.

The NIST Manufacturing Interoperability Program listed several factors that affect the efficacy of interoperability (van der Veer & Wiles, 2008) and these are still strongly relevant today:

- Transfer of data between systems that may be similar or dissimilar.
- Transfer of data between software made by the same vendor but having different versions on the systems.
- Compatibility between different versions of software.
- Misinterpretation of terminology used, or in the understanding of the terminology used, for exchange of data or information.
- The use of nonstandardized documentation on which the exchange of data is processed or formatted.
- Not testing the applications that are deemed conformant, due to the lack of means to do so between systems.

A concerted effort has been made to develop frameworks that incorporate semantic interoperability to meet these requirements.

Ontologies, which are defined as a formal specification of shared conceptualizations containing concepts, relations, instances, and axioms, are one such approach. Ontologies are important in knowledge management because they allow for domain knowledge analysis, modeling, and implementation (Bruno & Antonelli, 2018). Ontologies are used for unambiguous communication, computational inference, organization of information, exchange, and knowledge reuse purposes in the computing world. An ontology can be used for the purpose of knowledge sharing and interoperability across multiple domains as a common basis for shared meaning (Shvaiko & Euzenat, 2013). Enterprise Integration and Networking requires a common core ontology to promote interoperability within a smart sensing enterprise system between different ICT systems (Palmer et al., 2018; Weichhart et al., 2016).

A review on manufacturing ontology understanding is provided by Palmer et al. (2017). Other work on ontologies in product development, PLM, and global product-service production are reported by Borsato (2014), Bruno et al. (2016), and Weichhart et al. (2016). The Process Specification Language was created to make it easier for manufacturing systems to exchange accurate and complete process information, such as scheduling, process modeling, process planning, production planning, simulation, project management, workflow, and business-process reengineering (Gruninger & Menzel, 2003). The use of ontologies in Information Technology (IT) architectures requires the use of the *Semantic Web* (Blomqvist, 2014). It includes Knowledge Graphs and is a promising technology that can help I4.0 implementations succeed (Yahya et al., 2021). Relevant ontologies have been developed for specific industrial and manufacturing domains such as process engineering, product development (Kumar et al., 2019) and robotics. Ontologies are needed for robotic systems, as I4.0 is heavily reliant on robotic agents to perform many of the operations in a smart manufacturing environment, as well as communicating with human operators, customers, and a variety of distributed partners (Fiorini et al., 2017).

A reference ontology is needed to provide semantic consistency across an enterprise. If data are shared by any pair of domain ontologies, then there needs to be a higher-level ontology that controls these ontologies. Fig. 2.4 illustrates conceptually how a reference ontology can be tailored to suit the needs of any domain and/or mapped to any specific company needs in order to link multiple software applications in an interoperable manner and to build a production knowledge base for the three enterprises concerned.

Wang et al. (2014) proposed a four-layered cloud manufacturing architecture to address interoperability. Lu et al. (2014) discussed interoperability that encourages users to use various cloud modes—public, community, and private clouds—through a Hybrid Manufacturing Cloud architecture. Additionally, the cloud production models were linked with STEP standards and application protocols by Mourad et al. (2016).

Semantic interoperability not only examines the meaning of the content but also applies logic to the information being transferred and used. XML and the Resource Definition Framework are widely used as standards for semantic interoperability. A comprehensive list of ontologies and comparison of solutions is done by Industrial Ontologies Foundry (IOF), (2016). The IOF initiative was adopted in 2017 aiming to create a suite of high-quality core and open ontologies covering the entire digital manufacturing field (ISO/IEC). *Syntactic interoperability* is a further term used that takes into account the format of the data. This type of interoperability can be greatly improved by standardizing data formats as well as communication modes (DIN, DIN SPEC 91345:2016—04).

2.2 The pyramid of industrial automation

The Automation Pyramid is the architecture delivered by ISA-95. The International Automation Society's international standard for delivering this platform has five layers, as illustrated in Fig. 2.5 (Coito et al., 2019). The automation pyramid must consider both CPS and *Wireless Sensor Networks* (WSN).

Interoperability across the automation pyramid takes two general forms in smart production. The first form is vertical integration and the second is horizontal integration as illustrated in Fig. 2.6 (Panetto et al., 2019).

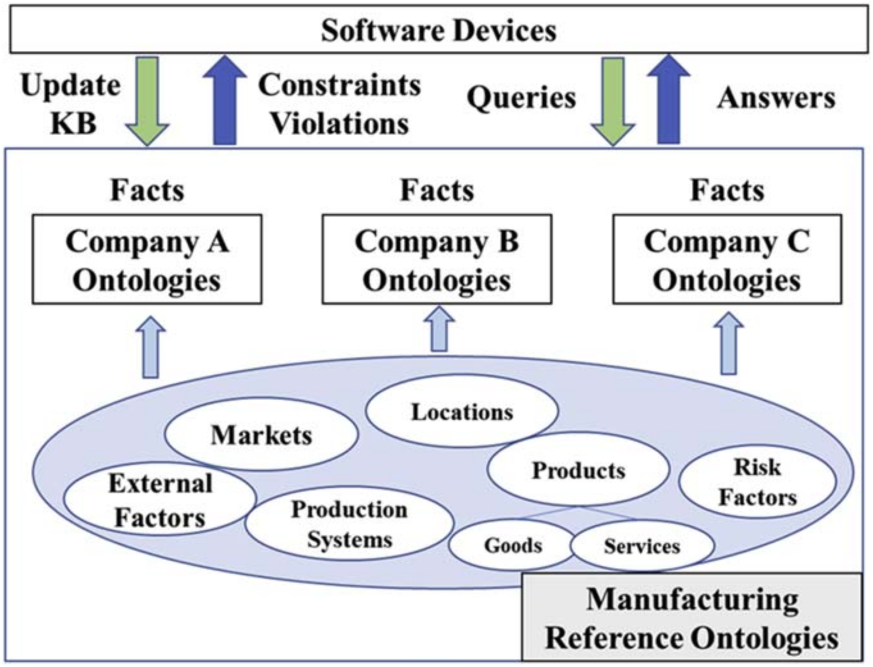


FIGURE 2.4 Exploiting a reference ontology for Knowledge Base (KB) construction and software interoperability. *Credit: Palmer, C., Usman, Z., Canciglieri, O., Malucelli, A., & Young, R. I .M. (2018). Interoperable manufacturing knowledge systems.* International Journal of Production Research, *56(8), 2733—2752. https://doi.org/10.1080/00207543.2017.1391416.*

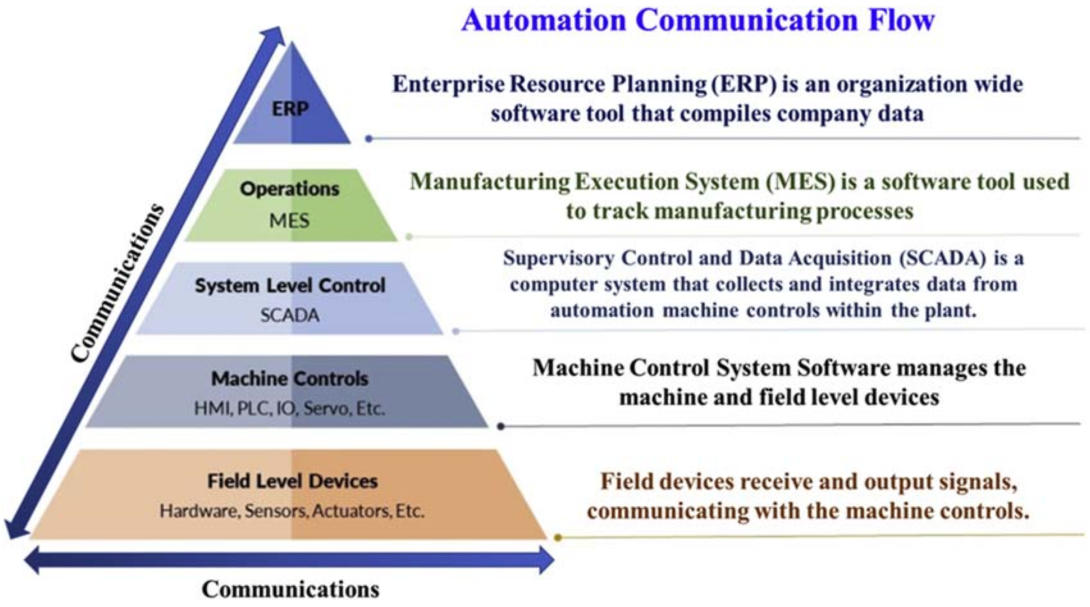


FIGURE 2.5 Current perception of the automation pyramid, consisting of five (0–4) different hierarchy levels and corresponding IT systems. *Source: Adapted from Coito, T., Viegas, L.J., Martins, M., Cunha, M.M., Figueiredo, J., Vieira, M.S., & Sousa, J.M. (2019). A novel framework for intelligent automation. IFAC-PapersOnLine, 52(13), 1825–1830.* https://doi.org/10.1016/j.ifacol.2019.11.501.

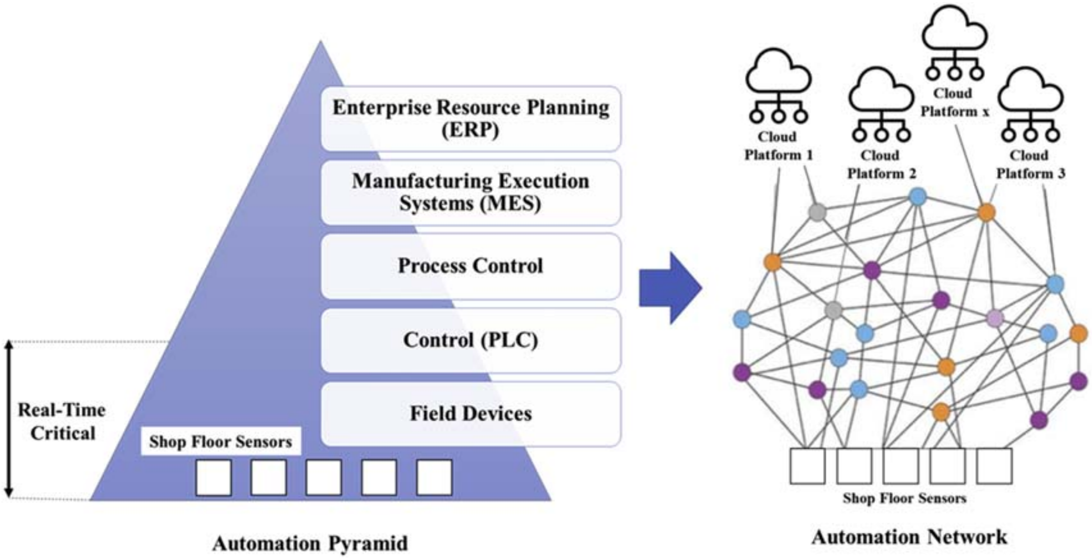


FIGURE 2.6 Positioning of CPS-based automation. *Source: Adapted from Panetto, H., Iung, B., Ivanov, D., Weichhart, G., & Wang, X. (2019). Challenges for the cyber-physical manufacturing enterprises of the future.* Annual Reviews in Control*, 47, 200–213.* https://doi.org/10.1016/j.arcontrol.2019.02.002.

CPSs have been defined as "the systems in which natural and human made systems (physical space) are tightly integrated with computation, communication and control systems (cyber space)" (Mourtzis et al., 2021; Mourtzis & Vlachou, 2018). In the context of CPS, a Service-Oriented Architecture (SOA) integrates complex and heterogeneous large-scale systems to provide high performance and reliable operation (Mourtzis, Vlachou, Xanthopoulos, et al., 2016).

Data from production resources can be tracked, collected, and analyzed to generate information. Radio frequency identification (RFID), ZigBee, and Bluetooth technology are the most common types of wireless sensors used (Chen et al., 2018; Salkin et al., 2018). In WSN, many wireless sensor nodes may be randomly deployed. Vital problems including topological changes, communication link failures, sensor node memory constraints, computational capabilities, and decentralized management need to be considered in the design of such networks. Machine Learning (ML) techniques have been successfully adopted to solve several WSN challenges, such as localization, clustering and data aggregation,

TABLE 2.1 Research work using ML to solve the WSN.

Wireless sensor network (WSN) challenges	Applied ML technologies (WSN)
Localization, clustering, and data aggregation	Kho et al. (2009); Kim and Park (2009)
Medium access control	Shen and Wang, 2008
Real-time routing	Mourtzis, Gargallis et al., (2020); Mourtzis, Angelopoulos, and Zogopoulos (2021); Zappi et al. (2008)
Event disclosure and query processing	Malik et al. (2011)
QoS, data integrity, and fault detection	Ivanov et al. (2018)

processing of events and queries, real-time routing, fault detection, and so on. Table 2.1 summarizes the different WSN challenges, which can be tackled using ML techniques.

2.3 Generic approaches to implement interoperability in smart manufacturing ecosystems

Manufacturing is becoming smarter, with self-awareness, autonomous decision-making, and adaptive excitation and collaboration capabilities. Standardization is a critical enabler for achieving the intelligence required for smart manufacturing (Lu et al., 2019, pp. 73—78). To accomplish this, manufacturing companies need to be able to exchange product data throughout the product development and product lifecycle processes. A collection of standards with minimal interoperability risks that allow a streamlined exchange of product data during the phases of design and production is presented in Fig. 2.7 (Lu, Xu, & Wang, 2020; Bernstein et al., 2017).

Table 2.2 summarizes the standards for several manufacturing application areas as per the literature.

2.4 The smart factory: connectivity, automation, and data

Smart manufacturing involves the networking of heterogeneous components and services within the limits of the factory or beyond (e.g., cloud-based service integration of a manufacturing cell). These two forms of integration have been referred to as vertical and horizontal (Chen & Vernadat, 2003, pp. 273—282). There are still many active research areas in CPS including real-time integration of different data from different sources, real-time analysis and shop-floor feedback, effective

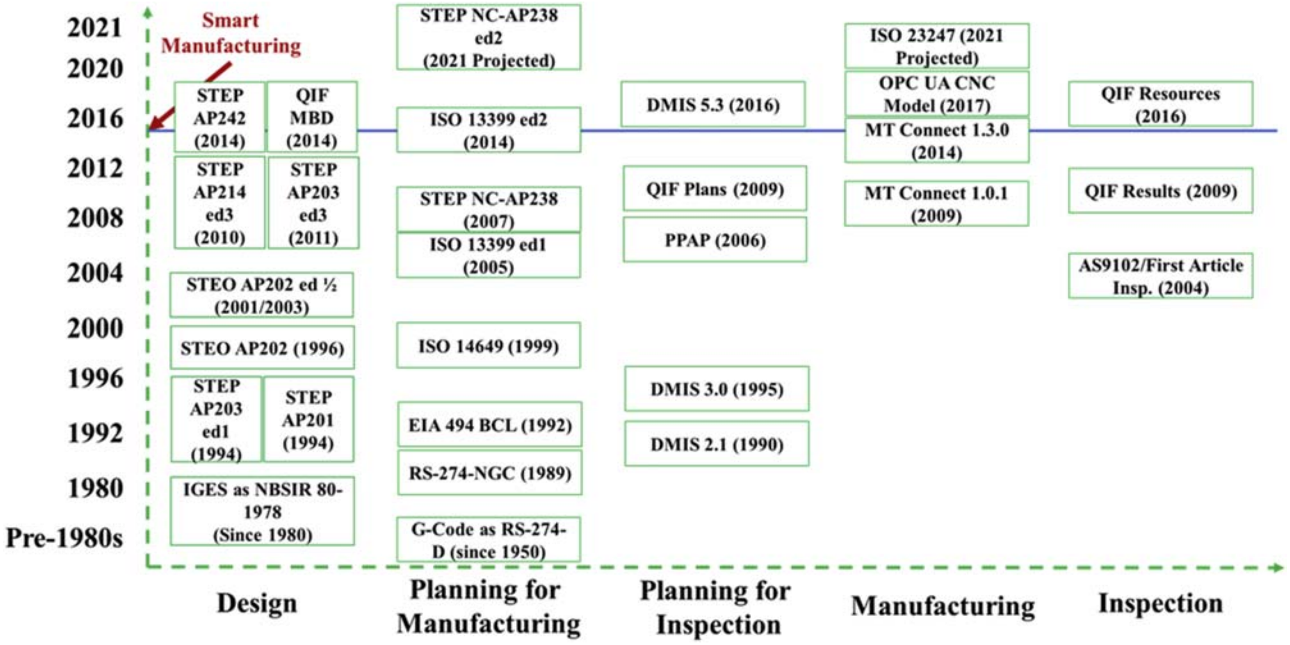


FIGURE 2.7 Timeline-based depiction of standards for different product lifecycle stages. *Source: Adapted from Lu, U., Xu, X., & Wang, L. (2020). Smart manufacturing process and system automation — a critical review of the standards and envisioned scenarios. Journal of Manufacturing Systems, 56, 312—325. https://doi.org/10.1016/j.jmsy.2020.06.010.*

TABLE 2.2 Standards for manufacturing application areas.

Standards for product data exchange	STEP AP242	Wardhani and Xu (2016)
		Venkiteswaran et al. (2016)
Standards for manufacturing	ISO 14649	Jana et al. (2013)
	ISO 10303-238	Liu et al. (2019)
Standards for manufacturing process monitoring	MTConnect	Liu et al. (2019)
Standards for smart inspection	Quality Information Framework (QIF)	Morse et al. (2016)
Standards for identification and application of data structures and models for manufacturing resources through product life cycle	STEP, WSDL (Web Services Description) Language), XML (eXtensible Markup Language)	Lu, Xu, and Wang (2020)

integration of planning and control systems through the integration of communication standards and protocols to enable interoperability, as well as advanced scheduling algorithms (Huang et al., 2009; Mourtzis, 2020c). A cloud-based CPS is illustrated in Fig. 2.8 (Mourtzis, 2020a). It consists of a monitoring system that includes a WSN and an information fusion technique and supports the Open Platform Communication-Unified Architecture standard for industrial communication.

2.5 IoT architectures for automation, interoperability, and monitoring of Industrial Big Data

The volume of data generated by sensors embedded in machine tools, cloud-based solutions, as well as by business management systems continues to increase. Consequently, special focus should be given to the transformation of the traditional production systems into CPS. The design and development of standard and secure communication protocols capable of interconnecting existing systems and collecting and exchanging production data is a major challenge to this transformation. Recently, Wang et al. (2021) discussed how edge computing techniques, which harness and use data close to their source, can be used for cyber-physical machine tool systems. A WSN-supported IoT application based on a standard industrial communication protocol showing how to generate Industrial Big Data is presented in Fig. 2.9 (Mourtzis, Vlachou, & Milas, 2016).

3. Interoperable Digital Twins and predictive maintenance in modern manufacturing

Industry 4.0 seeks to provide on-demand services with high reliability, scalability, and availability through digital transformation. Digital Twins are an important pillar technology in I4.0 (Xu, 2012). In a Digital Twin, a physical thing is re-born as a digital model. Following a review of the industry applications of Digital Twins, Tao et al. (2018) conclude that a unified Digital Twin framework is urgently needed. The terms "digital" and "cyber" may frequently be confused. However, omitting one may cause a reference model to fail. To that end, Fig. 2.10 illustrates a Digital Twin reference model. It consists of a Physical layer, a Digital layer, and a Cyber layer, with communication for data exchange among and across the three layers. Data exchange carries real-time data as a mapping between selected physical elements and their digital model and processes in cyberspace (Aheleroff et al., 2021). A Digital Twin can be utilized in a wide range of manufacturing applications, for example in maintenance.

Maintenance is a critically important manufacturing function that can benefit from Digital Twins. Maintenance professionals have traditionally used a combination of quantitative and qualitative techniques to predict impending failures and reduce downtime in manufacturing facilities. Maintenance departments in manufacturing plants are working to adapt to the challenges raised by Industry 4.0 (Chen et al., 2020). However, Fraser et al. (2015) note the lack of empirical research in the field of maintenance. More recently, Bokrantz et al. (2020) have presented an empirically based research agenda to guide scholars and practitioners in the field of *Smart Maintenance*.

Production-integrated sensors now enable flexible and targeted predictive maintenance (PdM) and control strategies (Tan et al., 2018) to be developed. IoT-based sensors can proactively monitor a device and send out alerts if it deviates

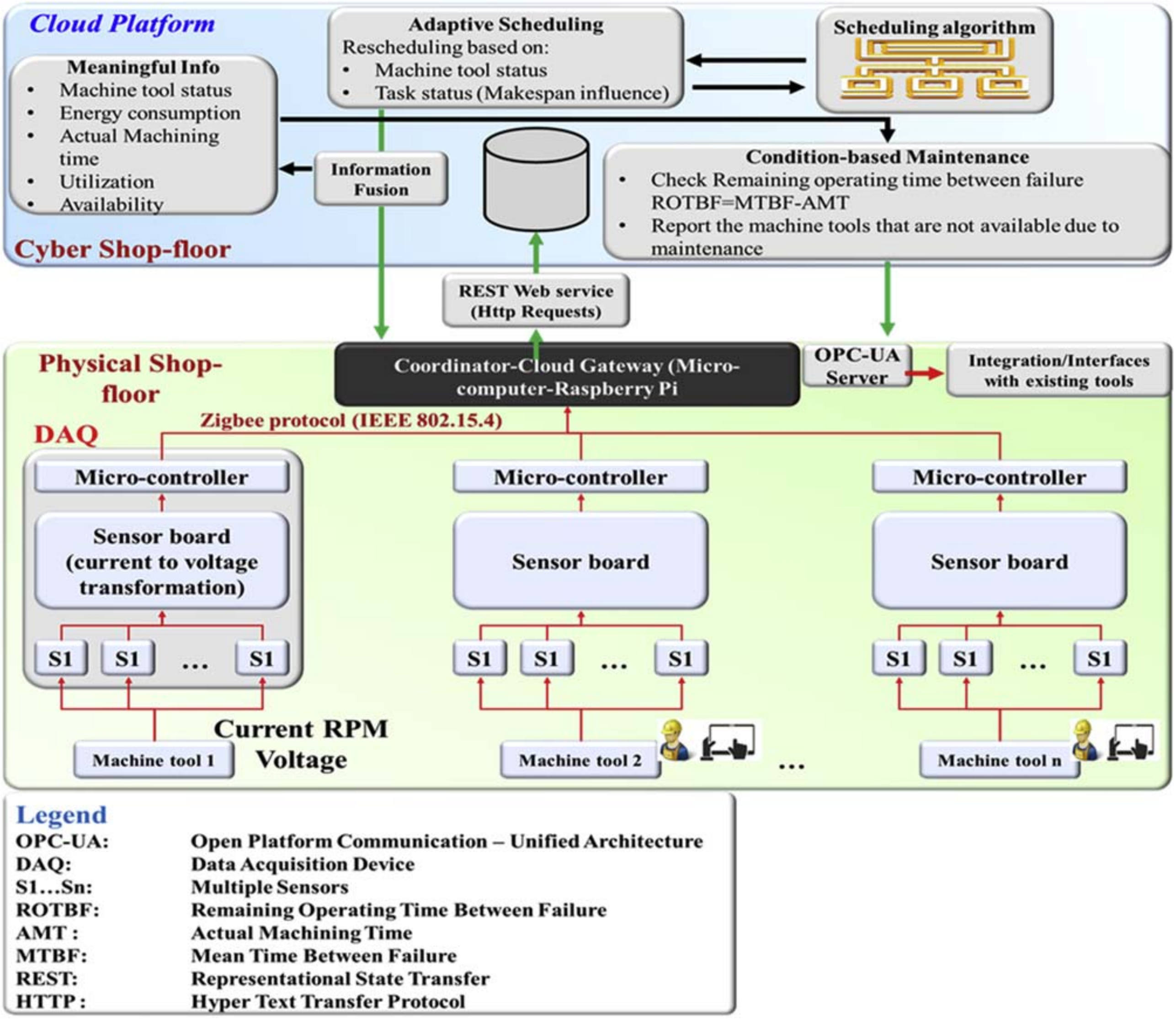


FIGURE 2.8 The cloud-based cyber-physical system. *Source: Adapted from Mourtzis, D. (2020a). Adaptive scheduling in the era of cloud manufacturing. In B. Sokolov, D. Ivanov, A. Dolgui (Eds.), Scheduling in Industry 4.0 and cloud manufacturing. International series in operations research & management science, Vol. 289. Cham: Springer.* https://doi.org/10.1007/978-3-030-43177-8_4.

from set parameters. PdM gives maintenance professionals the ability to optimize maintenance tasks in real time, extending the useful life of their equipment while minimizing downtime. PdM aims to reduce maintenance costs, implement zero-waste production, and reduce the number of major failures (Mourtzis, Angelopoulos, & Panopoulos, 2021; Li et al., 2019). To optimize maintenance efforts, PdM seeks to predict system failures and determine when specific maintenance is required. Continuous monitoring allows maintenance to be done only when required (Carvalho et al., 2019). The literature distinguishes between different approaches for PdM—mathematical modeling, knowledge-based approaches, and data-driven approaches, the latter of which we see most frequently in current PdM developments (Zonta et al., 2020). Farooq et al. (2020) differentiate between experience-driven and data-driven maintenance. PdM based on experience gathers information about production equipment and then uses that information to plan future maintenance. Data-driven predictive maintenance, on the other hand, is based on analyzing a large amount of data, as illustrated in Fig. 2.11.

Considering an industrial case, Mourtzis, Angelopoulos et al. (2020) present the design and development of a predictive maintenance framework for industrial refrigeration equipment that uses a Digital Twin. The work presents a custom Data Acquisition device (DAQ) and the Data Processing Framework applied to the Digital Twin of the refrigeration equipment to calculate the Remaining Useful Life of critical components and supports predictive maintenance. The Digital Twin of

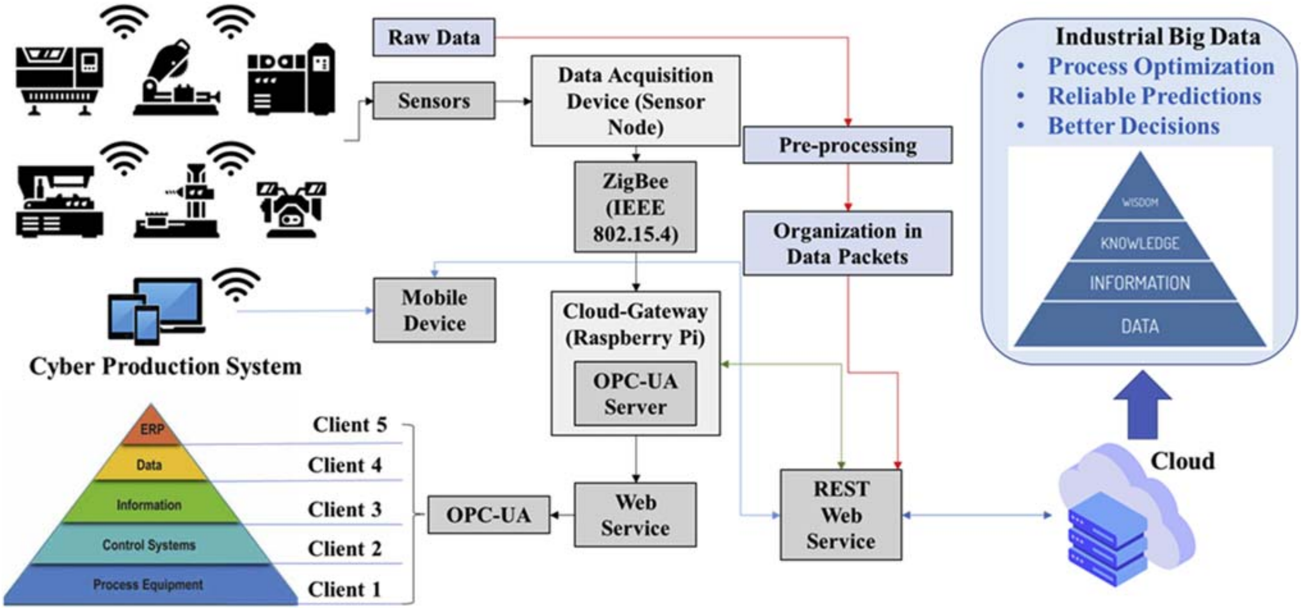


FIGURE 2.9 Industrial Big Data generated by the developed IoT application. *Source: Adapted from Mourtzis, D. (2016). Challenges and future perspectives for the life cycle of manufacturing networks in the mass customisation era.* Logistics Research, *9(2).*

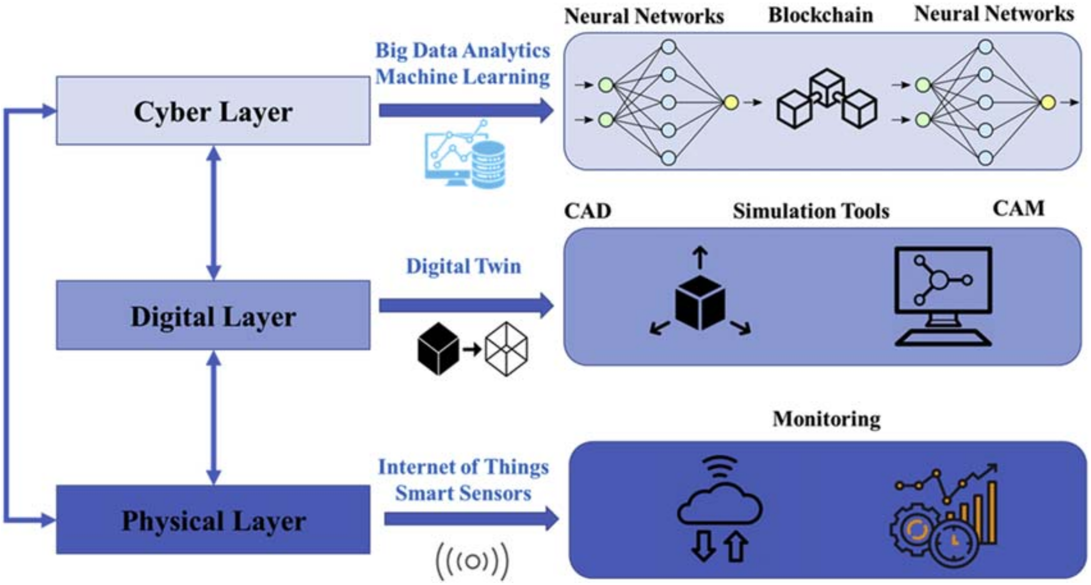


FIGURE 2.10 A conceptual digital twin reference model. *Adapted from Aheleroff, S., Xu, X., Zhong, R. Y., & Lu, Y. (2021). Digital twin as a service (DTaaS) in Industry 4.0: An architecture reference model.* Advanced Engineering Informatics, 47, *101225. https://doi.org/10.1016/j.aei.2020.101225.*

the equipment allows the monitoring of key variables such as humidity or pressure to provide predictive maintenance services for possible malfunctions. The objective is to analyze the data collected from the DAQ devices and to predict future equipment malfunctions based on a simulation model. In the case of industrial refrigerators, the physical model is recreated in the Simulink programming environment. MATLAB Software is used for the set up and the simulation of the digital model. The system is outlined schematically in Fig. 2.12. By using simulation techniques with Digital Twins, raw data are transformed into information. Such knowledge becomes a powerful tool in the hands of engineers, who are

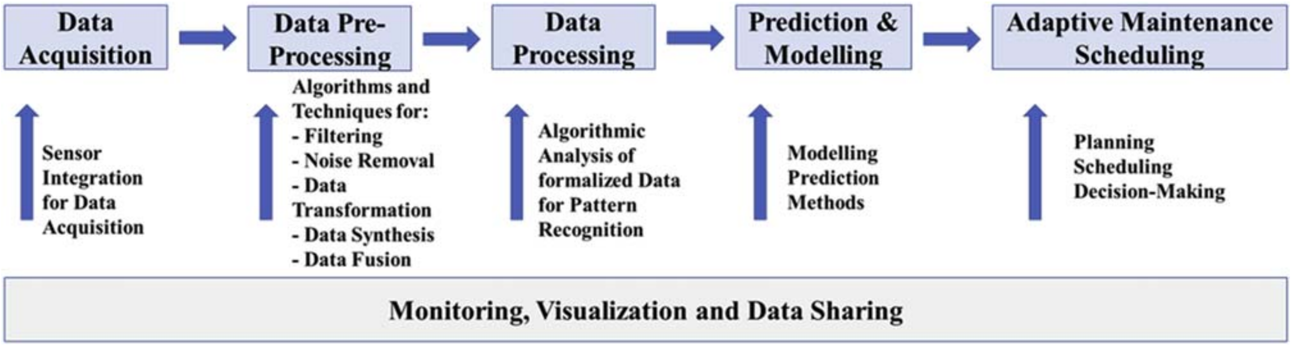


FIGURE 2.11 Data-driven predictive maintenance.

becoming increasingly capable of remotely monitoring complex equipment and making proactive decisions before equipment malfunctions occur. This approach can be carried out remotely.

4. Digitalization and smart factories: trends and future challenges

4.1 Product lifecycle management

PLM stands for "product lifecycle management," which refers to the creation, storage, and retrieval of data, information, and knowledge throughout the lifecycle of a product, from its conceptualization to its disposal or recovery (Siemens, PLM Software, 2021). In manufacturing industry, PLM is seen as one of the core concepts for meeting several business requirements such as completeness, high transparency, rapid accessibility, and high visibility of all product data throughout the product lifecycle. PLM is implemented using IT systems such as product data management systems, which result in a high level of interoperability between related applications. By avoiding errors and misunderstandings, industrial companies can gain advantages in shorter cycles, lower costs, and better quality from the adoption of effective PLM systems.

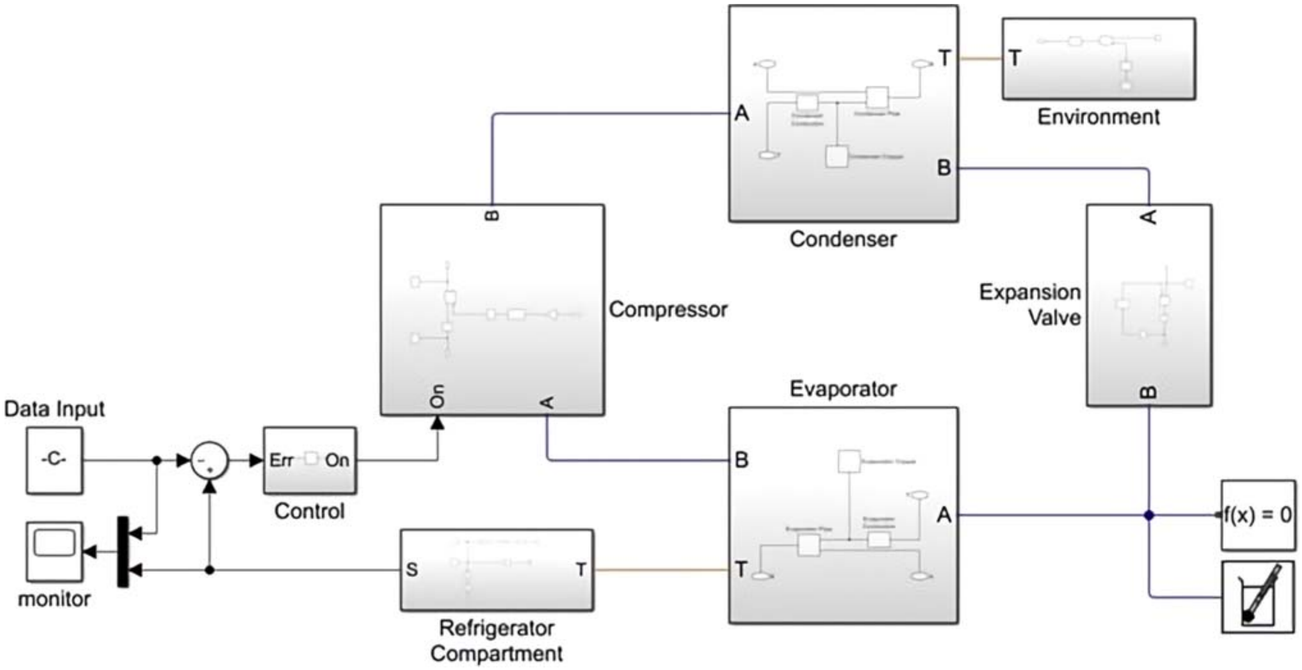


FIGURE 2.12 Refrigerator model in MATLAB Simulink (Digital Twin Virtual Model). *Source: Adopted from Mourtzis, D., Siatras, V., Angelopoulos, J., & Panopoulos, N. (2020a). An augmented reality collaborative product design cloud-based platform in the context of learning factory.* Procedia Manufacturing, 45*, 546–551. https://doi.org/10.1016/j.promfg.2020.04.076.*

In increasingly complex enterprises, PLM becomes the enabler for better, faster, and digitally based product development. PLM manages product information from the first concept to the end of life of a manufactured product. PLM is not only a process and system integration concept but is also a requirement for other methods and technologies like requirements engineering, digital mock-up, and design variant management. PLM requires the standardization of methods, interfaces, and processes, and thus is a strong driver of information technology standardization. International organizations such as ISO, OMG, OASIS, and many national standard initiatives of relevant industry associations such as VDMA, VDA, or VDI in Germany host relevant standards in the context of PLM (Perdikakis & Kiritsis, 2016).

The digital era is characterized by an increase in the amount of data that must be managed in real-time and fed into simulation models that can quickly investigate various scenarios and provide decision support and system optimization. The major identified gaps for each product and production lifecycle sector are discussed in Mourtzis (2020). MacCarthy and Pasley (2021) emphasize the importance of considering and capturing decisions as distinct units of knowledge in PLM, identifying six decision-making principles to support PLM. The principles allow for the codification, recording, and review of PLM decisions.

4.2 5G for smart manufacturing and Industry 5.0

The third and the fourth generation mobile networks (3G, 4G) and communication technologies are limited in meeting the demands of Cyber-Physical Management Systems (CPMS) for high data transmission rates, high reliability, high coverage, and low latency to minimize delays in data transmission. This impedes their development and implementation. Emerging technology scenarios in the future digital supply chain demand high data transmission rates, high coverage, low latency, multidevice connectivity, high reliability, and high security (Lu, 2017). Due to the fact that legacy systems (such as 4G, WiFi, Bluetooth, and Zigbee) are fragmented and unable to meet the real-time data transfer requirements (Agiwal et al., 2019), an advanced wireless communication network, such as 5G, is required (Lu, 2017). More specifically, this fifth generation of mobile, cellular technologies, networks, and solutions has the potential to deliver 10 Gbps data rates with less than 1 ms latency, increased network capacity for a great number of devices, high reliability and security, and significant energy savings. Furthermore, network slicing is used to make these networks more flexible and cost-effective (Rao & Prasad, 2018). As such, 5G has a lot of potential to promote the Industrial Internet of Things (IIoT) and CPMS as an advanced wireless transmission technology underpinning future manufacturing.

The manufacturing landscape is changing fast, and Industry 5.0 concepts are already being promoted (Mourtzis, 2021). The concept of Industry 5.0 can also be described as reintroducing the "human/value-centered Industry 4.0" dimension that was previously lost in consideration of manufacturing systems (Müller, 2020). It aims to provide businesses with the ability to produce more effectively, sustainably, and safely by combining the capabilities of increasingly powerful machines with better-trained human experts. The goals of Industry 5.0 are summarized by the European Commission (2020), as follows: (a) Cost optimization, (b) Personalization and Creativity, and (c) Greener and sustainable solutions. The framework highlights the key features, the goals, the technological enablers, and the challenges of Industry 5.0 (Müller, 2020). Industry 5.0 is a new way of thinking about manufacturing with implications for technology, productivity, economics, business, as well as society more generally.

5. Conclusions

This chapter has reviewed the evolution of traditional manufacturing as it moves toward an Automated and Interoperable Smart Manufacturing Ecosystem, mapping the milestones from the early CIM concepts to today's manufacturing environment that incorporates the Industrial Internet of Things (IIoT) and the fourth industrial revolution. First, we traced the evolution of production systems and the transition of the traditional tools toward CIM in digital manufacturing, which has provided the basis for Smart Manufacturing. Next, we reviewed interoperability and automation challenges within the smart factory context, presenting several smart manufacturing automation scenarios and cloud-based systems and platforms. Digital Twins in manufacturing and their use in predictive maintenance have been discussed briefly, along with PLM systems and the emergence of 5G communication technologies.

This chapter has highlighted the need for and examined the progress made on interoperability for Industry 4.0. The importance of core ontologies to achieve interoperability is highlighted. Continuing research is being conducted using ontologies to develop semantic interoperability for the integration of many devices in industrial environments and the automatic discovery of such devices when added to an industrial network. This chapter has concluded with a brief discussion of Industry 5.0 concepts, which emphasizes the role of the human expert in advanced manufacturing systems.

Glossary of acronyms

AI Artificial intelligence
CAD Computer-aided design
CAE Computer aided engineering
CAM Computer-aided manufacturing
CAPP Computer-aided process planning
CIM Computer-integrated manufacturing
CNC Computer numerical control
CPMS Cyber-physical management systems
CPS Cyber-physical systems
DIN Deutsches Institut für Normung
ERP Enterprise resource planning
FMS Flexible manufacturing system
I4.0 Industry 4.0
ICT Information and communications technology
IEC International Electrotechnical Commission
IIoT Industrial Internet of things
IoT Internet of things
IoF Internet of everything
ISO International Organization for Standardization
MES Manufacturing execution system
ML Machine learning
NC Numerical control
OPC-UA Open platform communications—Unified architecture
PdM Predictive maintenance
PDM Product data management
PLC Programmable logic controller
PLM Product lifecycle management
PSL Process specification language
Qif Quality information framework
RDF Resource definition framework
RFID Radio frequency identification
SCADA Supervisory control and data acquisition
SMS Smart manufacturing systems
STEP STandard for the Exchange of Product model data, (ISO 10303−242:2020) written using the EXPRESS modeling language
XML eXtensible Markup Language
WSDL Web services description
WSN Wireless sensor network

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Smart warehouses—a sociotechnical perspective

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Abstract

In this chapter, we discuss the smart warehouse concept and the challenges it entails with the increasing digitalization of the supply chain. The principal enabling technologies that play a major role in the progression toward smart warehouses are identified and discussed in the context of the changes occurring across business, industry, and the retail economy. The warehouse processes affected and potential influences of the technologies on warehouse management and operations are described. This chapter focuses on one of the most important process steps in the smart warehouse, order-picking, which is currently subject to major developments and transformations. Using a technological grid, four types of order-picking system are derived, which systematize how technologies can support human operators in warehouses to reduce physical workload and/or improve cognitive ergonomics. The four system types are classified based on supportive (digital) and substitutive (automation) technologies. The impacts of increased digitalization in warehouses on the physical, cognitive, perceptual, and psychosocial human factors are examined from a sociotechnical perspective. These manifold influences are exemplified for the case of a collaborative order-picking system and broken down using an analysis framework that can be used for the systematic development of sociotechnical systems in the digitalization of the supply chain.

Keywords: Autonomous picking robot; Digital transformation; Human factors; Industry 4.0; Order-picking; Sociotechnical system; Warehousing.

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1. The digital supply chain transforms the requirements for warehousing

Warehouses play a critical role in the digitalization of supply chains. In addition to enabling new applications of technologies and a more efficient operation of warehouses, the digital transformation sets new demands on warehouse operations (Winkelhaus & Grosse, 2020). These new demands originate from substantial changes in the retail economy and e-commerce growth characterized by small batch sizes and individual orders that increase the variety of stored goods and simultaneously reduce the predictability of the retrieval of goods (Hofmann & Rüsch, 2017; Kagermann et al., 2013). Shorter product life cycles and the growing number of new product introductions increase the uncertainty of inventory requirements (Hofmann & Rüsch, 2017; Kagermann et al., 2013). Increased demands on the capability to deliver small orders to individual addresses and speed of delivery (up to same-day delivery) result in increasing uncertainties in warehouse resource scheduling and in the need to maintain sufficient and flexible resources (Boysen et al., 2019).

Efficient and effective warehouse operations for successful and resilient supply chains gain importance because of the need to satisfy this increased demand (Winkelhaus & Grosse, 2020). The e-commerce boom and the importance of warehousing is reflected in current employment figures, which show record levels of warehouse employment, higher than prepandemic levels. For example, in the United States, 1.4 million employees have been registered in March 2021 in the warehousing and storage sector (BLS, 2021). In Europe, warehouses were among the sectors with the highest prospect scores in 2020 on real estate investments (Statista, 2021a). Due to increasing investments, the size of the warehouse automation market worldwide is expected to grow from 7.9 billion US dollars in 2012 to 30.15 billion US dollars in 2026

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(Statista, 2021b). These trends generate the need to reconsider traditional management methods, operating policies, and technical solutions in the warehouse to develop new methods of human−technology interaction and work systems.

In recent decades, there has been a shift from traditional warehouses to smart, more efficient warehouses (Kumar et al., 2021). In this transition, warehouses have developed from manually, paper-based operated storerooms with no or very limited technical support to paperless facilities where operators are supported with information and digital technologies (e.g., from PDAs to pick-by-light or pick-by-voice to data glasses, Glock et al., 2021). In addition, advancements in automation and robotics as well as warehouse management systems have transformed warehouses to become highly automated facilities, e.g., from automated storage-and-retrieval system (AS/RS) and automated guided vehicles (AGVs) to autonomous picking robots (Azadeh et al., 2019). Besides these technical developments, research on warehouse management has developed from solving cost-focused decision problems (e.g., de Koster et al., 2007) to more integrated planning approaches, considering human factors (Grosse et al., 2015) and environmental impact (Bartolini et al., 2019). In this transition, technologies are being applied to provide the warehouse with features required to address this complex and dynamic environment. These properties are related not only to the described changes in the retail economy but also to advancements of technology (Kumar et al., 2021) and the characteristics of Industry 4.0 and Logistics 4.0 (Winkelhaus & Grosse, 2020). Smart warehouses play a major role in the digital transformation of industries and the economy.

Directed toward autonomous operations, the smart warehouse relies on both digital technologies and automation. It is modular, reconfigurable, and provides highly efficient, customized services (Culot et al., 2020; Winkelhaus & Grosse, 2020). A smart warehouse is characterized by a significant integration of different partners and stages within the supply chain, relying on real-time information flows. Therefore, technological standards and interoperable technologies are applied that enable seamless information transmissions and integration (Culot et al., 2020). A virtual representation of the warehouse can be used for its management by using the data gained in each process step in the warehouse (Culot et al., 2020). Based on this, a smart warehouse can be defined as:

> *A highly integrated warehouse that uses advanced digital technologies and automation for efficient and effective operations to adapt to the dynamic business environment of today's economy.*

There are various survey articles available that review key components underlying this definition, see, for example, Liu et al. (2018) on localization and communication in the smart warehouse, Custodio and Machado (2019) on flexible automation in warehouses, Azadeh et al. (2019) on robotized warehouse systems, Jaghbeer et al. (2020) on automated order-picking, Glock et al. (2021) on assistive devices for manual materials handling in warehouses, Fragapane et al. (2021) on autonomous mobile robots in intralogistics, or Winkelhaus et al. (2021) on order-picking 4.0.

In this chapter, the concept and components of smart warehouses are described. First, the fundamentals of warehouse management are discussed briefly. Then, an overview of technologies that enable the smart warehouse is provided. Order-picking remains the most time-consuming and expensive process in a warehouse. Hence, this chapter focuses on a detailed description of order-picking in the smart warehouse. We argue that the technology-centered approach to smart warehouses must be complemented with a socio-technical perspective to jointly optimize the human and technological subsystems of the smart warehouse for overall effectiveness and profit enhancement.

2. Warehouse management

Seven main process steps can be differentiated within a warehouse: receipt, put-away, storing, order-picking, value added services, packaging, and shipping (de Koster et al., 2007; Tompkins et al., 2010). These process steps include the physical material flow from receipt and put-away to storage until a request for an item(s) is made by a customer. At this point, the order-picking process starts. Following this, in certain warehouses, additional value-added services (such as repackaging or kitting) are provided before the picked items are packaged for shipping. The process steps in *person-to-goods* and *goods-to-person* systems differ. In *person-to-goods systems*, the items are transported to the storage location by a human operator and picked out of this storage location by a human order-picker who travels through the warehouse to retrieve the items from a shelf. In *goods-to-person systems*, the items are stored in an AS/RS at a fixed workstation and are transported by the automated system to the order-picker, who retrieves the items at the fixed workstation when required.

For each warehouse process step, different managerial decisions have to be made that impact the efficiency of the warehouse and affect its service level. This begins even before the warehouse is constructed (see, e.g., Boysen et al., 2019; Heragu, 2008; de Koster et al., 2007, 2017; Tompkins et al., 2010): How large should the warehouse be? Which storage technology should be applied? Should the warehouse apply manual order-picking or AS/RSs? Which warehouse layout is the optimum? How many operators work within the warehouse? How should ergonomics be considered within workplaces in warehouses (see, e.g., Helander, 2005)?

After the warehouse is constructed, further questions arise that differ between smart and traditional warehouses (Boysen et al., 2019; de Koster et al., 2007, 2017). The following are among the most important management decisions in warehousing (see for reviews, for example, de Koster et al., 2007; Masae et al., 2020): (1) inventory management, (2) routing, (3) storage assignment, (4) batching, and (5) zoning.

The smart warehouse applies different technologies to perform these tasks effectively and efficiently and to resolve various challenges that have been identified. These technologies are discussed in the following section.

3. Smart warehouses: enabling technologies

Warehouse managers are challenged to perform the processes efficiently despite increasing uncertainties owing to increasing e-commerce sales with small batches, shortening lifecycles, and tight delivery schedules in a complex environment. The use of technologies is promising to overcome these challenges. Two types of technology can be applied within a smart warehouse: (1) digital technologies that support human work to be more efficient and reduce uncertainties and (2) automation technologies that substitute human work and perform repetitive tasks efficiently while maintaining flexibility to address uncertainties.

Digital technologies enable the monitoring and handling of information acquired from sensors and identification systems (e.g., RFID tags) on the flow of goods within all parts of the supply network. Data Analytics techniques also enable forecasting and can support managerial decisions (Addo-Tenkorang & Helo, 2016; Winkelhaus & Grosse, 2020). The acquired information can be shared within the supply chain to enable better network management and to optimize the overall flow of products and information. Furthermore, digital technologies also support cognitive tasks within the warehouse, e.g., pick-by-vision technologies.

Meanwhile, automation technology allows the physical material flow to be automated. Human operators can be substituted for routine tasks and goods can be stored and retrieved efficiently. A major part of the workload can be handled by automated systems applying autonomous robots and AGVs (Azadeh et al., 2019; Fragapane et al., 2021; Jaghbeer et al., 2020). Adaptable and scalable systems allow for effective application in warehouses with varying workloads (Custodio & Machado, 2019). Hence, there is a twofold effect: information available from systems that combine sensors and software together with information generated by automation technology is used to support humans in obtaining a better overview of the present state of a warehouse and to support and automate cognitive tasks. This information also facilitates further automation of physical tasks, which results in a transformation from automated to autonomous systems. An overview of important features and related technologies and their impact on different process steps as well as warehouse management is presented in Table 3.1.

TABLE 3.1 Technologies of smart warehouses.

Features	Example technology	Impact on material flow	Impact on warehouse management
Identification and in-door positioning	RFID	Receipt, put-away, order-picking, packing	Inventory management
	Smart lighting	Put-away, order-picking	Routing
	Blockchain	Receipt, shipping	Inventory management
Virtualization/simulation	Digital twin	All process steps	All process steps
Support	Wearables	Receipt, put-away, storage, order-picking, packing, shipping	Routing
Performance	AGV	Put-away, order-picking	Routing, storage assignment, batching, zoning
	RMFS	Put-away, order-picking	Routing, storage assignment, batching, zoning
	Autonomous robot	Put-away, order-picking, packing	Routing, storage assignment, batching, zoning
	Drone	Shipping	Inventory management
Creation	Additive manufacturing/3D printing	Value-added services	Inventory management

Within the warehouse, these features are achieved using different technologies and affect the described warehouse process steps and management actions, as summarized below.

Identification and Indoor Positioning: RFID is generally considered a key enabler of smart warehouses (Custodio & Machado, 2019; Lee et al., 2017; Liu et al., 2018). The application of RFID facilitates traceability and information generation (Atzori et al., 2010; Friedewald & Raabe, 2011). It also improves the warehouse process efficiency and responsiveness (Atzori et al., 2010). For example, inventories can be managed more efficiently, inventory differences are prevented, accurate and real-time information on stocked quantities is available, and the overall visibility is improved. This also reduces errors such as those caused by incorrect article retrievals (Sun, 2012; Winkelhaus & Grosse, 2020). Hence, efficiency is increased at the management level as well as on the shop floor. In particular, customer service is improved. Apart from these advantages, there are challenges in the application of RFID to smart warehouse practices. These are particularly concerned with imperfect read-rates, security and technology standards, supply chain integration, and system costs (Tadejko, 2015; Twist, 2005; Winkelhaus & Grosse, 2020). For indoor positioning, other technologies have recently reached the market, such as smart lighting systems, which are discussed for warehouse applications based on visible light communication (Füchtenhans et al., 2021).

Blockchain technology is considered as a major feature for future supply chain management processes. However, warehouse processes are also affected. Blockchain develops trust in information and, thereby, may enhance and facilitate receipt and shipping tasks. It may not be necessary to validate documents and quality controls. Because the information is stored in a tamper-proof way in the blockchain, it can be used in the warehouse without being reassessed (Pournader et al., 2020). In addition, this technology may enable the capture and tracking of warehouse performance, thereby making it available for invoicing.

Virtualization/Simulation: The smart warehouse is deeply connected to the concept of a digital twin. Beyond being pure data, digital twins include algorithms that describe their real counterpart and decide on the actions to be performed in the production system (Kritzinger et al., 2018). Hence, apart from being a virtualization of the status quo, the digital twin can potentially be applied in management, simulations, optimizations, and "what-if" type analyses. With these characteristics, the digital twin of a warehouse can affect all the process steps within the warehouse and warehouse management, e.g., planning capabilities, optimized routing, and support of order-picking (Leng et al., 2019).

Support: Wearable devices can help improve the efficiency and quality of warehouse operations. Within the *Operator 4.0* paradigm, an operator such as an order-picker is equipped with diverse wearable technologies according to his/her needs (Romero, Bernus, et al., 2016; Romero, Stahre, et al., 2016; Ruppert et al., 2018). Diverse technologies for warehouse applications are available in the market and are used in practice (Glock et al., 2021). These include Augmented Reality glasses, smart watches, smart gloves, and health trackers, which are examples of cognitive and sensory equipment. Augmented Reality has the advantage that it provides an adaptive and flexible method for presenting information to operators and, therefore, differs from pick-by-voice systems (Glock et al., 2021). In addition, operators can focus on the process because information is provided within the direct field of view, whereby both his/her hands are free for material handling. This impacts cognitive ergonomics and may increase the efficiency of the operator. Nevertheless, headaches and higher perceptual loads are reported as negative side effects because focusing on the near field is perceived as strenuous (Glock et al., 2021).

In addition to Augmented Reality, smart watches are also discussed. In a warehouse, a pick-by-watch system can support the operator by displaying information on a smart watch (Gerpott & Kurt, 2020). This is similar to pick-by-voice systems. Smart gloves particularly focus on data generation and transmission to examine the quality of each activity while it is performed (Scheuermann et al., 2016). This can, for example, reduce picking errors. Health monitoring systems can also be implemented using smart watches (Romero et al., 2018). These trackers can monitor the operators' health and support them in preventing overloading of their system. For example, human well-being may be improved, and cognitive and physical loads reduced. This would enable the optimization of the overall system, e.g., by minimizing the risk of injuries (Romero et al., 2018).

A main application of wearable physical support comprises *exoskeletons* (Glock et al., 2021). Exoskeletons are widely used to reduce the physical loads imposed by wearable devices (Bogue, 2018; Romero et al., 2018; Winter et al., 2019). Exoskeletons are worn by an operator and reduce the loads on parts of the body during material handling such as lifting tasks or palletizing. By not restricting the operators' physical movements, exoskeletons can potentially facilitate physical tasks, improve health and safety, and reduce injuries within the warehouse. However, issues in wearing comfort and user handling have been reported and only limited support for operators has been observed, indicating that much further research and development is necessary (Glock et al., 2021; Winter et al., 2019).

With this diversity, *wearables* impact all the performance steps of human operators within a smart warehouse. Information can be acquired and displayed immediately to the operators. Thereby, tasks can be scheduled, exceptions can be considered in each task, and routes can be optimized.

Performance: AGVs enable the autonomous transport of goods within a warehouse. This can be achieved by different methods (Azadeh et al., 2019; Boysen et al., 2019; Löffler et al., 2021). Apart from the transportation of goods within the warehouse from one station to another, more advanced and interactive systems are available. An example of their application is transportation wherein robots interact directly with human operators in a shared workspace. The AGV can follow an order-picker to transport collected goods or connect different zones of a warehouse to collect items of a customer order from different order-pickers (Löffler et al., 2021). The AGV can also drive to a pick location and wait until an order-picker retrieves the item from this location, before it travels to the next location. Many other systems are possible. These are not described in detail here because of space constraints.

A widely discussed application of AGVs to a smart warehouse is the so-called robotic mobile fulfilment system (RMFS). Herein, racks are moved by AGVs to the operator, who picks the requested items before the AGV transports the rack back to a storage area (da Costa Barros & do Nascimento, 2021). For example, this technology is frequently applied in warehouses of the e-commerce retailer Amazon (Bogue, 2016; D'Andrea, 2012) to reduce walking distances and search times and increase worker productivity.

Autonomous robots can generally perform different tasks within a smart warehouse. Autonomous mobile robots are "industrial robots that use a decentralized decision-making process for collision-free navigation to provide a platform for material handling, collaborative activities, and full services within a bounded area" (Fragapane et al., 2021). For smart warehouses, various autonomous robots are already available on the market and new ones are being introduced that can perform tasks that are not limited to transportation tasks but can also perform tasks such as unloading trucks or palletizing (Boston Dynamics, 2021). However, these gain special relevance within the order-picking process because it is among the most time-consuming and expensive process steps. Autonomous order-picking robots can assist and substitute human work either for the picking task or for additional tasks (such as sorting of goods while the human picks items out of the shelves) (Fager et al., 2020). An example of an autonomous order-picking robot is Toru, produced by the company Magazino, a robot that is capable of traveling through the aisles of a warehouse, identifying the storage location, and retrieving the items, while collaborating with humans in a shared workspace (Magazino GmbH, 2019). Other methods of supporting an order-picker with an autonomous robot have been described by Fager et al. (2020). Therein, the robot performs the sorting of goods picked by human operators. Nevertheless, material handling solutions are limited to certain shapes and goods and their packaging (Azadeh et al., 2019). The physical grasping of different goods is subject to many diverse restrictions compared with human capabilities, although there has been steady progress in addressing these issues (Correll et al., 2018).

Drones (also called unmanned aerial vehicles) can be applied to different tasks in a smart warehouse. Drones are particularly relevant for performing tasks in locations that are not conveniently accessible to human operators and robots. Applications can be identified in the context of inventory management, where drones can systematically, and in some cases also autonomously, fly to all storage compartments and carry out an inventory scan (Wawrla et al., 2019). Other applications within a warehouse include transportation tasks between different stages and locations and inspection tasks performed with devices including drones (Wawrla et al., 2019).

Creation: 3D-printing (or additive manufacturing) can be considered as a major feature among the value-added services within warehouses. Value-added services can be highly diverse: from repairing to certain packaging and simple assembly tasks (de Koster et al., 2017). However, in an increasingly diverse and heterogeneous portfolio of stocked goods, small, infrequently demanded goods can also be manufactured directly in the warehouse. For example, this can be beneficial in spare-part warehouses or for service parts, where a large variety of goods has to be handled and the frequency of usage is highly unpredictable (Li et al., 2016). Additive manufacturing of plastics or metal powders is an opportunity to increase the range of goods that a warehouse can provide to customers without the need to store a large variety of goods. Hence, additive manufacturing is capable of improving value-added services of the warehouse, enhancing the availability of goods, decreasing the variety of goods stored, and thereby, improving the overall flow of material within the warehouse, particularly for slow-moving parts.

The technologies described above can be combined with advanced and integrating ones such as Cloud computing and warehouse management systems to develop technological building blocks. The three most important ones among these are described in the following.

Internet-of-Things (IoT): The IoT is one of the major technological building blocks for a smart warehouse. However, it is also one of the less well-defined concepts (Atzori et al., 2017). The IoT includes different interacting concepts that are not always included in the applications discussed in the literature under the term IoT. Within the warehouse, there is a strong reliance on RFID technology for identifying different goods, but further technologies are applied to make the data available, e.g., Cloud computing. The IoT is considered to be one of the most important and potentially transforming applications to gain transparency and visibility within the warehouse and for its integration in the supply chain. This enables the handling of individualized goods at the data level and facilitates the management of warehouse resources.

Cyber-Physical Systems (CPSs): CPSs are important for enabling smart warehouses and are technologically advanced. CPSs are based on the interconnection of the cyber and physical spheres. "Embedded computers and networks generally monitor and control physical processes by using feedback loops, where physical processes affect computations and vice versa" (Lee, 2008). The main physical tasks to be performed within a warehouse are the transportation and material handling tasks. Hence, material handling and transportation robots are the main applications of CPSs. In addition, wearables can be considered in CPSs as they provide a human technology interface and support the integration of human actors in a cyber-physical environment (Sahinel et al., 2019).

Big Data: Big data is another key enabler for smart warehouses, particularly in making the data generated within the IoT available, processable, and interpretable (Addo-Tenkorang & Helo, 2016). Big data applications are strongly interconnected with the IoT and CPS applications. Internal processes can be monitored, and operational data can be used to gain information on the interrelations between processes and to optimize the warehouse. Hence, management actions in the warehouse can be supported using internal big data for process improvement as well as big data from other sources, e.g., to improve inventory management and supply chain decisions (Bertsimas et al., 2016).

The technological building blocks discussed above significantly impact warehouse operations. Nevertheless, within the foreseeable future, for warehouses in different sectors and industries, certain processes will rely largely on humans and on manual operations (cf. current employment figures in warehousing, which is at an all-time high, BLS, 2021). For example, within a typical e-commerce warehouse, tens of thousands of different goods are stored. These are of different shapes and materials and are, therefore, not conveniently graspable by robots. This currently necessitates reliance on human operators, particularly within the order-picking process (Grosse et al., 2015, 2017). This is discussed in the following as an example.

4. Order-picking in the smart warehouse

Order-picking is still one of the most time-consuming process steps within the warehouse. Surveys show that order-picking relies on human operators in most cases (Behnisch et al., 2017; de Koster et al., 2007; Michel, 2016, 2019). It is one of the most expensive process steps within a warehouse and should, therefore, be considered in more depth. Notwithstanding the reliance on human operators in many cases, the order-picking process is impacted significantly by the technologies applied within the smart warehouse; these technologies can be either automation or digital technologies.

While focusing on the order-picking process, which requires a physical task to be performed to pick the items, automation technologies can be considered as *substitution technologies* (Winkelhaus et al., 2021). This is because these are capable of substituting the human operator completely. Meanwhile, digital technologies are *supportive technologies* because these can support the human operator in fulfilling the tasks more efficiently and possibly with less human effort. In addition, the level of automation differs for different technologies used in the order-picking process. For example, only simple decisions are made for a conveyor belt, i.e., to operate or not. There may be a few switches or buttons to operate, or occasionally there may be speed adjustments. However, the degree of adaptability in relation to the environment is very low. In contrast, autonomous mobile robots in warehouses are more flexible and adaptable. These are at a significantly higher level of automation and can fundamentally impact the processes within the warehouse. This differentiation is also applicable to supportive technologies. The simplest technical support for the order-picker is a barcode scanner that replaces a paper-based picklist. In contrast, one of the most adaptive technologies available is an Augmented Reality application that continuously adapts to the evolving context and guides the order-picker through the warehouse (Glock et al., 2021). In addition to information presentation, information generation is enabled through the integration of other technologies such as RFID, which substitute the cognitive process of verifying the pick (Andriolo et al., 2016).

Fig. 3.1 shows a technological grid and the resulting order-picking systems (OPSs) (Winkelhaus et al., 2021). Here, on the x-axis, supportive technologies are approximately divided into traditional, non-adaptive technologies and highly adaptive ones. On the y-axis, a similar distinction is made for substitutive technologies. Four types of OPSs can be identified based on the use of technology (to achieve smart order-picking) and on the potential to efficiently perform order-picking tasks. The four quadrants are described briefly.

Traditional OPS: The traditional OPS relies on constrained, inflexible, and non-adaptive technologies. Examples of the application of automation technologies are conveyor belts and stacker-crane-based AS/RS. The supportive technologies comprise displays that provide information similar to paper-based picklists. Traditional OPSs can be either person-to-goods or goods-to-person systems (de Koster et al., 2007). Although both these systems (semi-automated and manual systems) can be operated highly efficiently, there are several limitations. With regard to automated systems, the expandability, scalability, adaptability to environmental transformations, size of storable goods, weight, climatic conditions, and other characteristics are subject to restrictions and constraints that cannot be altered economically once fixed (Custodio & Machado, 2019). In addition, these goods generally have to be graspable by humans as the picking process is typically

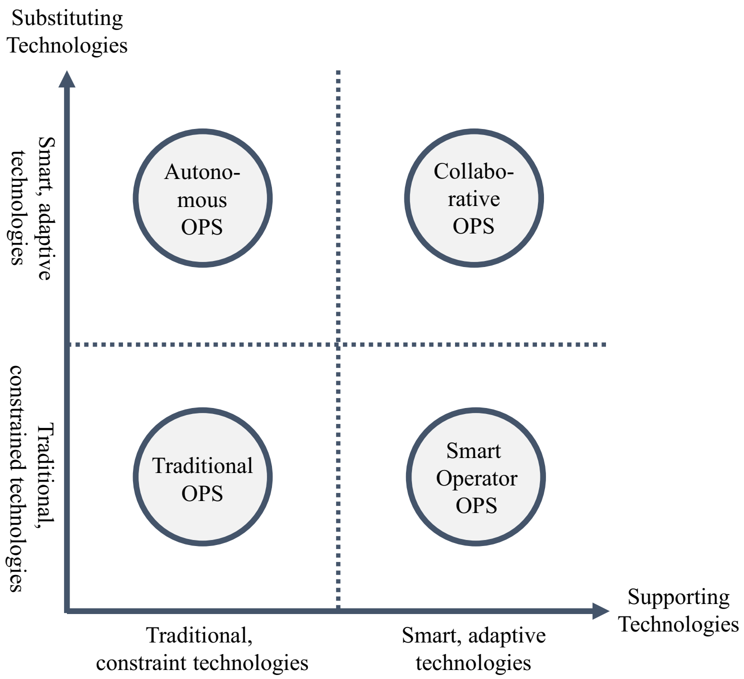

FIGURE 3.1 Order-picking system types.

performed manually. This increases the picking frequency but does not replace the need for human operators. Compared with this, the frequency of order-picking is generally significantly lower in person-to-goods systems (Boysen et al., 2019). However, the systems are more flexible because human operators can conveniently respond to alterations in the process or demand structure. Therefore, an investment in traditional automation technology is profitable only if the future development is sufficiently secure and the picking volume is sufficiently large. Considering the new requirements that are likely to evolve within the digital supply chain because of e-commerce growth, shortening product lifecycles, and shortening delivery times at constant cost pressure, it is debatable whether traditional OPSs would be the best option in increasingly dynamic business environments.

Smart Operator OPS: Smart operator OPSs apply automation technologies to a similar (low) degree compared to traditional OPSs. However, these equip the operator with other, more advanced technologies such as *wearables*. Supporting technologies generally focus on the cognitive and documentation aspects of the order-picking process. For example, Augmented Reality can be applied to develop an adaptive method for providing information to the operators supporting them, particularly in the search for the correct item location in manual *person-to-goods* systems (Glock et al., 2021). Other technologies that support the operator during the picking process are *exoskeletons* that reduce the physical load on the operator during the picking process and wearable health trackers (Romero, Stahre et al., 2016).

In addition to the support during picking process, the smart operator can also be equipped during the planning and learning of the picking process. For example, virtual reality and motion capture can be used to enhance learning outcomes even before the first real process is performed, and ergonomic requirements during the performance can be trained (Elbert et al., 2018). Virtual reality can also be used for process visualization and the subsequent optimization.

Although smart operator OPSs mostly focus on manual *person-to-goods* OPSs, they can also be applied to AS/RS. This is particularly noteworthy while considering the reduced movements and the higher frequency of picking of goods when such systems are applied (which could result in partially higher physical loads).

The new demands on a smart warehouse can be addressed by applying the smart operator OPS. This is because its high flexibility makes it significantly more efficient than traditional OPSs. Illnesses and injuries are reduced by limiting the loads on the operator, and processes and tasks are performed more efficiently and effectively because of the better information availability (Romero, Stahre et al., 2016). The resulting OPS is comparable to the traditional one, although it applies technologies to optimize the processes. However, this OPS is also subject to criticism. This is because the main objective is to increase human capabilities to fit to the systems requirements that are set externally, rather than the design of an OPS that fits human capabilities (Neumann et al., 2021). In addition to the potential for diverse applicable technologies, these must be suitable for and accepted by the employees to realize the potential benefits (Romero et al., 2018). It is clear that wearable and tracking systems must be implemented carefully and with caution (Kaasinen et al., 2020).

Autonomous OPS: Autonomous OPSs strongly focus on adaptive and flexible automation technologies. Although RMFS are not adequate for this type of OPSs, these are being increasingly applied in practice (Azadeh et al., 2019). In RMFSs, the number of human tasks is not reduced compared with that in AS/RSs. However, the types of storage and retrieval are different. In RMFS, AGVs travel around the warehouse and carry shelves (from which items have to be picked) to the operators. Hence, these types of OPSs provide more flexible solutions and more convenient scalability; thereby, the order-picking process is improved, and picking efficiency is increased (Boysen et al., 2019). Nonetheless, several restrictions within these systems need to be resolved. For example, there are restrictions on the storage of goods, and the minimization of human tasks results in insufficient workplaces.

There are also applications for fully autonomous order-picking robots within a smart warehouse, depending on the variability of goods (Azadeh et al., 2019; Dallari et al., 2009). Within this OPS, the trends and future demands can be satisfied, particularly those concerning high storage density and picking efficiency. In terms of autonomous pick actions, these systems are still constrained. However, future developments with regard to investment costs, flexibility, and the capability to pick diverse goods may resolve present restrictions.

Collaborative OPS: A collaborative OPS combines advantages of both flexible human OPSs and the highly efficient autonomous OPSs. In a collaborative OPS, autonomous robots as well as human OPSs are applied to a shared workspace, and these cooperate or collaborate for order fulfilment (Kauke et al., 2020). Within such OPSs, high-level automation technologies are applied in conjunction with appropriate technologies for smart operator OPSs.

In a collaborative OPS, human flexibility and adaptability and the capabilities for grasping, problem solving, planning, and error correction are applied to perform picking and sorting tasks and to support the automation technology (Verbeet et al., 2019). Meanwhile, automation technology can perform tasks with high precision, efficiency, and high average performance. Its applications range from AGVs that interact with human operators, follow them to the pick destination, and transport goods for the order-picker, to fully autonomous order-picking robots that collaborate with operators for order fulfilment (e.g., in performing sorting or picking tasks in unergonomic conditions Zhang et al., 2021). The operators in such systems can be supported by smart operator systems. This also facilitates the interaction of human operators with robots.

By combining these characteristics, available OPSs can be optimized to yield collaborative OPSs that can satisfy future requirements. High flexibility can be maintained while improving efficiency and effectiveness. Furthermore, most applications require small, decentralized units rather than large installations. Therefore, these are also applicable to small warehouses and city hubs.

5. Smart warehouses are sociotechnical systems

As outlined, humans play a significant role within all warehouse processes, particularly within the order-picking process. Smart warehouses are sociotechnical systems (cf. Clegg, 2000), which require the application of a sociotechnical systems perspective to their design, operation, and management. It is not feasible to optimize warehouses by focusing only on new technological possibilities. Rather, the social part of sociotechnical systems must also be considered to prevent suboptimal results (Sgarbossa et al., 2020). In particular, in an evolving context such as the digitalization of the supply chain, it is important to consider human factors and ergonomics to prevent an innovation pitfall and ensure the sustained performance of the system (Neumann et al., 2021).

In recent years, human factors and ergonomics have been discussed widely within the warehouse context with the focus being generally on traditional OPSs (Grosse et al., 2015; 2017). However, when the tasks to be performed within a warehouse or the methods of performing these tasks are altered, human factors are also impacted. The physical and mental load that the human is exposed to is likely to be altered, which can result in underloading or overloading of human capabilities. Thus, in a smart warehouse, human factors must be considered and systematically analyzed from a sociotechnical perspective (Winkelhaus et al., 2021). This enables to successfully implement new technologies developing the necessary capabilities of the operators, prevent a drift toward unsafe states, and ensure sustainable competitiveness. In the following, the concept of smart warehouse order-pricking is analyzed from a sociotechnical perspective.

Four human factors can be identified as a basis for the analysis (Grosse et al., 2017):

(1) Perception, which is the use of the human sensory system to gain information on the environment;
(2) Cognition, which focuses on processing the sensory information using previously gained knowledge and newly acquired knowledge, and decision-making;
(3) Motor action, which is the physical performance of an action; and
(4) Psychosocial factors, which include motivation and the interaction of humans with colleagues and supervisors.

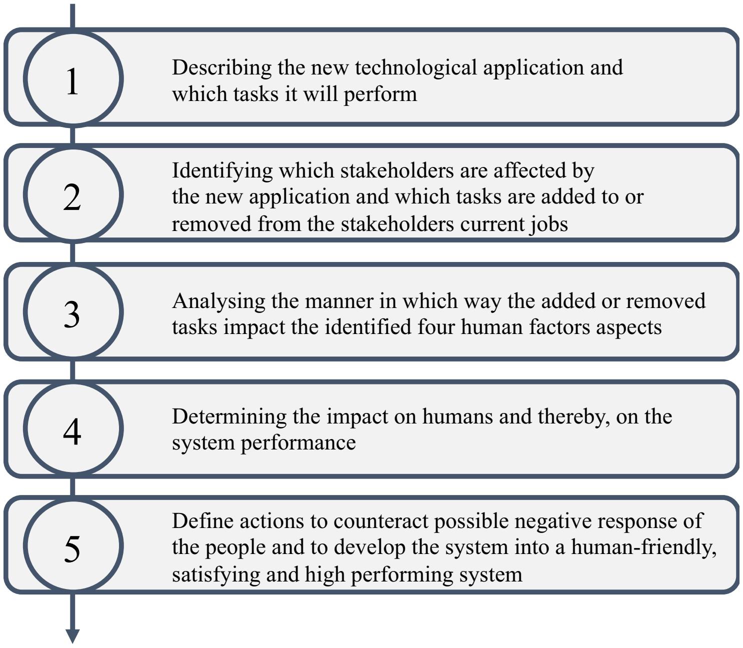

FIGURE 3.2 Process model to analyze human factors within the smart warehouse.

These four aspects must be considered while analyzing the impacts of transformations caused by warehouse digitalization on human operators. The potential impacts and conflicts can be analyzed in five steps using a process model, as shown in Fig. 3.2.

As an example of the application of this process model, we discuss the transformation of a manual *goods-to-person* OPS into a collaborative OPS through the application of autonomous picking robots (Neumann et al., 2021). Please note that we only provide an overview of the process and describe the example to a limited extent.

(1) We assume that the application of an autonomous order-picking robot, such as the Toru from Magazino, in a previous completely manual *person-to-goods* OPS (Magazino, 2019). Toru is capable of performing all order-picking tasks in a similar manner as human operators. However, their grasping capabilities are limited to a certain number of goods stored within the warehouse (Correll et al., 2018). The robots are designed to be safe in all cases where these interact with humans. Hence, human operators are still employed within the warehouse to pick the remaining goods and as additional capabilities for peak loads. The warehouse is organized such that ergonomics for human operators are optimized and goods picked by robots are stored at the top and bottom levels of the shelves. An example application of Toru is shown in Fig. 3.3.

(2) The most affected stakeholders are human order-pickers who work in the warehouse. They have to pick a limited range of goods and co-work with robots in a shared workspace. They may also have to support the robots in case of an error or failure. In addition, the warehouse maintenance staff members are affected because complex robots are now applied in the warehouse. This could involve tasks completely different from those performed earlier. Similarly, the IT department is affected considerably because these robots require input data and may need additional IT support. Furthermore, managers are affected because they have to manage new systems that are less flexible compared with order-pickers and are confronted with new planning and control tasks. Suppliers are likely to be affected because certain goods may require different packaging.

(3) In this process step, for each affected stakeholder, the impacts on human factors can be analyzed based on the changing tasks. As outlined above, the important human factors are perceptual, cognitive (including knowledge), physical, and psychosocial factors.

  (3.1) Order-Pickers: Perceptual human factors are affected by the application of picking robots. In the new scenario, robots also work on the shop floor, which may result in different interactions and perception requirements even if the robots are safe. Moreover, the reduced range of goods picked by human operators also limits the variety of goods to be processed. However, these may be more difficult to grasp, handle, or identify than other goods in the warehouse, which may increase the perceptual loads. Cognitive loads are impacted because 1) the task variety is

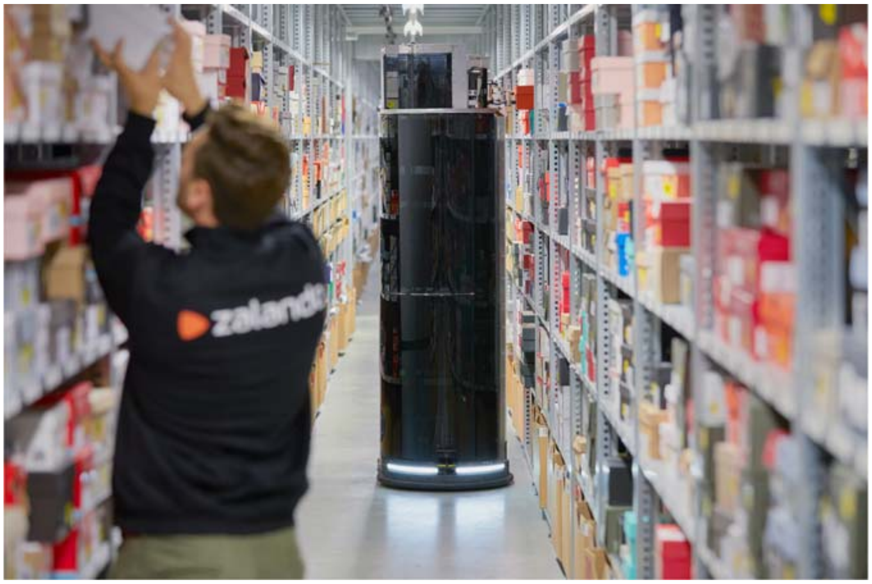

FIGURE 3.3 Collaborative order-picking employing Toru and human operators. *Credit: Magazino GmbH, Oliver Jung.*

limited by the constraints on the variety of goods and 2) the picking robots must be supported in case of failure. Hence, there is a shift in the knowledge requirements and task variety. Physical ergonomics are improved because of the better grasping conditions and less required stretching and bending, which, in turn, is because robots pick the articles from very high and very low rack levels. Finally, psychosocial human factors are also affected. This is because fewer colleagues are likely to operate in the warehouse, autonomy may be impacted, and performance now depends on that of both humans and robots.

(3.2) Maintenance staff: Impacts on human factors can be assumed comparably low, as we assume that maintaining the robot is still performed by the robot distributor. Nevertheless, cognitive and knowledge needs change. Minor problems will have to be solved by on-site personnel and work methods in general might change. This requires new knowledge that may not have been in focus so far, for example, from control and automation technology. Hence, psychosocial human factors are also affected owing to these changed demands. Additionally, working hours might change, because robots can perform for longer periods without rest-breaks, but still need to be supervised by maintenance staff.

(4) The shift in work tasks influences how operators respond to the changed work system.

(4.1) Order-pickers: Changes in tasks can increase perceptual demands, and new knowledge requirements can result in additional performance impacts and ramp-up effects. This may be because of the new interactions with robots that need to be learned, which can reduce the system output. Meanwhile, a change in tasks can improve ergonomics, thus reducing physical fatigue. This increases the performance of operators and may reduce the number of days of illness and turnover. Psychosocial factors may increase the fear of job loss and reduce the motivation and job satisfaction of the operators. As can be observed, it is not easy to predict the overall effect on the system (including the order-picking process step) because opposing factors act on the overall system performance.

(4.2) Maintenance staff: Applying an automation system requires changes in the warehouse that also affect the maintenance personnel. Previous working methods are questioned as to whether they lead to disruptions in the robots and thus to the entire warehouse. Thus, ramp-up effects are probable, because new knowledge must be gained through training and human–robot interaction must be balanced also for the maintenance staff. Additionally, changing working-hours and new demands set by the complex system could not only lead to technology rejection but also provide more motivation arising from new challenges and more diverse tasks.

(5) Various actions can be performed to actively manage the implementation of the new technology and positively impact the system.

(5.1) Order-pickers: Order-pickers can be involved early in the design process, and transparency within the introduction can reduce the fear of job loss. Training prior to robot implementation can positively impact the ramp-up process and accelerate the learning processes. However, there may be a need for additional operators during the

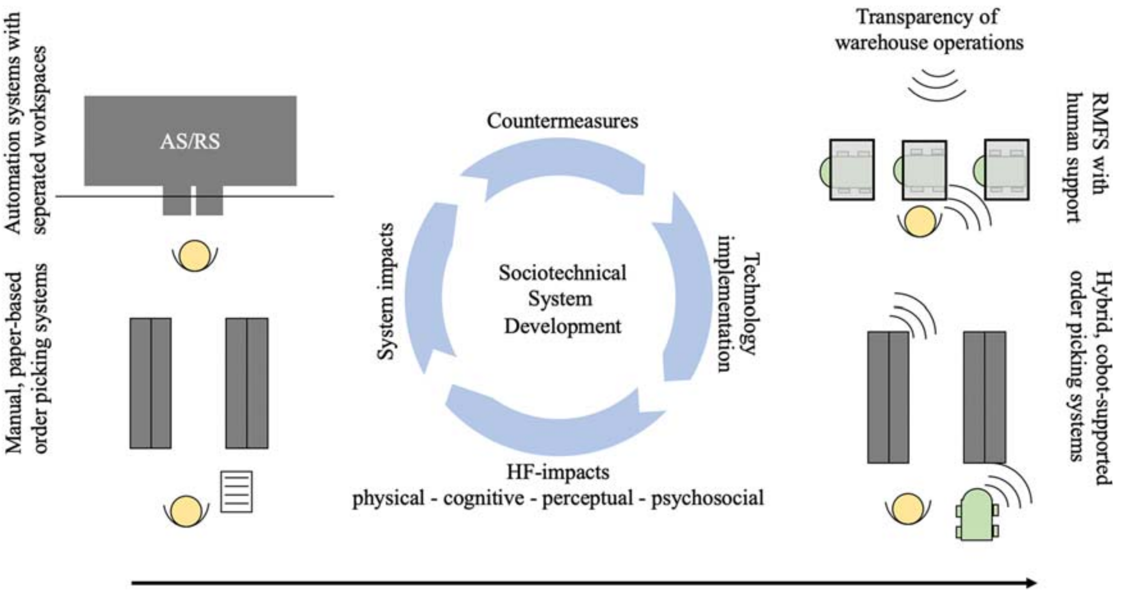

FIGURE 3.4 Transition from traditional to smart warehouses (example).

introduction phase. This is to prevent overloading of the system in the attempt to ensure constant output while addressing new tasks. Other motivational programs can be implemented for operators (e.g., for high picking-frequencies) to compensate for the reduction in diversity of goods.

(5.2) Maintenance staff: New knowledge and new demands need to be anticipated to minimize the risks of technology implementation. Hence, training is needed and should be applied early in the process. New personnel may be needed to support the team with new know-how. Transparency and clear managerial guidance could support the motivation and reduce fears caused by the new demands.

As a result of this process model, we obtain a map of different impacts of a new technology on the humans in a work system and possible effects on the overall system performance. In addition, we obtain a catalog of possible measures for improving the system implementation and more accurately forecasting the implementation costs of the new technology. Fig. 3.4 shows an example for the transition from a traditional OPS to an OPS within a smart warehouse from a sociotechnical system perspective.

Although the proposed process model does not necessarily have to be carried out in a particular way, a step-by-step application is recommended, getting more detailed in each level of application. For example, it can be used by top management in an initial potential assessment of a warehouse technology to make a preselection, which may initially be at a high level. As plans become more detailed, it can be refined. As planning progresses, the affected employees who are closer to the workplace will need to be involved. Lastly, this may involve supply chain partners to estimate also financial impacts and the feasibility of the identified solution.

6. Conclusions

To conclude, the smart warehouse combines not only diverse technological solutions for an overall optimization of a system with human operators but, beyond this, also social and environmental questions need to be considered. As recently outlined by the European Commission, there is a shortfall in the concept of Industry 4.0 in focusing solely on technologies (Breque et al., 2021). The next step of industrial evolution must build on technological developments, but especially focus on a human-centered perspective in which technology supports human operators rather than human operators supporting the technology. Additionally, Industry 5.0, as called for by the European Commission, aims for sustainable and resilient supply chains that take into consideration the natural boundaries of the planet and human needs (Breque et al., 2021). In this regard, the smart warehouse as described in this chapter plays a major role. By applying different technologies, the smart warehouse can enable a resilient and resource-efficient logistics service for supply chains. Additionally, adopting the view of sociotechnical theory, a human-centered approach needs to be applied that ensures the smart warehouse is a fundamental brick in future supply networks.

Although smart warehouses are an important step toward future industrial systems, there are several challenges in implementing these in enterprises and transforming existing work systems. Apart from the internal challenges that need to be addressed concerning the human-centered transformation, supply chain integration is also important. Therefore, technology standards are needed as interoperability of warehouses is essential for future success. The implementation of a smart warehouse facilitates this integration because it reduces the barriers between companies and different stages of a supply chain and integrates different material flows.

We expect that in the future, warehouses in almost all areas will rely more on supporting and automating technologies in order to respond to the challenges of today's business environment, meet sustainability goals, and to remain competitive. Autonomous robots will probably play an increasing role, but it is likely that humans will remain essential to perform work in warehouses. However, this also means that human−technology interaction will increase and must be given more importance in operational planning and the skills for this must already be developed during the vocational training of future employees. Accordingly, we assume that professional and active management of sociotechnical interactions will gain importance, which can partly be taken into account by providers of new technologies already in the design of the technology but must also take place in their explicit application within the smart warehouse. Otherwise, there is a risk of drifting toward unsafe states and a poorly performing system (Neumann et al., 2021; Rasmussen, 1997).

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Chapter 4

The Internet of Things—an emerging paradigm to support the digitalization of future supply chains

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Abstract

The many potential uses and benefits of the Internet of Things (IoT) have spurred great interest from practitioners and researchers to investigate IoT applications in supply chains and logistics systems. IoT-based supply chains are enabled by technologies such as Radio Frequency Identification, Wireless Sensor Networks, Machine-to-Machine systems, and mobile apps. IoT may allow reduced human intervention in decision-making processes through controlling, optimizing, planning, and monitoring of the supply chain virtually. This chapter provides an overview of IoT and investigates IoT applications and challenges in the context of supply chains. Different IoT technologies are being actively trialed in a wide range of supply chain applications including cold chains, perishable products, agriculture and crops, and some manufacturing supply chains. However, the application of IoT technologies in supply chains is challenging. Security and data privacy, standards and naming services, technology adoption, and big data generation are some of the critical issues. We present a framework—the *IoT Adopter*—for organizations to critically assess IoT adoption and implementation in supply chain applications. The framework identifies four fundamental stages that should be considered in deploying IoT across a supply chain: adoption rate calculation, profitability computation, architecture design, and continuous improvement.

Keywords: Cyber-physical systems; Digital supply chains; Industry 4.0; Internet of Things (IoT); IoT supply chains; Smart supply chains.

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1. Introduction

Emerging digital technologies have altered the interactions between firms, suppliers, and customers (Batran et al., 2017). Digitalization is changing the way supply chains are managed, leading to the emergence of the Digital Supply Chain (DSC). A wide range of technologies are bringing new opportunities for DSCs, ranging from supply chain performance improvement (Gunasekaran et al., 2017; Kinra et al., 2020) and cost reduction (Korpela et al., 2017) to more rapid and improved product development (Büyüközkan & Göçer, 2018). The rapid adoption of Industry 4.0 concepts also supports the transformation of traditional supply chains into DSCs (Queiroz et al., 2019).

Industry 4.0 was first introduced for Germany's economic amplification in 2011 (Roblek et al., 2016). It seeks to ensure that traditional industries are connected internally and digitalized effectively (Shafiq et al., 2015, 2016). Industry 4.0 has the potential to equip factories with cutting-edge technologies such as robotics, augmented reality, digital twins, and simulations (Masood & Sonntag, 2020). These are supported by emerging novel information systems and technologies, including *Cyber-Physical Systems* (CPSs), *Internet of Things* (IoT), and *Cloud Computing* (CC) that can provide an intelligent environment in factories (Zhong et al., 2017). Here we focus on the emerging and central role that will be played by one of these technologies—IoT. Among Industry 4.0's fundamental concepts, IoT is a solution for collecting and distributing data (Jagtap et al., 2021).

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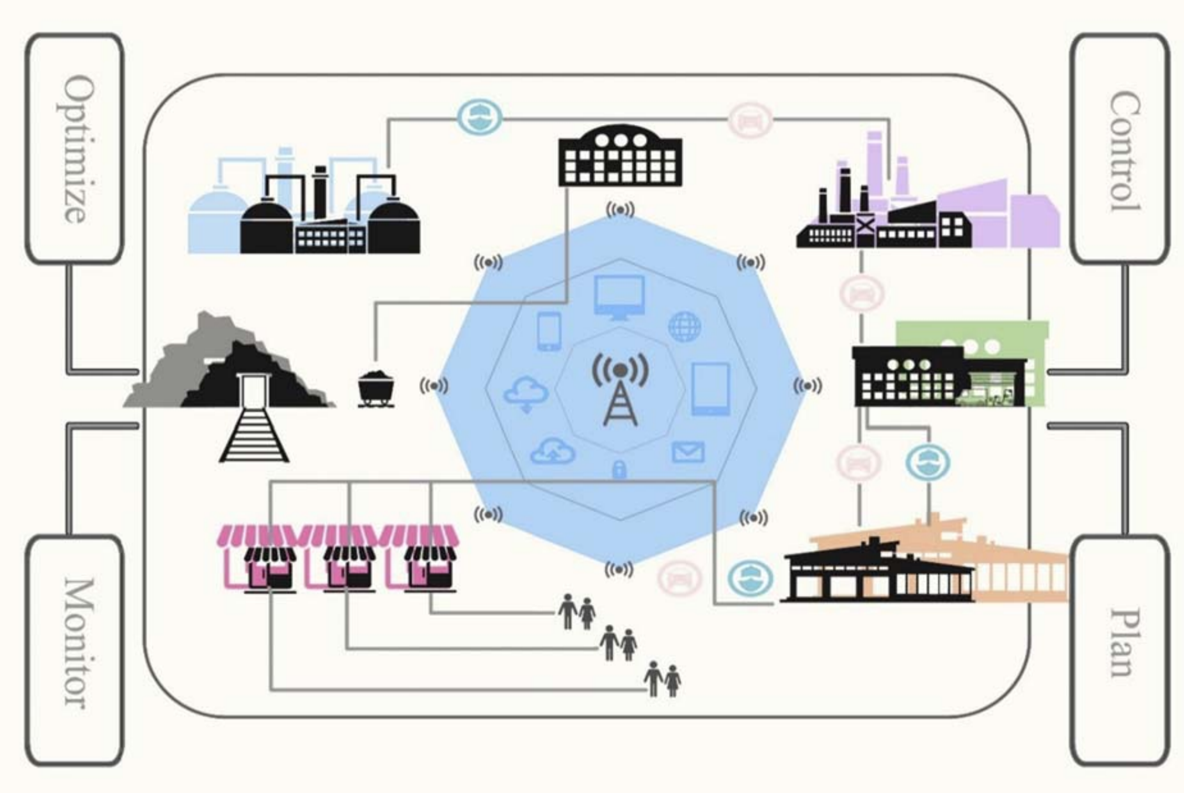

FIGURE 4.1 An overview of IoT-based supply chains.

IoT systems allow objects and devices to be connected over a communications network, where physical things can sense and process data about many aspects using their embedded sensors (Goyal et al., 2021). These might include environmental features such as humidity and temperature, or the performance and condition of machinery, and the data can then be transmitted over the network (Li et al., 2015; Ogonji et al., 2020). The transferred data can be used in a variety of tasks, for example, monitoring COVID-19 patients (Ravi Pratap Singh et al., 2020), predicting parking occupancy (Provoost et al., 2020), and making service recommendations (Mashal et al., 2015).

IoT, as a set of interconnected objects that can be sensed and monitored through the Internet or other communications networks and that interact with each other (Reka & Dragicevic, 2018), enables physical objects to be "virtualized." IoT changes the physical environment into a smart and virtual atmosphere (Goyal et al., 2021) and has the potential to be utilized for virtual supply chain management (SCM) (Verdouw et al., 2013). It has been claimed that IoT will be the leading technology that will enable Industry 4.0 (Gilchrist, 2016). Cost reduction, waste decrease, and service delivery improvement are some of the claimed IoT application benefits (Ogonji et al., 2020). By applying IoT, more responsive operations in supply chains may be possible and agility may be improved in the context of resource allocation, actions, multiorganizational coordination, and conditional assessment (Yang et al., 2013). From the SCM perspective, IoT may allow supply chains to make decisions autonomously or with minimal intervention (Zhou et al., 2015). In addition, IoT may enable managers to dynamically control and optimize supply chains, execute plans, and monitor the logistics processes remotely (Mithun Ali et al., 2019).

Fig. 4.1 briefly illustrates the concept of an IoT-based supply chain in which physical objects' data are collected with embedded sensors and tags and sent across wireless networks to be captured in a cloud-based platform. The platform's gathered data contain a virtual instance of the physical environment, which changes over time. This can aid managers to monitor, control, and plan the physical environment and material flows, resulting in increasing optimization in the DSC.

In addition to supply chains, IoT can be integrated in Logistics systems, giving rise to the concept of the *Physical Internet* (PI) (Tran-Dang et al., 2020). PI is a global logistics system that seeks to improve efficiency and sustainability by interconnecting logistics networks in an intelligent way. Collaboration protocols, modular containers, and interfaces are standardized by PI in logistics systems (Ballot et al., 2014). A high interconnectivity level is required among a designed PI to manage, store, and transport logistics products effectively. IoT technologies need to be integrated with PI to provide end-to-end visibility in PI-based logistics (Tran-Dang et al., 2020).

A wide range of review and survey studies have been conducted on IoT technologies (Atzori et al., 2010; Brous et al., 2020; Goyal et al., 2021; Khan & Salah, 2018; Yan et al., 2014). A few of them have concentrated on the confluence of IoT and food supply chains (Ben-Daya et al., 2019; de Vass et al., 2020). De Vass et al. (2020) mainly concentrated on retail sectors; Birkel and Hartmann (2019) investigated the IoT-based supply chains from security and risk aspects. Researchers are also trialing IoT technologies in diverse supply chain settings. Gill et al. (2016) developed an IoT-based architecture called Resalert, enabling emergency supply chains to send emergency alerts to older adults when disasters occur. Baranwal et al. (2016) presented an IoT-based system for repelling rodents in agriculture. There are also many exciting and promising IoT-related emerging systems in development by commercial companies for manufacturing,[1] transportation,[2] logistics[3] (e.g., Telenorconnexion), asset management[4] (e.g., IOT Factory), and maintenance[5] (e.g., Nokia).

Notwithstanding the increased research intensity and claimed benefits, IoT has not yet penetrated supply chains widely (Manavalan & Jayakrishna, 2019). This chapter explains and discusses the potential role of IoT technologies in the era of DSCs through a review of the research literature. Section 2 explains the main concepts of the IoT field. Section 3 concentrates on introducing novel technologies and IoT in the era of SCM. Section 4 summarizes the different IoT applications in supply chains. Section 5 discusses the critical challenges of IoT-based supply chains. Section 6 presents a framework for IoT implementation in DSC domains. Finally, we conclude and present some limitations and avenues for future work in Section 7. A glossary of the most important terms can be found in Appendix A.

2. The basic concepts of IoT

The IoT term was introduced by Kevin Ashton in 1999 initially (Ashton et al., 2009). In 2015, S. Li et al. in their frequently cited paper, presented a formal definition for IoT based on a review of different sources (IERC, 2013; Kiritsis, 2011; Li, Xu et al., 2012; Li, Hou et al., 2012). They consider IoT to be a network of interconnected physical and virtual objects that can be connected to each other autonomously via intelligent interfaces and integrated as an information network based on standards and interoperable communication protocols (Li et al., 2015).

In contrast to the Internet, in which data are generated and inputted by people, in an IoT system, data are generated by objects (Madakam et al., 2015). Identifying and sensing of objects are two main features of the IoT. Objects can be connected and interact with each other through the Internet (Goyal et al., 2021). IoT increases data availability (Ng et al., 2015) and enables people and organizations to track the physical environment and potentially control objects virtually (Goyal et al., 2021). The virtual representation improves collaboration capability in IoT-enabled supply chain environments by integrating suppliers (Wang et al., 2006). IoT therefore has the potential to transform the physical environment into a smart and virtual atmosphere.

An IoT-based supply chain is a set of digitally connected objects, which can be sensed, monitored, and interact with each other within an organization or its suppliers, resulting in an agile supply chain. IoT-enabled supply chains can potentially obtain the capability of auto decision-making, requiring minimal or no human intervention (Zhou et al., 2015), and can facilitate intelligent data analysis (de Vass et al., 2020). Additionally, controlling, planning, and coordinating are all simplified through information sharing, tracking, and visibility features (Ben-Daya et al., 2019). IoT is being considered in a broad spectrum of supply chains, including food (Accorsi et al., 2017) and agricultural (Leng et al., 2019), customized manufacturing supply chains (Song et al., 2019), and perishable products (Bogataj et al., 2017) utilizing a diverse range of IoT technologies.

IoT implementation comprises various hardware and software components—sensors, actuators, protocols, and software − integrated with an architecture (Gigli et al., 2011). However, the adoption of IoT technologies suffers from a lack of universally agreed architecture (Goyal et al., 2021).

2.1 IoT architectures

Although there is no universally agreed architecture for IoT yet (Madakam et al., 2015), there is a fundamental architecture referred to by researchers, which is classified into three main categories: Internet-oriented, things-oriented, and semantic-oriented (Atzori et al., 2010). Internet-oriented implies communication protocols and technologies (Al-Sarawi et al., 2017).

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[1] https://www.engineering.com/story/what-iot-can-do-for-you-looking-forward.

[2] https://www.maritime-executive.com/editorials/standardized-iot-for-containers-is-the-key-for-smart-supply-chains-1.

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[4] http://iotfactory.eu/.

[5] https://www.nokia.com/networks/private-wireless/?did=d000000002dg.

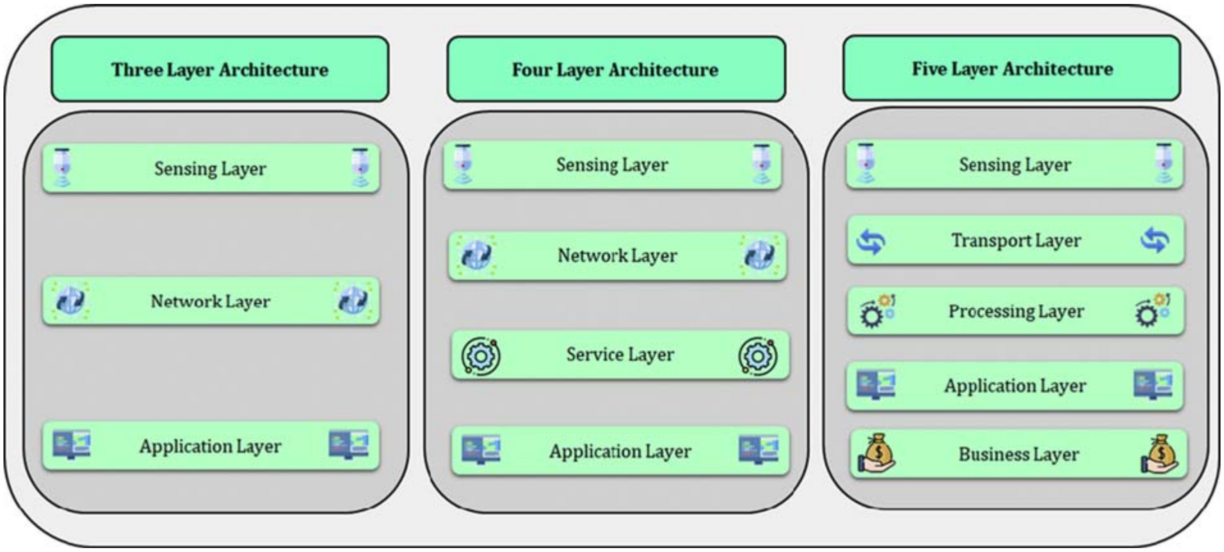

FIGURE 4.2 Different IoT architectures.

Things-oriented concentrates on smart objects such as sensors and radio frequency identification (RFID) tags (Saleem et al., 2016). Semantic-oriented refers to managing intelligent objects' data through a web interface (Aggarwal et al., 2013).

Different architectures have been employed in IoT-based supply chains. The most commonly used architectures are shown in Fig. 4.2. Some utilized three-layer structures (Liang & Pan, 2014; Liu et al., 2013), some four-layer (Gnimpieba et al., 2015; Qiu et al., 2015; Verdouw et al., 2013), and five-layer architectures (Laxmi & Mishra, 2018; Yi Liu et al., 2016). Additionally, some papers introduced their own architectures for specific domains, e.g. (Mengru, Ming, et al., 2018a,b), for production logistics and supply chain systems.

Typically, an IoT architecture is comprised of three core layers: the sensing layer (hardware, device, things, physical, or perception layer), the network layer (connectivity, or transport layer), and the application layer (cloud layer) (Ning et al., 2013). Sensing, network, and application layers refer to things, the Internet, and semantic reasoning, respectively (Atzori et al., 2010).

Sensing layer: This layer is the backbone of an IoT architecture, utilizing various sensors and actuators (Ning et al., 2013), gathering environmental data, and virtualizing them in a cyber-platform (Yan et al., 2014). Environmental parameters are measured, and smart things are identified in this layer (Sethi & Sarangi, 2017). The identification process is executed by some Identification Schemes such as the Universally Unique Identifier (O.I.D.), International Mobile Equipment Identity (IMEI), and Electronic Product Code (E.P.C.) (Al-Fuqaha et al., 2015).

Network layer: This layer concentrates on network ingredients configured with heterogeneous networks such as Wireless Sensor Network (WSN), mobile cellular networks, ad hoc networks, and Internet (Yan et al., 2014). They enable physical objects to connect to the cloud through gateways (Mohamad Noor & Hassan, 2019). Briefly, raw data transmission and processing are the critical roles of this layer (Sethi & Sarangi, 2017).

Application layer: This layer primarily focuses on providing intelligent services (Ning et al., 2013) to end-users (Yan et al., 2014). The application layer plays the service delivery role to the end-users (Sethi & Sarangi, 2017). Three-layer architecture is one of the fundamental IoT-based architectures that can be implemented quickly (Kumar & Mallick, 2018). However, a three-layer architecture may not keep up with IoT applications that require doing more tasks (Sethi & Sarangi, 2017). Accordingly, more layered architectures such as four-layer, five-layer, six-layer, seven-layer, and cloud and fog-based layer architectures have been proposed (Goyal et al., 2021; Kumar & Mallick, 2018; Sethi & Sarangi, 2017).

To improve the flexibility of the three-layer architecture, a service layer has been added to with the service-oriented architecture (SOA) for IoT systems. The service layer (middleware, or interface layer) lies between the application and connectivity layers to improve the data services (Lin et al., 2017). Thus, an SOA-based IoT architecture comprises four layers, including sensing, connectivity, service, and application layers (Suo et al., 2012), as shown in Fig. 4.3. However, the story does not end here, and comprehensive multilayer architectures such as five-layer architectures have been proposed.

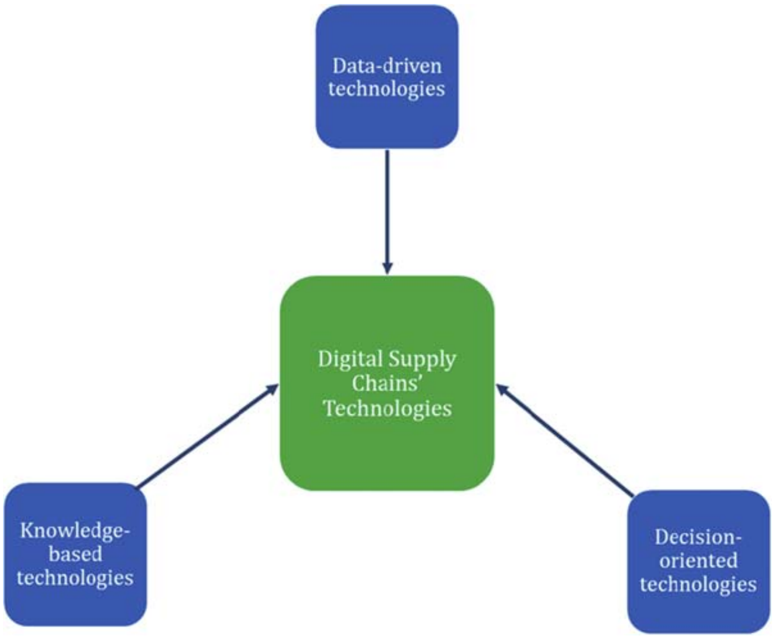

FIGURE 4.3 Digital Supply Chain technologies.

Five-layer architectures comprise of perception, transport, processing, application, and business layers. The perception and application layers act like their counterparts in the three-layer architecture (Sethi & Sarangi, 2017). The three other layers are explained as follows:

Transport layer: This layer transmits the collected data from sensors to the processing layer and contrariwise in the opposite direction. Some of the leading network technologies used in this layer are Bluetooth, RFID, and NFC.

Processing (middleware) layer: The data received from the transport layer are stored, analyzed, and processed in this layer. In other words, this layer is a core component of services that should be managed and created for lower layers. Databases, Big Data analysis, and CC are some of the critical technologies of this layer.

Business layer: This layer plays the manager role for all IoT systems, including applications and business-to-business (B2B) models and manages privacy.

In some cases, architectures with more layers are required. For instance, a six-layer architecture was introduced by Kumar et al. (2018), and a seven-layer one was proposed by Darwish (2015). Munir et al. (2017) introduced a flexible and reliable IoT architecture called IFCIoT (Integrated Fog Cloud IoT Architecture), which claims benefits such as better performance and reduced energy consumption. Response time is also decreased, and localization is facilitated in IFCIoT architecture (Wang et al., 2018). The IFCIoT is strictly related to three leading technologies, i.e., CC, Fog Computing (FC), and Edge Computing (EC). The reported supply chain applications tend to utilize conventional IoT architectures rather than novel ones such as IFCIoT.

2.2 IoT and CPSs

IoT should be seen in the context of CPSs, which are novel systems that enable the physical world to interact with humans through an integrated environment (Baheti & Gill, 2011). In a CPS, computational elements such as sensors and communication tools are embedded in the different objects for controlling the physical environment (Minerva et al., 2015). The emergence of IoT has added new value for CPSs in which many physical devices such as Wireless Sensor Nodes and mobile robots can be connected internally via the web and interact with each other. IoT enables the handling of the physical environment through digitalized data (Chaâri et al., 2016). Indeed, CPSs play an agent role in IoT-based systems, collecting sensory data for problem-solving (Fortino et al., 2014). To put it differently, CPS is considered as a new scenario of IoT (Bordel et al., 2017).

3. Supply chain management, novel digital technologies, and IoT

Novel digital technologies seek to improve the performance of supply chains (Govindan et al., 2018), enabling them to perform better and change rapidly in the era of digitalization (Büyüközkan & Göçer, 2018). Digitalization provides a new form of information exchange and collaboration in supply chains through virtualization processes (Nasiri et al., 2020) in which almost everything can be digitized and handled without or with only minimal human interaction (González-Rojas et al., 2016). Digitalization of supply chains has the potential to increase information availability, collaboration, and communication, leading to more reliable, efficient, and agile management (Raab & Griffin-Cryan, 2011). It also provides opportunities for evolving to the next generation of supply chains (Büyüközkan & Göçer, 2018). A DSC may be a network utilizing technological and analytical concepts to introduce new business value (Kinnett, 2015), in which the DSC is transformed into a critical part of decision-making and strategic planning (Büyüközkan & Göçer, 2018). The emergence of cutting-edge technologies provides opportunities for self-learning situations in DSCs and supports autonomous decision-making in operations (Hanifan et al., 2014). Industry 4.0 is premised on supply chains that allow data acquisition and information sharing by sensor technologies, providing enough data for decision support systems and analytical decision-making (Esmaeilian et al., 2020).

Based on Esmaeilian et al. (2020) and our own knowledge, novel Internet-based technologies in DSCs can be divided into three main categories: data-driven, knowledge-based, and decision-oriented technologies (see Fig. 4.3). Data-driven technologies focus on data collection, storage, and information exchange between involved objects. Collected data from data-driven technologies are transferred to knowledge-based technologies for analysis. Finally, analyzed data are fed to the decision-oriented technologies to enable the best decisions to make about the received raw data. IoT, as one of the leading information and communication technologies (Xiao et al., 2016), comprises a wide range of sensing technologies including RFID, WSNs, and machine-to-machine (M2M), enabling companies to control and exchange the data through unique identifiers embedded in objects (Uckelmann et al., 2011). Furthermore, analyzing the collected data by IoT injects intelligence into the system, facilitating managers' decision-making processes (de Vass et al., 2020).

IoT technologies aim for data collection and enable various objects in supply chains to communicate with each other through an information exchange process (Nettstraeter et al., 2010). CC, as a data storage platform, provides virtual services enabling users to connect and access anywhere (Schmidt et al., 2015). Furthermore, with the growing tide of data generated through IoT technologies, utilizing knowledge-driven technologies such as Big Data Analytics is essential to ensure these data are available for effective decision-making processes (Ge et al., 2018) through decision-oriented technologies such as Decision Support Systems (DSSs) (Esmaeilian et al., 2020). This is summarized in Fig. 4.3.

Data collection and sharing are the first stages in a DSC, providing the raw material for knowledge-based technologies. For instance, different environmental measures such as humidity, temperature, and light intensity may be collected by data-driven technologies such as RFID tags and IoT-related sensors across a supply chain. In sharing the collected data, other data-driven technologies including Cloud and WSNs are employed. Gathered raw data without analytical tools may be useless. Hence, knowledge-based technologies including methods from Big Data analysis and AI are necessary. Analyzing raw data aids managers in managing and controlling the DSC. In addition to knowledge-based technologies, decision-oriented ones provide appropriate directions, recommendations, and guidelines, helping managers to make suitable, appropriate, and timely decisions.

4. IoT applications in OM and SCM

IoT may enable supply chains to integrate internally and externally and yield significant benefits from cost reduction and quality improvement to flexibility and performance enhancement (de Vass et al., 2020). Additionally, IoT may enable supply chains to monitor material flows, reduce the wastage rate, and rectify services in the event of disruptions, constraints, or impediments (Shah & Ververi, 2018). As noted, IoT is being trialed in some supply chains such as food (Accorsi et al., 2017), agricultural (Leng et al., 2019), and manufacturing (Song et al., 2019) and there are many promising commercial systems in development. What is the role of IoT technologies in different supply chains?

4.1 Agri-food

The food supply chain is one of the high-risk industries needing accurate control systems in the face of perishable foods, supply variation, and the requirements to meet food standards and regulations (Singh & Erdogdu, 2004). Internet technologies enable food supply chains to handle perishable products and uncertain demands in a dynamic environment. Additionally, controlling food safety and meeting sustainability requirements can be facilitated in an Internet-based supply chain (Verdouw et al., 2016). In an IoT-enabled system, end-users and suppliers can monitor and handle food products (Liu et al., 2016) through an autonomous tracing system (Chen, 2015).

Given the critical nature of safety in the food sector and consumer sensitivity, real-time response is required to avoid or protect against food safety scandals. An appropriate traceability system can mitigate the risk of unsafe and low-quality foods. Existing labeling systems are not effective enough to authenticate food quality, and traceability architecture is needed to ensure customer trust (Aung & Chang, 2014). Today, IoT technologies such as RFID and WSNs have the potential to improve food safety systems by enabling supply chains to trace their products (Tian, 2017). This is similarly true for agricultural supply chains, particularly in the logistics domain (Liu et al., 2016). Despite the IoT's extensive range of potential applications, the food industry has concentrated on the traceability concept (Jagtap et al., 2021).

4.2 Cold chains

The cold chain is a type of supply chain focusing on product temperature control (Hulea et al., 2018). A cold chain includes a network of nodes that seek to hold and transport temperature-sensitive products at an assured temperature from production to delivery (Mercier et al., 2017). Pharmaceuticals, foods, flowers, and chemicals are some of the common temperature-sensitive products (Smith, 2005) concentrating on cold chains to prevent spoilage of perishable goods (Heng et al., 2016). Nowadays, the emergence of IoT provides an intelligent environment for real-time monitoring of the perishable products' temperature and humidity in cold chains (Heng et al., 2016). To make cold chains more efficient, an intelligent warning system is added to the IoT architecture, informing users about the critical situations of sensitive parameters (Zhang et al., 2018). Defining a suitable threshold for each sensitive parameter in a warning system enables operators and supervisors to be aware of unusual or unacceptable conditions (Tsang et al., 2018). Pharmaceutical (Ting et al., 2010) and food supply chains (Bogataj et al., 2017) are two important temperature-sensitive cold chains that can utilize IoT technologies to help guarantee that the products meet the required conditions across the entire supply chain.

4.3 Other manufacturing domains

In a simple model of a manufacturing supply chain, raw materials are transferred from suppliers to the production lines. The processed products are stored in warehouses for packing. Then the packed products are loaded and delivered to the end-users usually through reatilers (Pal & Yasar, 2020). As a potential enabler of manufacturers, IoT has attracted a tremendous amount of attention (Bi et al., 2014). As one of the first efforts of IoT-based manufacturing supply chains, Mengru, Ming, et al. (2018a) introduced an IoT-based architecture for manufacturing supply chains that helps to monitor product flows and orders at any moment. Products can be tracked by the introduced architecture. In other research, Mengru, Ming, et al. (2018b) have investigated how to integrate CPS and IoT through an IoT-based CPS architecture in which M2M capability is added to the previous architecture.

Some researchers have concentrated on Reverse Supply Chains (RSCs) where consumers and producers work collaboratively for waste mitigation and sustainability by processes such as remanufacturing, reusing, recycling, or disposing of products (Bouzon et al., 2016; Govindan et al., 2012). Much of the research has focused on consumers recycling their products (Xu et al., 2011). The emergence of IoT may enable traditional RSCs to be transformed to Smart RSCs, aiding in achieving optimized energy consumption, resource recycling, and creating a compatible green and circular manufacturing environment (Xu et al., 2011). Awareness of critical conditions for temperature-sensitive products such as perishable foods, pharmaceuticals, vaccines, and flowers may prevent or reduce spoilage and waste generation. However, the way of IoT usage in industrial environments is different. In manufacturing supply chains, machines need to interact with each other. IoT cannot do this solely by itself. There is a need to integrate IoT technologies with CPSs to provide both human-to-machine and M2M interactions (Schätz et al., 2015, p. 611430).

Despite the potential benefits of IoT technologies for supply chains, reported research investigations on IoT-based supply chains are few, particularly on systems that have been implemented. As a result, there is a need to study the different uses of IoT technologies across diverse supply chain environments. The remaining sections discuss the challenges and limitations of IoT applications in the supply chain.

5. Future challenges for IoT in the supply chain

5.1 Security and data privacy

Employing IoT technologies can affect different domains' privacy and security, particularly concerning their use in supply chains (Weber, 2010). Due to the lack of appropriate agreed IoT systems protocols, security and data privacy remain two major critical challenges (Mohanta et al., 2020). Data transformation in an intense network of devices extends the security blind spots, exposing IoT systems to potential hacking (Ogonji et al., 2020). IoT systems may suffer from insufficient security controls in several cases, particularly in authentication and encryption (Ho-Sam-Sooi et al., 2021).

Each organization within a supply chain has its own security level and attitude to risk, which may be significantly different from other organizations in the same chain. The part of the supply chain having the weakest cyber-security may be the target for aggressors. A hacker may be able to access each part of the supply chain by leveraging the weakest ones and gaining access in a connected network of organizations (He et al., 2016). Hence, IoT-based supply chains' intense data and physical networks may face a high risk of vulnerability (Omitola & Wills, 2018). Despite the many potential uses and benefits of IoT, it poses threats to supply chains from a security perspective. Indeed, IoT has been characterized as a risk management problem in supply chains (Hiromoto et al., 2017). Many efforts have to be made to deal with both the security and privacy of IoT-based systems (Goyal et al., 2021) in terms of data privacy, confidentiality, and integrity; authentication, authorization, and accounting; service availability; energy efficiency; and single points of failure (Khan & Salah, 2018).

5.2 Standards, identification, and naming services

Unique identification of connected devices is a primary requirement of IoT, even before security issues. Through an appropriate identification method, each object and its properties can be found effectively and efficiently (Zhang et al., 2014). In an IoT-based network, a wide range of devices are connected to each other, creating a dense network of objects. Because of the dense network nature, a new challenge has emerged for naming the services, devices, and contents (Nour et al., 2020). There are different standards for service naming, e.g., object name service (ONS: defined by GS1 EPCglobal) (Traceability, 2009), Object Identifier (OID), and ucodeRP introduced by Japan's Ubiquitous ID Center (Center, 2009). The ONS is the most favored naming service utilized in SCM (Yi Liu et al., 2015).

ONS enables supply chains to capture and store data on a web-based infrastructure (Zhao et al., 2015). Indeed, ONS allows users to analyze the product through a query-based process and receive feedback from them, leading to better SCM (An et al., 2021). Despite the popularity of ONS, it faces some challenges, such as slowness, forcing enterprises to design new name services in their supply chain. For instance, iotNS is one of the naming services, that claims to be five times faster than the OSN system (Liu et al., 2015). The proposed naming service (*H-ICNIoT*) by Nour et al. (2020) improved the memory consumption and lookup time. Creating enterprise-oriented naming services may be very useful for supply chains because they are designed and customized based on the enterprise's specific supply chain.

5.3 Big data generation

In an IoT network, many physical devices seek to collect and exchange data, thus providing potentially vast datasets (Lo & Campos, 2018; Pigni et al., 2016). Traditional data processing methods may not be able to deal with these large provided datasets. Also, the nature of real-time data generated through a wide range of IoT devices forces supply chains to apply big data analysis as a critical SCM element (He et al., 2020). Accordingly, the big data term has emerged in the IoT domain.

The main challenges of IoT-based supply chains are indicated in Fig. 4.4. Big data transforms IoT-based supply chains into IoT-enabled big data−driven supply chains, supporting supply chains to analyze the status of their resources and products in a large-scale environment to make the supply chain more efficient. The confuence of IoT and big data needs much more research effort in the context of supply chains (He et al., 2020).

6. Perspectives on IoT adoption and implementation in supply chains

The supply chain is one of the most exciting domains for investigating IoT applications and adoption (Kamble et al., 2019). However, despite its extensive potential uses and benefits, IoT adoption is accompanied by barriers and risks in companies, as discussed in the previous section. Moreover, despite the perceived benefits claimed, the industrial environments have not yet been convinced to adopt it on a large scale (Mengru, 2018). An organization may be adversely affected if it chooses IoT based on its benefits without considering its risks and the structural changes needed (Brous et al., 2020). Consequently, investigation is required to understand the influential factors in order to develop a roadmap for decision-making for IoT adoption in organizations (Ehie & Chilton, 2020).

Supply chains require consideration of diverse factors (Wamba & Boeck, 2008). Overall, nine main parameters affecting IoT adoption in SCM have been highlighted: perceived benefits in performance; hardware and infrastructure; cost; security and data privacy concerns; adoption willingness; data complexity; peers and government support; technical knowledge; and compatibility (Affia et al., 2019). Calculating technology adoption rate (AR) has been investigated in different domains such as energy-saving (Hanes et al., 2019), tourism (Dhirasasna & Sahin, 2021), and freight

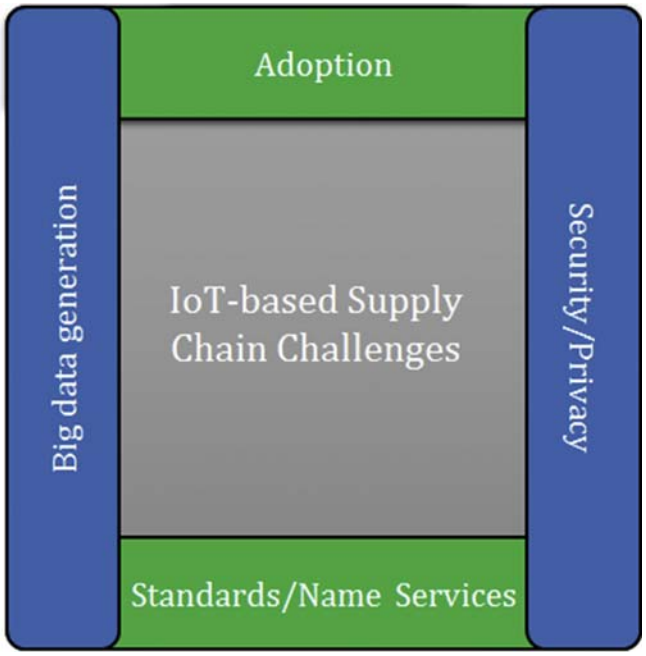

FIGURE 4.4 IoT-based supply chain challenges.

organizations (Simpson et al., 2019). In our context, the AR explains how much a supply chain accepts an IoT technology. It is vital, therefore, to understand and estimate the IoT AR in the SCM context.

Based on an ongoing engagement with experts and a review of more than 140 academic publications related to IoT-based supply chains, we introduce a framework for implementing IoT projects in supply chains, called the *IoT Adopter*. The *IoT Adopter* framework is illustrated in Fig. 4.5. Based on Fig. 4.5, the *IoT Adopter* seeks to support the "go/no go" decision for IoT technology implementation in the supply chain.

In the adoption phase, the framework recommends calculating the AR of IoT technologies across the entire supply chain. If the AR is lower than a threshold (Th), IoT cannot be applied successfully. However, if the AR is more than the threshold, the profitability of IoT projects is calculated. IoT implementation revenues and costs are predicted based on appropriate methods such as mathematical modeling and data mining. If the project is profitable (revenue is significantly

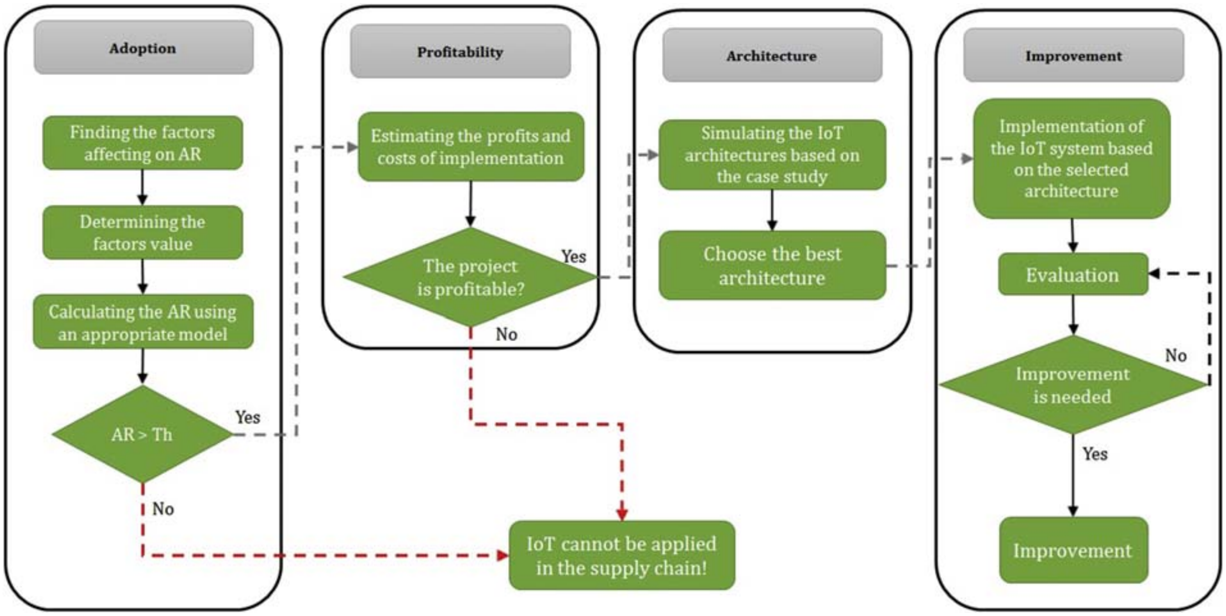

FIGURE 4.5 The IoT Adopter: a proposal for IoT implementation in supply chains (Black dotted line—Go; Red (dark gray in print version) dotted line—No Go).

higher than costs), an appropriate architecture should be designed for IoT implementation. Conventional IoT architectures have been discussed in Section 2.1. However, novel architectures can be investigated based on the configuration and complexity of a particular supply chain. After IoT implementation, continuous monitoring and improvement strategies are needed to ensure that benefits are derived in the IoT-based supply chain. System performance should be tracked, and the system's weaknesses should be found and dealt with appropriately.

7. Conclusions, limitations, and future research

This chapter has focused on IoT as an emerging DSC enabling technology. Explaining the fundamental concepts and definitions, IoT architectures, applications, and challenges was the main purpose. Additionally, based on the surveyed papers, a proposed framework—the *IoT Adopter*—was introduced to make decisions on implementing IoT in and across supply chains.

Agri-food, cold, and manufacturing supply chains are the pioneers for applications of IoT currently. IoT-based Agri-food supply chains have mainly concentrated on traceability. When they deal with temperature-sensitive goods, IoT-based cold chains have emerged in which a warning system is created for alerting decision-makers about noncompliance in the chain, providing real-time awareness of critical conditions for temperature-sensitive goods such as perishable foods, pharmaceuticals, vaccines, and flowers to prevent spoilage and waste. Interesting and promising developments are also occurring in utilizing IoT technology in logistics and transportation (Golpîra et al., 2021). However, the manner of IoT usage in industrial environments is somewhat different. In manufacturing supply chains, machines interact with each other, and IoT technologies need to be integrated with CPSs to facilitate both human-to-machine and M2M connections.

A number of challenges affect IoT supply chains, including security and data privacy, standards and naming services, adoption, and big data generation. The intense interconnectivity of IoT supply chains increases security blind spots, resulting in a lower level of cyber-security. Also, a high number of connected objects present supply chains with service naming problems. Big data generation is another consequence of intense networks of IoT-enabled supply chains, making the analytical processes more challenging. In some cases, managers do not have a comprehensive overview of IoT's advantages and disadvantages for supply chains, leading to incorrect decision-making about the IoT implementation in supply chains. The *IoT Adopter* framework may help researchers and practitioners to gain a more comprehensive overview of the potential for IoT implementation in specific supply chains. Utilizing the proposed framework may help to prevent managers from implementing IoT in a risky environment that could result in financial losses. Although IoT brings many positive benefits for DSCs, IoT-based supply chains are on a critical development path.

This chapter has sought to cover a diversity of research related to the field of IoT-based supply chains. IoT is fast developing and its exact purposes, applications, and structure are continually being redefined and updated. Another challenge is that it has considerable overlaps with other related areas such as the PI and CPSs. The literature on IoT and related areas continues to grow. Human effort alone cannot survey and review such a large body of work in a feasible time horizon. Accordingly, utilizing text mining approaches such as co-word analysis (Hosseini et al., 2021; Pourhatami et al., 2021), topic modeling (Abuhay et al., 2017), and Natural Language Processing (Zhou et al., 2021) is recommended for further analysis and knowledge extraction from the large, wide ranging and growing number of publications and sources on IoT.

Appendix A

TABLE A1 Glossary of the used terms.

Term	Abbreviation	Description	References
Wireless sensor network	WSN	A WSN is interconnected sensor nodes communicating remotely for gathering environmental data.	Patil and Chen (2017)
Internet of things	IoT	An IoT is a set of physical objects connected through an interconnected network, interacting with other physical devices through the minimal intervention of humans.	Ahmadi (2019)
Industry 4.0	I4.0	I4.0 is high-level of digitalization, integrating novel technologies such as cloud computing, big data, and IoT.	Neumann et al. (2021)

TABLE A1 Glossary of the used terms.—cont'd

Term	Abbreviation	Description	References
Digital supply chain	DSC	A DSC is an intelligent system that enables supply chains to synchronize organizations' interactions through collaboration and communication of digital technologies.	Büyüközkan and Göçer (2018)
Cyber-physical systems	CPS	CPS refers to systems embedding sensors and communication tools in physical objects for controlling the physical environment.	Minerva et al. (2015)
Physical Internet	PI	By interconnecting logistics networks in an intelligent way, PI is a global logistics system that strives to improve efficiency and sustainability.	Ballot et al. (2014)
Naming services	–	In computer networks, name services are used to translate human-readable names into identifiers that can be used for communication.	Sooraj et al. (2017)
Integrated fog cloud IoT	IFCIoT	It is a flexible and reliable IoT architecture that incorporates cloud and fog computing technologies, allowing for improved performance and low power consumption, speeding up response times, and localizing operations.	Munir et al. (2017)
Sensor layer	–	An IoT architecture relies on this layer to utilize a variety of sensors and actuators, gather environmental data, and virtualize the information in a cyber-platform.	Ning et al. (2013), Yan et al. (2014)
Network layer	–	It focuses on network components relating to heterogeneous networks such as ad hoc networks, wireless sensor networks, mobile cellular networks, and the Internet.	Yan et al. (2014)
Application layer	–	As a service layer, the application layer delivers services to end users.	Yan et al. (2014), Sethi and Sarangi (2017)

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Chapter 5

The cloud, platforms, and digital twins—Enablers of the digital supply chain

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Abstract

The continued advancement of computing and digital technologies is transforming markets, economics, businesses, and society. We discuss the characteristics and applications of three important developments that are generating transformative change in the management of supply chains and business operations—Cloud-based systems, Digital Platforms, and Digital Twins. The cloud provides computer resources and computing services via the Internet. It has changed the economics of IT, enabling easy access to vast computing resources and the elastic scalability of IT solutions to match demand. Migration to the cloud is strongly affecting corporate IT strategies. Rapid developments in Software-as-a-Service (SaaS) include Enterprise Resource Planning applications offered through various modes of cloud delivery. Digital platforms have changed the nature of markets in many sectors, most notably across the retail economy. As well as facilitating commercial transactions, digital platforms can also nurture business ecosystems that support product and service innovation. Cloud Manufacturing offers the potential to deliver Manufacturing-as-a-Service (MaaS) through a platform. Digital Twins encompass a range of emerging technologies that capture the characteristics of a system, with dynamic exchange of information between the system and its digital representation. We define Digital Supply Chain Twins and discuss their potential to improve supply chain resilience.

Keywords: Cloud; Cloud manufacturing; Digital twins; Platforms; Supply chain.

1. Introduction

A number of developments in computing have had major transformative effects over the last two decades on how businesses, markets, and societies operate. We discuss three important developments that impact business and supply chain operations. Two of these are firmly established—Cloud-based Systems and Platform Commerce—and one is emerging strongly, the concept of the Digital Twin and its enabling technologies. Each of these will play a significant role in supply chains and their management as the digitalization agenda continues.

Cloud computing refers to the provision of computing resources, infrastructure, software, data and information management services and applications via the Internet. The National Bureau for Economic Research noted at the end of 2018 the explosive growth and plummeting prices in cloud services.[1] In 2019, Gartner noted the dramatic and all-pervasive shift by businesses to the cloud,[2] particularly for new initiatives in digital business. The impact of the cloud as a key enabler and driver of business innovation is projected to continue to grow strongly.[3] The benefits of cloud-based computing include easy access to computing resources and the flexibility to scale systems with business needs. The cloud is an attractive and

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1. https://www.nber.org/digest/dec18/explosive-growth-and-plummeting-prices-cloud.
2. https://www.gartner.com/smarterwithgartner/cloud-shift-impacts-all-it-markets.
3. https://siliconangle.com/2021/01/15/2025-cloud-will-key-driver-business-innovation/.

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viable option to satisfy a wide range of computing needs (Cusumano, 2010). The opportunity to select and pay for computing services "on demand" and avoid investment in significant "on premises" hardware and software (e.g., Software-as-a-Service (SaaS)) has been truly revolutionary in business information systems.[4] Migration to the cloud will continue to influence corporate IT strategies strongly.[5]

Digital platforms allow multiple actors from different sides (e.g., customers and suppliers) to engage, interact, and, where appropriate, conduct commercial or business transactions. The impact of platforms and e-commerce on markets has clearly been substantial, resulting in fundamental changes in the retail economy, a trend that is predicted to continue to grow.[6] Platforms benefit significantly from network growth effects (Parker et al., 2016). They can also foster business ecosystems and allow value creation in areas such as entrepreneurship, new product development, and supplier portals (Gawer & Cusumano, 2014). Platforms and the cloud come together in Cloud Manufacturing (Adamson et al., 2017), which offers the potential for the delivery of Manufacturing-as-a-Service (MaaS).

Digital Twins are emerging technologies that seek to capture digitally the essential characteristics of a physical system with real-time bidirectional interaction between the digital and physical systems (Kritzinger et al., 2018). Although the enabling technologies are still in development to achieve and deploy this digital vision, such twinning of physical systems with their digital representations promises powerful applications in diverse areas. These include predictive maintenance, warehousing and supply network management (Liu et al., 2021), as well as supporting resiliency in supply chains (Ivanov & Dolgui, 2021).

We examine each of these three technologies in this chapter. We first discuss the origins and novelty of cloud-based systems, how they have developed, and the different kinds of services and the modes of delivery and deployment the cloud offers. We note the advantages of the cloud computing paradigm and some of the challenges it raises. We look at the strongly emerging SaaS model, as well as cloud-based Enterprise Resource Planning (ERP) solutions, both of which are critically important in the supply chain context. Section 3 discusses platform concepts, particularly in relation to platform-mediated markets and business ecosystems. Cloud concepts and platform technologies come together in Cloud Manufacturing, where manufacturing is envisaged as a service that can be delivered through a platform that utilizes a "cloud" of manufacturing resources. Section 4 describes the emergence of digital twin concepts and their potential impact on decision-making in supply chain management. Section 5 concludes with an indication of future developments.

2. Perspectives on cloud-based systems

Most studies in the literature identify the origins of cloud computing in IT outsourcing (Willcocks et al., 2013, 2014). Application Service Provision (ASP) made it possible over 2 decades ago for software and IT infrastructure to be outsourced via the Internet (Kern et al., 2001). However, ASP was hampered by insufficient bandwidth and lack of computing power (Kern et al., 2002), little customization (Smith and Kumar, 2003), and failure to provide an attractive value proposition (Currie, 2004). Improvements came from better coordination of large-scale computing resources, particularly by providing "on-demand" services (Venters & Whitley, 2012). In addition, large data centers began to be developed by companies such as Google, Amazon, and Microsoft. The transition from individual PCs and privately maintained data centers to large external public data centers accessible over the Internet became known as cloud computing (Armbrust et al., 2010; Boss et al., 2007). The origin of the term cloud computing has been traced back to Compaq computers in 1996 but gained more widespread prominence following its use by Google's then CEO, Eric Schmidt, in an industry conference in 2006 (Regalado, 2011).

Thus, the characteristics of cloud computing are not completely novel. They can be found in earlier technologies. For example, utility computing has similar features such as on-demand and pay-per-use (Rappa, 2004). A key enabling technology in cloud computing—virtualization—emerged in mainframe computers in 1970s. The novelty of cloud computing lies in the creative design of the new architecture, particularly with the emergence and widespread adoption of large data centers. This has led to a fundamental transformation and migration from traditional IT architectures to cloud-based architectures. A cloud architecture provides a new technological context with new data structures, new data storage systems, new file management systems, and new programming models (Chang et al., 2006; Dean et al., 2004; Zhang & Ravishankar, 2019). The development and delivery of contemporary corporate IT services has evolved in this new context.

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[6] Digital Commerce Platform Market https://www.futuremarketinsights.com/reports/digital-commerce-platform-market.

2.1 Defining cloud computing

A number of definitions in the literature highlight different features of cloud computing (e.g., Youseff et al., 2008; Buyya et al., 2009; Armbrust et al., 2010). Mell and Grance (2011) from the National Institute of Standards and Technology presented a definition that articulates all the important characteristics of cloud computing, as well as the various services and deployment models it affords (see Table 5.1). They define Cloud Computing as "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction" (Mell & Grance, 2011). This definition is widely accepted in both academia and industry (Gao & Sunyaev, 2019; Venters & Whitley, 2012).

Mell and Grance (2011) classify cloud services into three categories—software as a service (SaaS), platform as a service (PaaS), and infrastructure as a service (IaaS). At the lowest level, IaaS offers fundamental computing resources such as storage, networks, and data centers. PaaS is a middleware layer, enabling programming environments with sets of well-defined APIs (Garg, 2020; Marston et al., 2011). SaaS is the highest level, offering software applications as services. Clients can access the software applications via various devices such as a web browser or a program interface. Cloud services may be delivered in different ways—public, private, community, and hybrid cloud. These differ in terms of ownership, structures, and operation. Public cloud is owned and managed by the service providers that offer a selection of computing resources (e.g., Amazon Web Services, Microsoft Azure). The resources can be accessed over the Internet for external use. By contrast, private cloud is self-operated and available for internal use only. The community cloud is provisioned for exclusive use by a community of organizations. The community cloud can be owned, managed, and operated by one or more of the organizations in the community, a third party, or some combination of them. A hybrid cloud model is a combination of two or more distinct deployment models (Garg, 2020).

2.2 Software as a service

SaaS is the provision of software applications offered as a service over the Internet (Cusumano, 2010; Armbrust et al., 2010) and is one of the most important service models in cloud computing. SaaS is now the largest segment of the global cloud market. It allows software applications to be developed and deployed very quickly compared to conventional noncloud software development processes. Additionally, deployment can occur simultaneously in multiple locations around the world. A recent Gartner report expects the global SaaS market revenue to reach $171.9 billion in 2022. With significant features such as multitenancy, ubiquitous access, pay-per-use pricing models, and minimal management effort, SaaS has changed fundamentally how software can be delivered and used. SaaS clients can utilize and combine software applications provided by multiple vendors without committing to ownership of the products (Martins et al., 2019). The SaaS model eliminates or reduces many of the traditional costs of ownership that clients need to bear, including the sunk cost of the purchase of the product and the costs related to hardware required to deploy the software or application (Kung et al., 2015).

Important factors influencing SaaS adoption include marketing efforts, security and trust, perceived benefits, attitude toward innovation, perceived usefulness, social influence, clients' behavioral intention, expert opinions and perceived ease of use (Wu, 2011). Among these factors, service stability is the most significant factor that determines clients' SaaS adoption (Martins et al., 2019). The Forbes Technology Council (2020) has provided guidance and tips when launching services through a SaaS platform, including developing partnerships with customers, using rapid-deployment methods, and consideration of revenue streams, scalability, customizability and features, continuous improvement, and security.

TABLE 5.1 Standards of cloud computing.

Characteristics	Deployment	Service delivery model
• On-demand self-service; • Broad network access; • Resource pooling; • Rapid elasticity; • Measured service.	• Private clouds; • Public clouds; • Community clouds; • Hybrid clouds.	• Software as a service (SaaS); • Platform as a service (PaaS); • Infrastructure as a service (IaaS).

From Mell and Grance (2011). The NIST definition of cloud computing.

2.3 Cloud-based Enterprise Resource Planning (ERP) systems

ERP systems provide the core information, planning, and execution systems for enterprises to support, manage, and integrate all major business processes and functions and are deployed widely across organizations of many types. ERP systems became the de facto business software solutions in the 1990s (Nazemi et al., 2012) and have remained the backbone of enterprise IT in many organizations since then, with major global providers dominating the market. ERP systems also became important for large enterprises to integrate their supply chain partners (Grabski et al., 2011; Lee et al., 2003).

By the millennium, these large-scale multimodule software packages were necessary for many organizations but were proving to be problematic (Kumar & Hillergersberg, 2000). Many challenges became evident over the following decade. Significant problems and failures were reported in seeking to successfully implement and deploy ERP solutions, with difficulties emerging in delivering business benefits and in customizing large-scale monolithic ERP systems for particular environments (Sprott, 2000; Chen et al., 2009; Gattiker & Goodhue, 2005). Today's organizations seeking ERP business solutions can look for tailored offerings from the cloud in a move away from "on premises" ERP systems (Peng & Gala, 2014; Chang, 2020).

As a segment of the SaaS market, cloud-based ERP has emerged and become popular because of cost-effectiveness and flexibility (Saran, 2021). In contrast to traditional ERP solutions, cloud-based ERP systems have all the characteristics of the cloud such as device and location independence, flexible pricing structures, cheaper upfront costs, and low switching costs (Zadeh et al., 2018). Organizations may choose to deploy ERP as a single tenancy Cloud system or adopt an ERP SaaS model (Schwarz, 2021). Oracle argues that "SaaS 'democratizes' ERP, making it accessible to many small and midsize businesses that otherwise would not have the budget nor technological resources or staff to consider on-premises ERP" (Schwarz, 2021). However, notwithstanding these strengths, there are also weaknesses. There may be limited customization options, concerns on data security, and high data storage costs. Seethamraju (2015) identified factors that influence SME's adoption of cloud-based ERP systems, including the vendors' reputation, the degree of software—business alignment, the potential willingness of the vendor to support the customer throughout the product life cycle, the vendor's participation in co-creation of value for customers, and the generic benefits of implementing an integrated ERP system. However, clients can be reassured by vendors in the postimplementation phase, e.g., by the willingness of the software vendor to work with organizations' requests for changes, and the continuous co-creation of value through improved product offerings. Cloud-based enterprise software is a rapidly developing space where many developments can be expected over the next decade in the provision and adoption of corporate IT and software solutions. We discuss below some of the critcal issues in considering and deploying cloud services.

2.4 Advantages and challenges for enterprises adopting cloud computing

Although some technical elements are not completely novel, cloud computing represents a new paradigm for accessing and using computing resources, software, and information services. We summarize briefly the main advantages of the cloud model and note some of the most significant challenges.

2.4.1 Advantages

Reduction in costs and time to market: Cloud-based computing enables organizations to access expensive hardware resources such as data centers with little or no upfront investment costs. The dramatic reduction in upfront costs can lead to the speeding up of "time to market" for many businesses, particularly for start-ups (Marston et al., 2011). Dropbox, Spotify, Workday, and others began as start-ups and expanded with much less IT investments than would have been required in a previous computing era (Nambisan, 2017). Furthermore, with the metered pricing element of the cloud, organizations pay only for their usage of selected services such as storage capacity or CPU cycles (Armbrust et al., 2010), avoiding the costs of creating a whole in-house infrastructure. This can transfer the cost of computing from a capital investment to operational expenditure incurred in day-to-day running costs, which is beneficial for many businesses.

Lowering the barriers to entry: Cloud computing makes large amounts of computational power and IT resources more affordable for startups or small firms. By lowering entry barriers to access and use valuable computing resources, which may previously have been available only to large enterprises, it offers many businesses opportunities. Thus, SMEs may be able to offer unique tailored services to target niche markets (Willcocks et al., 2014). Significantly, cloud computing allows the creation of new businesses, particularly in areas such as business intelligence, big data analytics, and artificial intelligence (AI). At the same time, it reduces the demand for skilled technicians normally required to ensure the availability of in-house IT infrastructure. Additionally, the location independence characteristic of the cloud enables organizations to build data centers where power and cooling costs are low, while allowing users to access services and data stored in the cloud through any mobile device connected via the Internet (Carreiro & Oliveira, 2019).

Scalability: Scalability refers to the ability to quickly add or remove computing resources at different granularity levels. Traditionally, such granular elements embedded in servers or data centers were slow and expensive to set up, deploy, or remove. In the cloud environment, it is much easier for organizations to scale computer resources elastically according to the level of demand. Computer resources such as CPUs or servers can be provisioned, configured, reconfigured, and removed dynamically, as needed (Nambisan, 2017). Such elastic scalability has been noted as "the true golden nugget of cloud computing and what makes the entire concept extraordinarily evolutionary, if not revolutionary" (Owens, 2010). Many authors agree that scalability is the most significant element of cloud computing (e.g., Al-Said Ahmad and Andras, 2019; Lehrig et al., 2018).

Innovation: In addition to hardware resources, software resources are also stored in cloud infrastructure including complementary components. Such components are hosted in PaaS systems, where each component can be assembled for specific functionality depending on a client's requirements. Cloud computing can therefore lower innovation barriers, and may offer significant innovation opportunities as there is no need to create and build a complete running platform from fundamental components. Entrepreneurs can simply adopt well-defined APIs to begin developing their innovative applications. Hence, the cloud can facilitate application development, strengthening and deepening an entrepreneur's specialization (Nambisan, 2017). Such "generativity," which refers to the capability of digital platforms to enable a recombination of elements for assembly, extension, and redistribution of functionality, can originate from the PaaS solutions in cloud architectures (Thomas & Tee, 2021).

Data security: A further advantage of cloud computing relates to data recovery and loss prevention. Local "on premises" hardware risks virus infections and/or system collapses with consequential data losses. When data are migrated and stored in a vendor's cloud, data protection responsibilities and maintenance operations are carried out by the vendor. To ensure data integrity and security, most vendors deploy data loss prevention (DLP) policies and tools (Zhang & Ravishankar, 2019). For example, in Alibaba's cloud computing service, clients' data are protected by a firewall and security suite. Each piece of data is duplicated automatically with three backup copies when migrated to, or updated in Alibaba's cloud. As well as deploying similar DLP policies, Amazon Web Services also provides DLP tools from its marketplace created by independent software developers for clients to select. Such efforts relieve clients of the burden of data security to focus on their core business operations.

2.4.2 Challenges

Service-based business models: Apart from the technological shift, cloud computing also underpins a radical shift from products to business services. Cloud-based services can be purchased to meet particular aims and objectives to generate business value. Businesses do not necessarily have to understand the technical details of computing services but can specify their requirements in terms of desired outcomes. However, to adopt cloud services successfully, businesses need to develop and utilize their internal knowledge and capabilities. Cloud success depends on the purposeful and creative deployment of internal capabilities (Garrison et al., 2012; Zhang & Ravishankar, 2019). Such capabilities require the ability to identify business processes that may provide a competitive advantage with acquired cloud resources; the ability to coordinate cloud implementation activities; and, the ability to develop positive and trusted relationships with the selected cloud vendors (Garrison et al., 2015). Clients' relational capabilities are influential in facilitating cloud success, as significant negotiation and contractual processes are involved. Vendors should also develop capabilities for effective service delivery (Zhang & Ravishankar, 2019).

Data security concerns: Several studies indicate that data security and privacy are the biggest concerns that inhibit organizations from adopting cloud services (e.g., Wang et al., 2020). Potential clients may have concerns about data security when their data are stored outside their companies' own hardware. Although most vendors claim that clients keep the ownership and have exclusive access, clients may still have concerns during the migration process including poorly implemented policies or system failures. Concerned organizations can adopt a hybrid cloud solution, in which key data are stored both internally and in an external cloud repository. However, the private cloud solution is expensive for organizations to deploy and may further deter potential clients from adopting cloud services, particularly SMEs.

Vendor lock-in: A further challenge for cloud adopters is the lock-in problem when a client adopts cloud services from a single vendor. There may not be easy mobility in selecting a different vendor in the future without incurring "substantial costs, legal constraints, or technical incompatibilities" (Armbrust et al., 2010; Oliveira et al., 2017). The lock-in problem may be more acute when applications are developed in a specific cloud platform environment such as the Google App Engine or Microsoft Azure and cannot be moved to a different platform. When organizations seek to change cloud vendors, they may find they are unable to migrate their applications or data because "the semantics of resources and services of cloud providers do not match with each other" (Opara-Martins et al., 2016). Additionally, both PaaS and SaaS as platforms create network effects that enable the growth of users across both supply and demand sides but this may also act to strengthen lock-in.

3. Platform technologies

The term *platform* is conceptualized and defined in different ways in different disciplines. Economics research considers platforms in multisided markets (Rochet & Tirole, 2003) that enable interactions between a supply side and a demand side (and potentially more sides). Such platforms perform two fundamental economic functions—they reduce search costs and shared transactions costs among the multiple sides of the platform (Hagiu, 2009). With the emergence of digital technologies, platform concepts have been extended and developed in Information Systems (IS) and in various management disciplines. In IS research, a platform hosted in a digital infrastructure refers to "a network of entities that are held together by a platform sponsor through formal contracting and/or mutual dependency to create joint value for consumers" (Tan et al., 2015). Platforms may be viewed more broadly than an economic market or a technical architecture. For instance, a platform may act as an intermediary that organizes and coordinates activities to motivate and foster innovation and product development (Gawer & Cusumano, 2014). In engineering, a product platform is a technical architecture partitioned into reusable assets and variable peripheral components that facilitate new product development (Zhang, 2015). This type of platform is less relevant to the contexts we consider here.

3.1 Characteristics of digital platforms

Although platform conceptualizations may be different across disciplines, they share some common characteristics. We note three important characteristics here. First, platforms enable interactions and transactions between two or more distinct sides, creating reciprocity for all actors involved in the platform. In this sense, platforms act as intermediaries by engaging external entities and bringing them "on board" (Zhu & Furr, 2016; Hagiu & Wright, 2015). There are four different types of multisided platforms—exchanges that include matchmaking activities such as dating or job agencies, advertising-supported media platforms such as magazines, newspapers or website portals, transaction systems like credit cards, and software platforms including video consoles (Loux et al., 2020). In each of these types of platform, value creation is dependent on interactions between different participants. Second, each side affiliates to the platform, i.e., each side is aware that investments or affiliation fees are needed to enable direct interaction with other sides (Hagiu & Wright, 2015).

Third, most multisided platforms generate network effects. These refer to "the increasing value of platform membership to an entity as the number of other entities on the platform increases" (Katz & Shapiro, 1994; Eisenmann et al., 2006). When the adoption of a platform grows, the value of the platform is enhanced, potentially for all participants. Network effects may also generate positive feedback loops—the number of resources inside a platform will increase to match the increasing value of the platform (Gawer, 2009). Network effects can be classified into two types—same-side or cross-side (Gawer & Cusumano, 2014). Same-side effects arise when the benefit to a platform user depends positively on the number of other users on the same side (e.g., in social networks such as Twitter or Facebook). They can be powerful, as more users on one side can increase the value of the platform. In particular, such network effects can be reinforced when the switching cost from one platform to another is costly or difficult (Eisenmann et al., 2006). Network effects can also be cross-side, i.e., the benefit to any side depends positively on the number of participants on other sides (e.g., Airbnb). Cross-side network effects reflect the interdependency between distinct sides engaged on a platform.

3.2 Platform commerce

Platform commerce has had a very significant impact in many markets in the last 2 decades and it is predicted to continue to grow strongly,[7] particularly through developments in omni-channel retailing.[8] Van Alstyne et al. (2016) argue that this represents a move from pipeline businesses to platform businesses. Pipeline businesses are organized as a linear sequence of activities along the value chain and follow traditional buyer—supplier relationships with straightforward processes from suppliers to customers. In contrast, multisided platforms are dependent on activities coordinated and controlled by actors from different sides (Boudreau & Jeppesen, 2015; Thomas et al., 2014).

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[7] Digital Commerce Platform Market https://www.futuremarketinsights.com/reports/digital-commerce-platform-market.

[8] https://www.mckinsey.com/industries/retail/our-insights/future-of-retail-operations-winning-in-a-digital-era.

The role of multisided platforms is not just to manufacture or resell products or services but to affiliate external actors for direct interaction and transaction between different sides of a market. Multisided platforms show strong interdependent relationships between affiliated sides with the presence of strong network externalities. From the cross-side network effect, a platform with a large base of suppliers offering products/service leads to greater demand from customers (Zhu & Iansiti, 2012). At the same time, more customers lead to a larger supply of products from suppliers, which encourages partners from both sides to keep joining and using the platform. To attract and lock-in participants for exchange, platform owners are likely to offer exclusive contracts and promotion deals, new features or add-ons, secure and reliable ways to conduct transactions, and effective solutions for matchmaking (Gawer & Cusumano, 2008; Zhao et al., 2020).

Another feature of a multisided platform is the hybrid revenue or monetization model. In contrast to pipeline businesses, multisided platforms may receive revenue streams from both sides. For example, Uber and Airbnb receive revenue streams from their customers and their facility suppliers. Significantly, platform owners can sacrifice profits on one side to attract a high number of customers, and therefore make the platform more attractive for suppliers due to the network effects (Clements & Ohashi, 2005). Such designs offer valuable insights into how customers' individual choices relate to the growth of the customer base and the impact on the evolution of the platform design over time (Zhao et al., 2020). A number of studies have found that structural and evolutionary mechanisms, and the alignment of partners and complementors, facilitate and foster value co-creation on platforms (Rietveld & Eggers, 2018).

A recognized challenge for the development of a successful multisided platform is the *chicken-or-egg dilemma*. This refers to the need for a platform to acquire a large base of sellers in order to attract sufficient buyers (Caillaud & Jullien, 2003). In other words, a platform owner has to decide how to engage external participants from all sides to affiliate to their platform (Rochet & Tirole, 2006). In the emerging, embryonic stages of development, a platform needs to have strategies to gain a critical mass to ensure customer participation. Network effects require a minimum number of participants, above which a platform will grow but below which it will shrink toward nonparticipation from one side and/or another (Evans & Schmalensee, 2010). This may occur with either the supply or demand side or may affect multiple sides. Therefore, platform owners must consider which side(s) are important to initiate platform growth. Price structure can be an effective solution to the chicken-or-egg dilemma (Rochet & Tirole, 2006; Armstrong, 2006; Eisenmann, 2008). Investment in one side of the platform may benefit the other through cross-group externalities (Bakos & Katsamakas, 2008). The decision on which segments to subsidize is dependent on the "relative network externality benefits" (Parker & Alstyne, 2005; Gawer & Cusumano, 2014), i.e., which side makes the bigger contribution to attracting the other. A pricing policy may evolve over a platform's life cycle (Muzellec et al., 2015). Parker et al. (2016) propose and discuss eight practical strategies to address the chicken-or-egg dilemma. For instance, *producer evangelism* refers to suppliers engaged on the platform bringing their customers to the platform.

3.3 Platform ecosystems

The concept of a business ecosystem describes a community of interacting companies that co-evolve their capabilities and roles, determined by one or more central players or firms (Iansiti & Levien, 2004; Senyo et al., 2019). In the context of digital platforms, ecosystems refer to "a network where a platform owner encourages third parties to develop complementary innovations and the resulting network of firms manifests significant interdependencies" (Cozzolino et al., 2021). In the strategic management literature, ecosystems generally revolve around central firms with a technological architecture, and may be dependent on brand, geography, or product characteristics (Rosenbloom & Christensen, 1994; Teece, 2007). Platforms provide value through their architecture that includes interfaces to allow external organizations to access the platform (Baldwin & Woodard, 2009).

When a platform acts as an ecosystem, there are several distinct players involved, including end customers of the platform, suppliers that provide products, applications and services, and other complementors (Helfat & Raubitschek, 2018; Rietveld & Schilling, 2021). The performance of a platform ecosystem relies not only on the interactions between the demand and supply sides but also on the interdependencies between multiple sides through network effects and the benefits each gets (Boudreau, 2012; Parker et al., 2017). Existing literature tends to focus on the strategic interactions among firms in an ecosystem rather than interdependency. For example, Cusumano and Gawer (2002) investigate the activities that focal firms undertake to attract partners to favor their technology platforms. Casadesus-Masanell and Yoffie (2007) explore the possible challenges when incentives across the ecosystem are not aligned. Ceccagnoli et al. (2012) argue that participation in an ecosystem may be associated with an increase in sales and a greater likelihood of issuing an initial public offering from a start-up.

Platform owners face a number of challenges in a platform-based ecosystem. First, since network effects do not automatically generate value, platform owners must design an effective governance structure for the ecosystem (Teece, 2018). Such a structure will include rules that determine how external stakeholders can access the platform and how open the ecosystem is. The governance structure may also include rules that determine how engaged sides interact via the platform. Second, apart from conducting the fundamental matchmaking, the platform leader generally offers a core product or service such as social networking with friends (e.g., Facebook) or taxi services (e.g., Uber) (Helfat & Raubitschek, 2018). When offering these services, platform owners must structure the platform by orchestrating resources in the ecosystem. Third, "the viability of an ecosystem depends on continued innovation" (Teece, 2018), particularly enabled by digital technologies. Because of the threat of competitive innovation, platform owners must ensure their platforms remain up to date. Following such insights, Helfat and Raubitschek (2018) argue that it is necessary for platform owners to develop, at a minimum, three significant dynamic capabilities for value creation and capture—"innovation capabilities, environmental scanning and sensing capabilities, and integrative capabilities for ecosystem orchestration."

3.4 Manufacturing as a Service (MaaS)—combining platforms and the cloud

Cloud technologies and systems make it possible for organizations to have immediate and remote access to a resource pool of computing resources. Such ideas have been considered for the manufacturing sector in the concept of *Cloud Manufacturing* (CM), which started to emerge over a decade ago (Li et al., 2010a, 2010b). CM seeks to realize "Manufacturing-as-a-Service" (MaaS) by offering on-demand access to a collection of manufacturing resources accessible through a CM platform. The core idea proposed for CM is the provision and virtual pooling of different types of manufacturing resources and capabilities, applicable across all phases of the product life cycle (Adamson et al., 2017; Li et al., 2012). The distributed manufacturing resources are encapsulated and managed in the cloud through platform services that mediate the interaction between customers and suppliers.

Initial studies saw CM emerging as a progression from the adoption of cloud computing services to the adoption and use of manufacturing resources as services (Xu, 2012; Wu et al., 2013). CM would provide a ubiquitous and on-demand network to a shared pool of configurable manufacturing resources and capabilities for the complete product life cycle. These would be centrally organized, controlled, and delivered as services to meet customer demands for manufactured products (Li et al., 2012; Xu, 2012; Wu et al., 2013). By connecting suppliers that have manufacturing resources with customers that have manufacturing needs through a multilayer platform architecture (see Fig. 5.1 from Adamson et al., 2017), CM seeks to enable unified interaction for trading and usage of configurable resources and dynamic collaboration during multipartner manufacturing tasks (Adamson et al., 2017).

Envisaged as an on-demand service, it follows the "pay-as-you-go" model, with little or no long-term commitments (Wu et al., 2013), which borrows features from SaaS. Customers can select the resources or capabilities without upfront investment costs. Usage of manufacturing resources is monitored, and thus the transparency of the deployed resources can be shown to both vendors and customers. Scalability is another claimed significant feature of CM (Xu, 2012). The manufacturing resources requested by customers can be scaled up or down on demand. In other words, customers can easily add, remove, or reconfigure requested resources to meet their requirements. In doing so, customers can align their purchasing of resources with multiple manufacturing tasks. Furthermore, SMEs could benefit from the access provided to manufacturing resources and solutions, which might otherwise be expensive to acquire and available only to large enterprises (Lu et al., 2014). The "pay-as-you-go" solutions, with no upfront costs of purchasing manufacturing equipment, may lower barriers to entry. By applying CM services, many costly expenses including IT systems, hardware, machinery and maintenance could be greatly reduced.

Examples of MaaS are beginning to emerge. For example, some start-ups such as Fractory,[9] Shapeways,[10] and Materialise[11] offer CM services including instant quotes, selection of materials, configuration of manufacturing parameters and quantities, and delivery. Customers can receive the products from CM vendors on demand with no upfront investments and much lower operating costs than if they manufactured the products themselves. These examples indicate that the platform-enabled Cloud Manufacturing model may be more likely to develop in services that focus on specific domains and specialist sectors that require particular core competencies. They will link knowledgeable customers with specialist producers that have the appropriate skills, competencies, and capacity to meet customers' needs. MaaS platforms may thus develop as focused business ecosystems (Senyo et al., 2019) with knowledgeable participants on each side gaining benefits from use of the platform and reducing the potential for negative externalities noted in the platform literature (Rochet & Tirole, 2006) such as the engagement of poor-quality suppliers or unreliable customers.

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[9] https://fractory.com.

[10] https://www.shapeways.com.

[11] https://www.materialise.com.

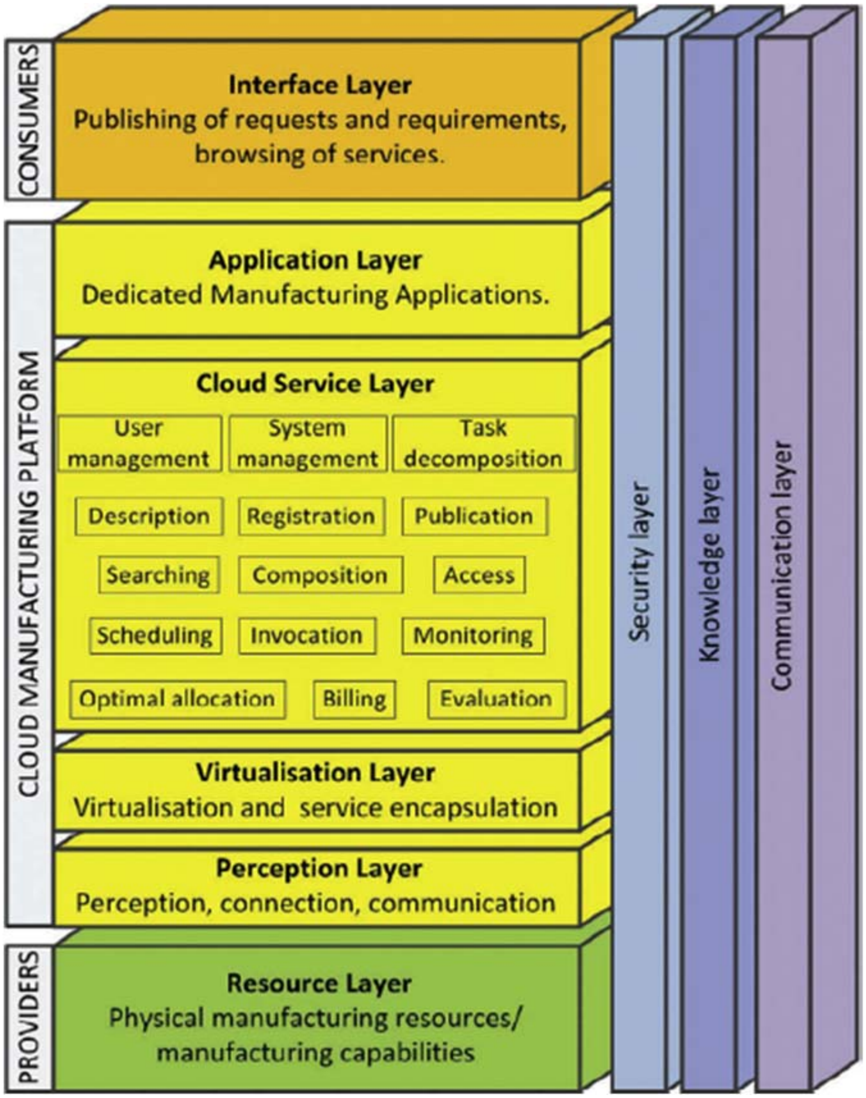

FIGURE 5.1 Cloud manufacturing architecture (From: Adamson et al., 2017).

4. Digital twins

Digital models of physical systems have been an inherent part of computer applications since the dawn of computing. In the manufacturing and operations domain, a digital model could be a simple CAD drawing defining the geometry of a part, a virtual model of a factory to compare different operational layouts, or a conventional simulation model of an assembly line to improve flow. Such digital representations have enabled the development of very sophisticated computer-aided systems for design, manufacturing, and the management of operations. However, the concept of a digital twin goes beyond just a virtual digital representation of a system. It seeks to capture digitally the essential essence of a dynamic physical system in real time.

Although the origins of the concept are much older, the widespread use of the term is usually associated with a publication from NASA in 2012 (Glaessgen & Stargel, 2012), as noted in a number of reviews (Kritzinger et al., 2018; Fuller et al., 2020; Liu et al., 2021). The concept has gained prominence in recent years because of the potential applications of such digitally created "twins." Definitions vary and continue to develop. Liu et al. (2018) provided a very useful conceptualization of the concept in a study on predictive maintenance in the aerospace sector, noting that a digital twin "creates a living model of a physical asset for predictive maintenance. The living model will continually adapt to changes in the environment or operation using real-time sensory data and can forecast the future of the corresponding physical assets …. A digital twin can be used to proactively identify potential issues with its real physical counterpart." Kritzinger et al. (2018) note differences between a *digital model*, a *digital shadow*, and a *digital twin* based on the level of integration between the physical system and its digital representation. There is no automated data exchange between a *digital model* and the physical object or system it represents, whereas a *digital shadow* updates when a change occurs in the physical systems. A *digital twin* goes further in seeking to have a bidirectional pairing that enables two-way data exchange with the physical system.

Although digital twins are at an early stage of development, they have been proposed or are being developed for use in many operational contexts, including maintenance (Liu et al., 2018), energy management (Mawson & Hughes, 2019), warehousing (Leng et al., 2021), layout planning (Uhlemann et al., 2017), product design (Tao et al., 2019), and supply chain management (Frazzon et al., 2021). van der Valk et al. (2021) discuss the emergence of different digital twin archetypes. The technology continues to develop with new products, services, and architectures being announced.[12]

4.1 Defining a digital twin in a supply chain context

Supply chains have been experiencing technological transformations on a scale unlike any seen before. Industry 4.0, additive manufacturing, advanced sensors, cobots, and visibility systems promise highly flexible and adaptable supply networks with structural variety and multifunctional processes. They provide new data acquisition and data utilization opportunities and render new business model possibilities. However, the emerging novel settings of cyber-physical systems that combine machine and human intelligence present not only new opportunities but pose new challenges for decision-making support. Classical optimization and simulation techniques need to be extended to provide both technology and data driven decision-support systems. Supply chain decision-making needs to embrace the concept of the digital twin to accomplish this (Frazzon et al., 2021).

Digital Supply Chain (SC) Twins are defined as "computerized models that represent the network state for any given moment in time" (Ivanov & Dolgui, 2021). Three main differences can be identified between digital twins and conventional simulation models—(1) system complexity, (2) real-time connectivity, and (3) decision-making integration. First, the level of system complexity captured in a digital twin is typically higher than in a conventional simulation model. Digital SC twins are comprised of multiple layers, including the network structure, flows, process control algorithms, and operational parameters. Second, data in a digital twin are updated through real-time connectivity with external systems and databases. Third, the level of integration of a digital twin to support decision-making is much higher compared to conventional models. Simulation and optimization models are important parts of digital twins but digital twins can offer more functions for real-time decision-making support compared to classical offline modeling, e.g., performance analysis of suppliers, updating supply chain data in ERP systems, and the comparison of the current processes with potentially optimal ones.

A digital SC twin is emerging as an important part of the supply chain management toolbox, enabling supply chain control towers to provide decision-making support at strategic, tactical, and operational levels. Digital SC twins enable real-time transparency about important logistics data such as key financial performance indicators (KPIs), inventory levels, stock levels, service levels, capacity, and transportation data. Performance-based simulation models help create efficient contingency plans to prevent or recover from disruptions by simulating and creating what-if scenarios that predict future impact. Data-driven modeling in digital twins can allow the use of AI to support decision-making by so-called "dispatch advisors" or "digital companions."[13] These terms are being used in industry to refer to collaborations between human operators and AI technologies. For example, an SC planner can use an AI component in the digital twin to find all current shortages in the SC and suggest possible ways to resolve these problems. In this case, an AI component would take over the dispatch advisor/digital companion role. In the next step, the identified shortage data can be used for optimization and simulation to develop the most appropriate action plans, which would then be evaluated and decided on by the human SC planner.

Ivanov et al. (2019) note the urgent need to visualize SC networks because of the increasing number of SC disruptions. Cavalcante et al. (2019) point out that digital SC twins display the "physical supply chain based on actual transportation, inventory, demand, and capacity data." Therefore, decision-makers can utilize them for SC planning, monitoring, and supervision. Hence, digital SC twins have the potential to facilitate and improve end-to-end SC visibility and provide the ability to assess contingency plans. Thus, digital twins can enhance SC resilience.

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[12] Announcing AWS IoT TwinMaker (Preview), a service that makes it easier to build digital twins, https://aws.amazon.com/about-aws/whats-new/2021/11/aws-iot-twinmaker-build-digital-twins/.

[13] e.g., https://transportation.trimble.com/resources/blogs/top-five-ways-trimble-dispatch-advisor- https://www.hexagonsafetyinfrastructure.com/products/smart-advisor.

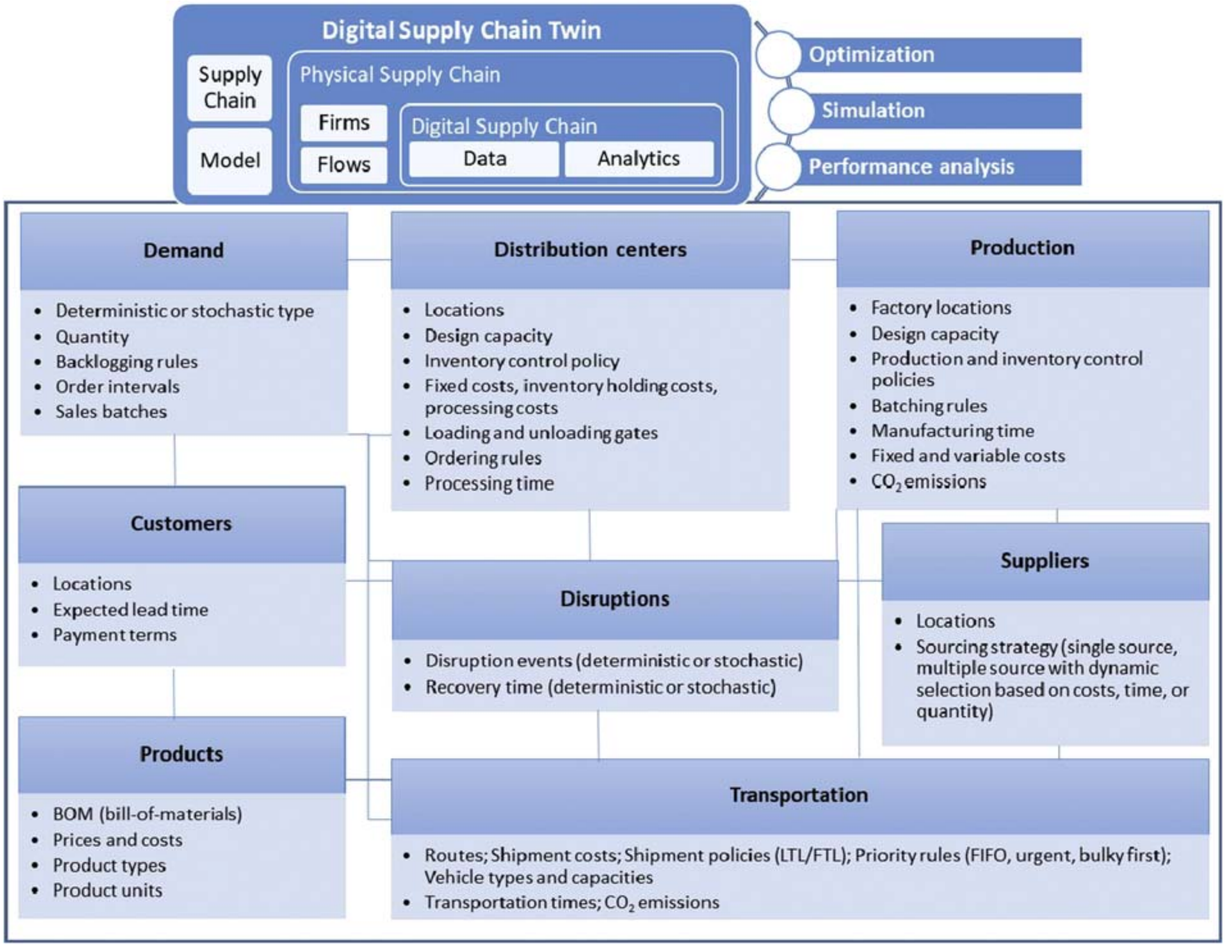

FIGURE 5.2 Digital supply chain design for disruption analysis using anyLogistix (From: Burgos & Ivanov, 2021).

4.2 Applications of digital twins for supply chain resilience management

Digital twins not only visualize SCs and associated risks but also offer supplier performance and risk analyses along with forecasts of SC interruptions and risks. In addition, they allow detailed backup routes to be identified, examined, and established, including estimated time of arrival calculations. During disruptions, digital twins utilize real-time data to calculate the impact of the disruption, build alternative SC networks, and perform KPI analysis based on real-time data about inventory levels, service levels, financial parameters, and demand (Ivanov, 2021). Here we describe the use of a supply chain simulation and optimization package to define and experiment with a supply chain digital twin.

Fig. 5.2 shows the structure of a digital SC twin created in a case study to analyze disruption analysis (Burgos & Ivanov, 2021) with the help of the anyLogistix SC simulation and optimization software.[14] This digital SC model has been created to study a multistage SC for a retail company in Germany comprising of 10 product categories and 28 supermarket locations in 5 different countries (Germany, Austria, the Czech Republic, Italy, and Hungary). A sample of 3 suppliers per product category (30 suppliers in total) has been created by analyzing supermarket data and manually identifying supplier locations. Three distribution center (DC) locations were selected, one in East, one in West, and one in South Germany. Next, production, ordering, sourcing, shipment, and inventory control policies have been defined and parametrized. Finally, COVID-19 pandemic scenarios were set up using compositions of different disruption and recovery events.

The digital SC twin encompasses three major perspectives—the network, the flows, and the parameters. The supply chain network can be designed using different location objects, including customers, DCs, factories, and suppliers. The flows in the network can be arranged flexibly to represent the specifics of different supply chains. The flows are associated

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[14] https://www.anylogistix.com/Anylogistix is a software system for supply chain simulation and optimization developed by The AnyLogic Company. It combines network optimization and simulation methods for supply chains and allows the creation of digital supply chain models.

with some design (i.e., maximum) capacities in production, warehouses, and transportation and controlled by the associated production, inventory, sourcing, and shipment policies. These policies can be adapted flexibly to the specifics of the SC and its management rules. Finally, different operational parameters such as demand, lead-time, and control policy thresholds (e.g., reorder points, target inventory, and minimum vehicle load) can be defined. With that functionality, a digital model of a physical SC (i.e., a digital SC) can be created and used for optimization and simulation to analyze SC operations and performance dynamics under disruptions.

The simulation outcomes allow SC resilience to be analyzed in different ways. First, the performance analysis dashboard visualizes different KPIs such as service level, sales, and inventory-on-hand, showing the gaps induced by different disruption scenarios. Second, the risk analysis experiments allow for the identification of disruption and recovery times (e.g., time-to-survive and time-to-recover, following Simchi-Levi et al. (2015) and Kinra et al. (2020)) under different thresholds of KPIs (e.g., minimum level of on-time delivery at which an SC is still considered to be nondisrupted). Third, all KPIs are represented dynamically showing their changes on a daily basis. This allows for a detailed analysis of SC dynamics under disruptions at a high level of granularity.

5. Conclusions

The computing developments and digital technologies discussed here—Cloud-based systems, Digital Platforms, and Digital Twins—are having transformative effects on the nature of business interactions and commercial transactions, and consequently on markets, businesses, and supply chain operations. Cloud-based systems have changed the way computing resources such as software and storage, are accessed, delivered and scaled in a way that was not imaginable in previous computing eras. Platforms have fundamentally affected the structure of markets in many sectors such as retailing. Digital Twins signpost a future where physical systems will be managed and controlled proactively with the help of a twin system that is a live, dynamic, and accurate virtual model. Each of these advancements will continue to develop and affect the configuration, coordination, and management of supply chains and how business operations are conducted. As the digital revolution moves forward, these developments will fundamentally change the information and decision systems we use to design, manage, and control supply chains.

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Chapter 6

Algorithms, Analytics, and Artificial Intelligence: harnessing data to make supply chain decisions

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Abstract
This chapter discusses how data and information from operations across the supply chain can now be processed to support managers in making intelligent decisions. Specifically, we introduce the topics of Algorithms, Analytics, and Artificial Intelligence, which underpin such decision making. Beginning with some of the classical algorithms that were developed decades ago in Operations Research, we discuss how, today, decision making relies on increasingly massive amounts of data and highly sophisticated and powerful mathematical models. We show how an algorithm helps by either describing the world, forecasting it, or providing the decision-maker with prescriptive recommendations and suggestions to consider. To help readers wanting to dig deeper, we provide a bird's eye view of the fields of Analytics and Artificial Intelligence. We give some examples of the most impactful current approaches, together with a brief overview of the mathematics involved. We then present possible paths in which these tools may transform how supply chains may work and be managed in the future. Most of the presentation aims at providing a brief introduction to the central topics. The intention is to spike interest for further reading. To that effect, a wealth of sources are provided for those who wish to dig deeper.

Keywords: Artifical intelligence; Algorithms; Data analytics; Prescriptive tools.

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1. Introduction

Picture a supply chain manager striding into her office in the morning. She has on a big screen on the wall facing her desk the supply chain network she is responsible for represented on a map with colored flows as arcs that extend from the third tier suppliers right through to the distribution's channels for the whole product lineup. The flows represent goods through plants, warehouses, distribution centers, and retail stores. The arcs are colored to represent the speed of the flows and can be flipped to show the various product families, product availability, strength of demand, etc. If an event occurs, messages pinpointing it appears, and the corresponding appropriate real-time responses are also shown. With a mouse click, information about the event can be summoned with certified traceability reports and information about origin and destination of any batch or box clearly identified. The analysis of the singular event is further reported with a shortlist of the most effective alternatives to address it. With insight into the features of the ranked alternatives, the choice of the implemented solution is then entrusted to the rational acumen of the supply chain manager. In the next room, managers discuss how to improve the operations of the network. To do so, they rely on a digital representation of this network and simulate various scenarios: "What if large cities in Europe reduce delivery time windows?", "Given evolving demand, where should we

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place a new distribution center?". They rely on the quasi real-time interpretation of massive amounts of information coming from stores, on-line orders, and inventories by digitizing 4M data (man, machine, material, and method) to understand and prepare for the shifts in the demand patterns.

Is this a vision of the future? Not any longer. The Control Tower concept (Chui & Fleming, 2011; Souza, 2014) and large-scale simulations involving thousands of units and alternatives (Abbasi et al., 2020; Inoue & Todo, 2019) are now reality (see Fig. 6.1). This chapter presents the state of the art on how the information collected is processed and interpreted so as to make the manager's decision-making process easy. For this to happen, several layers of intermediate evaluation of the raw information coming from the field with corresponding interpretation and decision-making processes must be in place so that the final picture can be taken in by a human intelligence.

Managers have been trying to make sense from the world that surrounds them since mankind started organizing to build, transport, and sell artifacts. Nowadays, they rely on computers which run software programs to help in sifting through the data available. Those programs, in turn, rely on algorithms, which are a series of operations on digital data, to obtain a result which can be used to formulate a conclusion. This conclusion usually refers to some understanding of a state and process of the world, which then serves as the base for decision-making. Major parts of the Operations Research effort since the second world war have focused on creating just such series of operations and algorithms. In turn, this effort in Operations Research has now evolved into what we can now call the Science of Analytics. This science combines mathematics and statistical tools, data science building upon computational power to provide insights and help in business decision-making. The combination of developments in algorithms, analytics, and AI with the rapid digitalization of businesses has brought new scenarios and new perspectives in how to see and understand the world of operations. We provide an overview in this chapter of some of the recent developments in this area to give the reader an appreciation of both existing applications and a perspective on future applications of advanced algorithms, analytics, and AI in supply chain management.

The most practical definition of an algorithm is of a method to solve a problem, and particularly a problem which can be stated in mathematical terms. The word comes from the name of the Persian 12th-century mathematician Al-Khwârizmî (The Story of Mathematics contributors, 2021). An algorithm is most useful if embedded in a computer program. The ingenuity of mankind has enabled thousands of specific algorithms to be created and embedded so that they are used in everyday life (think of looking for the fastest route to go from one city to another). In some cases, such combinations of algorithms make the computer programs running them seem *smart* as compared to human intelligence, leading some to label them as Artificial Intelligence (AI).

AI works on algorithms based on neuronal analogies of the human brain and extensive amounts of correlated data to recognize patterns and solve complex problems (Finlay & Dix, 1996; Rohaya et al., 2018). In recent years, AI has made considerable progress, mainly thanks to increased computation capacity. Computation is becoming a powerful complement to human capabilities by improving supply chain management (Atkinson, 2016). The combination of computing power and algorithms provides historical and increasingly real-time data in order to make predictions, recommendations, and even

FIGURE 6.1 Supply chain control tower with a vision into a network from supplier to customer.

automate decision-making. In fact, AI is a convergence of statistical models and algorithms using computers for a variety of purposes such as problem-solving, reasoning, pattern recognition, learning, detection, or even creating new knowledge (Shadrin et al., 2017; Siurdyban & Møller, 2012). These algorithms include machine learning and Deep Reinforcement Learning as two of the most prominent branches of AI to derive strategies or predictions from a given (usually very large) dataset, typically termed the training process (Heger et al., 2016).

Lee and Billington (1995) described a supply chain development scenario from the 1980s where, to reduce inventory and improve order fulfilment, their procedure involved production site visits, surveys, and in situ studies to reveal sources of disruption in the supply chain such as nonuniform data recording, unreliability of delivery, or nonalignment of parts of the distribution network. Given their comparatively basic information system, Lee and Billington (1995) stressed the necessity of physical immersion of the supply chain managerial team in the industrial network. Given the extensive data collected across today's supply chains, such physical immersion can now be now replaced by a digital immersion. Their conclusion that immersion by the managerial team is a must, however, still stands. To do so, supply chain models are generated composed from software components that represent supply chain agents, constituent controls, and interaction protocols (Swaminathan et al., 1998).

Today, AI has implications for almost every aspect of supply chain operations. AI is introduced into systems at all levels to provide agility and resilience to the ever-changing environment. Tasks that used to require several human operators are now performed by one robotic machine or program, saving both time and money (Jermsittiparsert & Panichayakorn, 2019). From the initial Control Tower concept of taking and acting on the data from a quantifiable IoT (Chui & Fleming, 2011), the next leap toward augmented knowledge from AI-based data analysis is occurring now.

Two McKinsey Analytics reports detail the clear competitive advantages from the adoption of a pervasive data-centered approach. "Analytics comes of age" highlights the industry's awareness of the value of data, but observes it is mainly approached as a "one-off" intervention (Henke & Kaka, 2018). The second report "Catch them if you can: How leaders in data and analytics have pulled ahead" shows that top business performers—those with "annual organic revenue growth rates of 10 percent or more in the past three years"—all fully embraced data as a strategy and have materialized its potential in the changed landscape of the COVID-19 pandemic (Gottlieb & Weinberg, 2019). In a recent survey, McKinsey analysts deplore the lack of progress in the general adoption of AI by industry while identifying that the COVID-19 pandemic has accelerated the scaling of AI and analytics in those firms that were already building the corresponding capabilities (Balakrishnan et al., 2020). They identify the human aspects of AI such as the alignment of senior executives around AI strategy and adoption of standard execution processes to scale AI across a supply chain. This chapter aims to help in aligning scholars and practitioners around a common vision of the scope and depth of what Analytics as a discipline, which combines traditional Operations Research and Management Science with Data Science and computer power, can do for supply chains.

In this chapter, we follow loosely a time axis to describe the evolution of algorithms, analytics, and AI. We start with the established and well-used tools in the next section, describing the prevalent techniques which today use AI and algorithms and we highlight some standard applications. We provide an explanatory overview of all the important algorithms and AI techniques at a high level but aim to provide a view "under the hood" where appropriate. The corresponding references are for the readers to dig deeper. Section 3 provides an overview of the algorithms and AI techniques which *today* have an impact on the way supply chains are managed. In a look at the future, Section 4 presents the fields and applications that the authors have identified where AI techniques can potentially have a profound impact in the *upcoming years*. We present in Section 5 some perspectives on the influence of AI and more generally of algorithms on the digitally enhanced and digitally managed supply chains *after 2030*.

2. Current and prevalent algorithms and AI techniques

We cover here the most general and historically well-known algorithms in operations and supply chain management. Such algorithms allow decision-makers to frame problems to be solved in mathematical terms using the available data.

One of the oldest algorithms aims at the calculation of the Economic Order Quantity (EOQ), which enables a warehouse manager to evaluate the optimal quantity to order given expected demand (Erlenkotter, 1990). Algorithmically, the ideal EOQ is obtained by minimizing the expression for the total cost of purchasing or producing, ordering, and holding goods. This classical method—dating back to Ford Whitman Harris' work in 1913—results in a simple solution of the

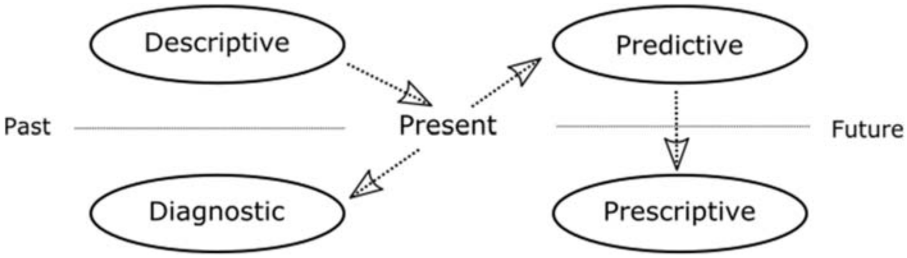


FIGURE 6.2 Analytic model types.

optimal number of units $Q = \sqrt{2DS/H}$, where D is the demand in unit, S is the order cost per purchase (or production), and H expresses the holding costs. As expected demand may not follow a normal distribution, or as multiple products are involved, the problem's complexity increases as does that of the corresponding algorithms. The complexity increases yet again if the demand follows seasonal patterns, with various products having different seasonality.

Such algorithms are called *prescriptive algorithms* because they prescribe courses of action to the decision-makers. More generally, algorithms can be deployed when reality can be represented sufficiently well in a mathematical form and can be solved to satisfaction using mathematics. The corresponding models can be classified into (see Fig. 6.2)

- *Descriptive and Diagnostic Analytics*: performed to assess historical data and extract and show trends (predictive). They usually involve known functional forms, the independent variables (those factors that explain or influence the phenomenon under investigation) are known or certain and the purpose is to represent or illustrate reality in its complexity. This group includes simulation, Program Evaluation Review Technique or PERT, queuing theory, Activity-based costing or ABC, Pareto classification schemes, network description, etc. Once the process has been realistically represented in this way (descriptive), usually other algorithms are applied to enable the decision-maker to further analyze or decide on the best course of action given the objectives (prescriptive: see below).
- *Predictive Analytics*: helps users to forecast and predict future events, conditions, and trends such as future demand, or commodity prices. They involve unknown or ill-defined functional forms, the independent variables' behavior are more or less known or are under the decision-maker's control. In this group we find regression analysis, time series analysis, discriminant analysis, stochastic processes, and dynamic systems. Many of these are valuable for the critical process of forecasting to inform and enable supply chain planning at different levels of aggregation and over different time horizons. Others try to reduce uncertainty surrounding the activities in a supply chain. We find in this category the risk prevention or mitigation techniques against equipment failure risks, climate risks, abnormal weather, political and social risks, etc. (Melançon et al., 2021).
- *Prescriptive Analytics*: produce recommendations for action. They involve known and well-defined functional forms, the independent variables are known or under the decision-maker's control. The decision that must be taken is identified. Belonging to this group are classical optimization, linear programming, integer programming, nonlinear programming, fuzzy programming, stochastic programming, multicriteria decision-making. Several of the newer inventory models can be classified in this category, along with vehicle routing and transportation models which prescribe how deliveries should be handled given constraints. Other problems which rely on such analytics include cutting stock, layout, aggregate planning, and bin packing problems.

2.1 Prescriptive techniques

Usually, prescriptive techniques are used for optimization or efficiency in operations, logistics, and warehousing. The most well-known originate in operations management. For example, stacking boxes in a container or in a semitrailer has now been optimized for space and weight as well as the order in which those boxes must be taken out. Mathematical models for the optimal way to cut fabric and material to reduce waste are also good examples of prescriptive algorithms (Bennell et al., 2013). In the logistics and transport sector, numerous applications provide responses to logistic challenges and events. The latest refinements allow for three-echelon supply chain optimization at the cross-docking station when truck selection is important, products have different sizes and weights, and demand for transport may be aggregated (Chan et al., 2016). Others involve modifying the location of items in a warehouse, for example, to reduce picking time by placing the fastest moving items near the packing areas so as to reduce the time taken by operators to pick such items (Arnaout et al., 2020; Önüt et al., 2008). The latest evolution in this field now arrange for robots to bring items to a human picker thus limiting movements and reducing the potential for injuries or professional health issues from developing (Wang et al., 2021). Amazon now organizes thousands of robots to work in a synchronized manner (Poudel, 2013). Beyond the warehouse and into the stores, the multioptimization of markdowns requires highly complex algorithms to make optimal decisions that reduce waste, inventories, and improve margins (Chen et al., 2021).

Another large area which has benefited from Operations Research over the years concerns delivering products. Previously, the design of milk runs (an important problem in logistics with applications in Just-in-Time systems) had to be optimized one by one. Then whole fleets of delivery vehicles were optimized. Whereas optimizing deliveries for sets of delivery points within the constraint of time windows and truck capacity (Sitek et al., 2021) used to be the most complex problems solved, nowadays, the objective is to prescribe optimal delivery schedules which take into account all of the above plus traffic conditions, pollution, and driver working hours (Alvarez et al., 2018; Dang et al., 2021).

The list of prescriptive applications where algorithms have benefited is long including those models applied in the areas of capacity and scheduling planning by deciding on resource allocation, the selection, and scheduling of orders (Weckenborg et al., 2020). We here note one last developing area: how to counter the negative impact of abnormal weather on sales. Rainy days are unfavorable for suntan oil and barbecue items. Recent algorithms now allow retailers to asses and mitigate such impacts (Bertrand et al., 2015, 2021).

2.2 Predictive techniques

In this section, rather than seeking to give a necessarily incomplete panorama of algorithms and their applications, we provide in-depth analyses of two of the most well-identified algorithms in the predictive category. We distinguish between the traditional tools provided by statistics from the newer ones grouped under the generic heading of AI.

A particularly critical area in which human intelligence is brought to bear is trying to predict the future. In the case of supply chains, this has critical relevance when it comes to ensuring that future demand can be or will be met. In practice, forecasting is ubiquitous in supply chains, with companies involved in responding to customer demand employing many personnel overseeing the forecasting process. While their job titles may vary from demand planner to sales forecaster or analyst, their major task is to provide forecasts of demand to other parts of the company, especially operations, production, distribution, and finance (Boone et al., 2019).

2.2.1 Predictive analytics using statistical tools

Linear regression is perhaps one of the most well-known and well-understood methods in statistics and machine learning. It is known as a textbook example of a simple machine learning algorithm, in which learning means estimating the values of the coefficients used to represent accurately a series of historical data (Russell & Norvig, 2020). We first briefly explain how it works before looking into the more general case, multilinear regression, where not one but various historical series are used.

The Linear Regression model, in its simplest form, uses the value of the independent predictor variable $X = x$ to predict the target value $Y = \widehat{y}$, with

$$Y = w_0 + w_1 x + \varepsilon$$

for some constants coefficient w_1 and bias w_0, and some random noise variable ε. The random noise satisfies the expectation $E(\varepsilon|X = x) = 0$ and variance $\mathrm{Var}(\varepsilon|X = x) = \sigma^2$. A further assumption is that the noise ε is uncorrelated across observations.

The simplest linear regression model has two variables, X and Y. We use X, the *predictor* variable, to try to predict Y, the *target* or *response* through a linear relationship $\widehat{y} = w_0 + w_1 x$ using the yet to be determined coefficient w_1 and bias w_0. In a typical situation, we have a set of m observations $\{(x^{(i)}, y^{(i)})\}$, which we presume are a realization of the model. Our goal is to learn the parameters of the model from these data, and to use those parameters to make predictions. We can estimate the parameters by the *method of least squares*: that is, minimizing the in-sample mean squared error:

$$\widehat{\mathrm{MSE}}(w_0, w_1) \equiv \frac{1}{m} \sum_{i=1}^{m} \left(y^{(i)} - \widehat{y}^{(i)}\right)^2$$

One can prove that the least-squares estimates solve the *Normal* equations. These equations correspond to the first-order optimality conditions applied to the function $\widehat{\mathrm{MSE}}(w_0, w_1)$. The solution to the estimating equations can be obtained for simple situations.

Building a multilinear regression tool for industrial applications involves labeling data samples in the form $\left(x_1^{(i)}, \ldots, x_n^{(i)}, y^{(i)}\right)$ which can have a very high number n of features (or dimensions, as predictor variables—the factors that influence the variable we seek to predict). The corresponding multilinear regression model $\widehat{y} = Xw$, with design matrix X—containing all the features of the data samples in its rows—is too large to practically compute the optimal solution. This computational aspect is a fundamental problem in the analysis of big multiattribute datasets using the traditional Normal Equation technique.

The Normal equation, for the simplest Linear Regression, is

$$\begin{cases} \overline{y} - \widehat{w}_0 - \widehat{w}_1\overline{x} = 0, \\ \overline{xy} - \widehat{w}_0\overline{x} - \widehat{w}_1\overline{x^2} = 0 \end{cases}$$

where $\overline{(\cdot)}$ stands for the average value over the m samples, and $\widehat{(\cdot)}$ indicates the optimal value of the model parameter. The solutions are

$$\widehat{w}_1 = \frac{c_{XY}}{s_X^2},\ \widehat{w}_0 = \overline{y} - \widehat{w}_1\overline{x}$$

where c_{XY} and s_X^2, respectively, are the covariance of feature X and target Y, and the variance of the feature X in the dataset. The expression of the solution $\widehat{\mathbf{w}}$ of the Normal equation solution for a general Linear Regression is given by

$$\widehat{\mathbf{w}} = \left(X^T X\right)^{-1} X^T y$$

with design matrix X and vector of target values y.

Some ingenious methods have appeared recently combining traditional regression, smoothing, and ARIMA (AutoRegressive Integrated Moving Average) techniques with "unobserved component models" and tested in forecasting for a franchise chain in Spain (Villegas & Pedregal, 2019). Such models aim to decompose a vector of time series into trend, seasonal and irregular components. Depending upon the type of data, such decomposition is not always feasible. Extra care must be taken to ensure proper validity of the ensuing model.

Times series forecasting is accomplished with the well-known ARIMA, with damped or exponential smoothing, usually combined with detrending and deseasonalizing of historical data (comb filtering). These techniques have been industry's standard for many years but should be applied only when the historical data are known to be well behaved (Franses et al., 2014), as is often the case in volume retail or utility services and similar large-scale data contexts.

The ARIMA equation will forecast the current value $\widehat{y}_t$ as a weighted sum of p observed previous values and q previous error terms;

$$\widehat{y}_t = \mu + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} - \left(\theta_1 e_{t-1} + \cdots + \theta_q e_{t-q}\right)$$

and μ is the drift, or linear time-dependent component.

The ARIMA algorithm forecasts the *current* value of the time series by an optimally weighted sum of historic values each with a corresponding error term. In practice, however, a real-world dataset is often too big to solve the Normal equation. More generally, even though forecasting in supply chains must support operations and help suppliers, recent substantial advances have been few and far between beyond the algorithms introduced by Brown, Box, and Jenkins several decades ago (Boone et al., 2019).

Take, for example, the case of a large network of apparel stores selling fast-fashion items. The heterogeneity of the population's tastes, body sizes, and spending patterns makes forecasting demand or understanding consumption patterns extremely complex. The complex material flow in this supply chain can be examined as families of time series of goods and data in key locations. This flow generates time-ordered data of production, delivery, stocks, and orders, and enables the prediction of future demands. Since organizations and managers are faced with streams of data flooding in from various channels and sources and at an accelerating rate, algorithms need to deal with such flows appropriately. Data overload can hamper the ability to derive valuable insights and make timely decisions. By leveraging the advantages of *Advanced Analytics*, supply chains can respond faster, be demand-driven and customer-centric. Such methods rely on the aggregation and pooling of data such as including temporal aggregation for several levels for demand forecasting (Kourentzes et al., 2014). Other algorithms have been developed to enable a decision-maker to choose among various forecasting methods given a large database (Babai et al., 2014).

A well-known third source of data for demand forecasting are the digital trails left by website visitors as to their tastes, their requirements (Salvador & Ikeda, 2014), and their willingness to pay for the available logistic services (Asdemir et al., 2009). The resulting massive information from site visitors can be built upon for planning, forecasting, and sharing information with upstream partners in the chain only after careful and extensive transformation using methods of descriptive and prescriptive analytics (Boone et al., 2019; Evtodieva et al., 2020; Schaer et al., 2019).

Given the variety of data sources, their heterogeneity in structure, and above all, their complexity, several new research fields have developed to make such data amenable to useful interpretation. One such field has been named "Data Fusion," which automatically or semiautomatically transforms information from different sources and different points in time into a representation that provides effective support for human or automated decision-making (Hall & Llinas, 1997; White, 1991). As data become available in ever larger amounts, the aim of data fusion is to obtain improved datasets with consistent, accurate information, and superior reliability (Meng et al., 2020).

A word of caution is necessary. Much of the recent research using Big Data (in particular from social networks, web surfing, etc.) appears to give spectacular results but the question of which series to choose to avoid overfitting or spurious correlations are still being debated (Yu et al., 2019). Another issue, often overlooked in choosing appropriate data series for predictive analytics, is when historical data are coming from nonlinear complex dynamic systems, such as epidemiological systems or weather systems. Forecasting will fail or give predictions with levels of confidence so low as to be useless. Nonlinear complex dynamic systems qualify as chaotic systems. They can be found in supply networks (Choi et al., 2001), in warehouse inventory levels forecasting (Wilding, 1997), or in railway networks (Dekker et al., 2018) among others. Hence, we argue that novel and entirely different algorithmic approaches should be given wider attention from the top managerial levels so as to inform the strategical development of better techniques. Such are the AI tools that we describe next.

2.2.2 Predictive analytics using AI

The increasing amount of data available to managers require sophisticated analytics to help make sense from them, and support effective decision-making. We give insights on how the application of Industry 4.0 to supply chains generates data which should be harnessed so that managers can derive actionable information. In particular, the increased data sharing among the partners of a supply chain allows for intelligence gathering and hence enables timely and informed countermeasures in case of disruptions or unforeseen events (Akbari & Do, 2021). We first describe the contributions from Machine Learning, Neural Networks, and, finally, Deep Learning. Fig. 6.3 illustrates how the above definitions relate to each other.

The theory and practice of forecasting has recently benefited from ingenious applications of Machine Learning and other AI techniques, spurred on by competitions to find the most effective forecasting algorithms (Hyndman, 2020; Pavlyshenko, 2019). Given the accumulation and availability of historical data about diverse human and natural phenomena, combined with the massive reduction in the cost of computing power, the rate at which new statistical and mathematical forecasting algorithms are created has accelerated. However, so far Machine Learning methods have been introduced with only mediocre performance. For example, the information about promotions by a firm or by competitors, even if collected internally (marketing department) or from market intelligence, has very little predictive value for Sales and Operations Planning (S&OP) (Fildes et al., 2019). Currently, the best performing methods rely on a combination of

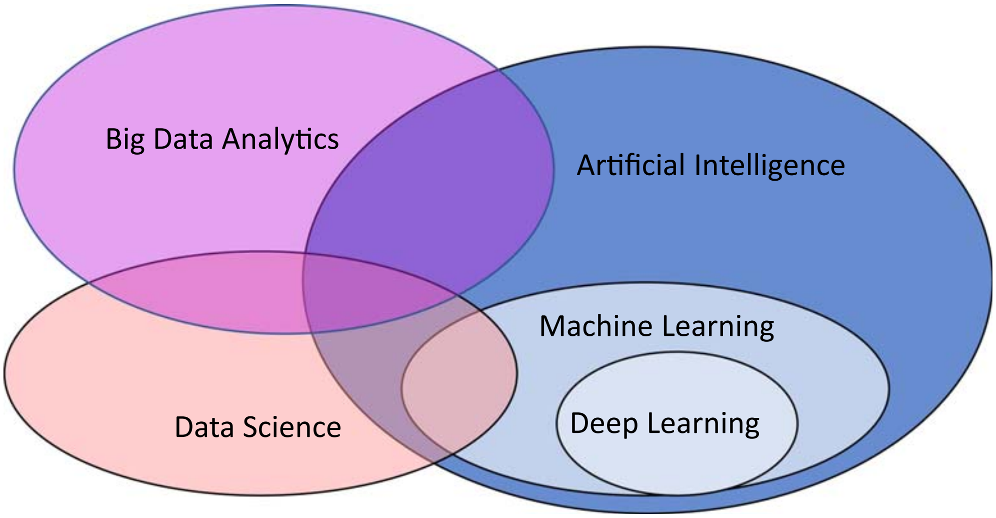


FIGURE 6.3 Artificial intelligence, big data analytics, data science, deep learning, and machine learning.

techniques applied sequentially to the data (Zougagh et al., 2021). The most sophisticated and successful achieve a good compromise by combining Machine Learning with more traditional statistical techniques and using several time series at once (Smyl, 2020).

An interesting application of knowledge generating AI from Big Data has been set up at Amazon.com (Rastogi, 2018a). To better understand the behavior of web surfing customers, the company uses not just the data from the Amazon website but also other data such as the calendar of sports, cultural or religious events, weather forecasts, expected promotions, or product launches to refine their inventory and ordering planning system. Such plans also feed their prepositioning system which enables warehouse managers to place the right items in the fulfillment center closest to the expected demand (Herbrich, 2017). The machine learning algorithms help to choose in milliseconds just the right few products and advertisements to show in a search and make just the right product recommendation (Rastogi, 2018b). Data mining systems and methods associate users with items based on underlying personas. The system associates each user account with one or more underlying personas to make item-related recommendations. Thus, for example, even though multiple individuals may share a computer and/or account, the item recommendations presented during a browsing session may be based primarily or exclusively on the past browsing behaviors of the particular individual conducting the browsing session (Rastogi, 2018a).

In another example, Customs and tax authorities in Europe are now implementing AI algorithms to identify fraud, counterfeit, and drug running from the massive information about containers, trucks, and other bulk carrying vessels arriving daily in Europe (OLAF, 2019).

Machine Learning is a subfield of computer science and AI. It describes a field that creates particular algorithms to make computer systems learn by using data without specific programming. Specifically, algorithms help computer systems or machines to learn (or be trained) and predict the world like a human being. More broadly, it is the study of making machines acquire new knowledge, new skills, and reorganize existing knowledge (Kanungo et al., 2002; Liu et al., 2018; Wei et al., 2017). It is subdivided into supervised, unsupervised, and semisupervised learning.

The expression *supervised learning* refers to the learning process of an unknown function obtained from labeled training data, based on example input—output pairs. In the supervised category, data are split between training and validation sets. Some forecasting algorithms use Long-Term—Short-Term Memory Neural Networks (LSTM), which allow nonlinear trends and cross-learning, where the model is learned based on multiple time-series, and machine learning or reinforcement learning (Smyl, 2020).

With the phrase *unsupervised learning*, we refer to the identification of previously undetected patterns and information in a dataset with no preexisting labels. Pattern recognition or identification typically uses clustering algorithms in unsupervised learning. Algorithms often extract features and patterns by themselves by classifying data into groups or clusters with similar attributes. The k-means clustering family of algorithms are the most famous (Kanungo et al., 2002; Liu et al., 2018). *Semisupervised learning* lies between supervised and unsupervised learning.

Finally, *Deep Learning* is a branch of machine learning that uses neural networks with many layers. An artificial neural network is one of the best performing model architectures of machine learning, inspired by the biological neural network which describes the way animal and human brains process information. Such networks learn how to perform tasks by processing information, even without being programmed with task-specific rules. Artificial neural network analysis has received a lot of interest in machine learning research and across industry for its large number of applications, for example, in image analysis, speech recognition, computer image quality, and text processing (Akbari & Do, 2021; Zougagh et al., 2021).

An artificial neural network comprises a collection of connected units or nodes, called artificial neurons, which resemble the behavior of neurons in the animal brain. Each connection within the network, called an edge or link, allows information to be transmitted to other neurons as synapses in the animal brain. A neuron receives information, processes it, and transmits the processed information to other neurons it is connected to. Neurons and edges have weights, which determine the intensity of the information transferred at each connection. Typically, information is transferred only if a certain threshold is crossed: in order for a neuron to produce information to transfer, it needs to receive and process a certain amount of information. Neurons are generally aggregated into layers, where different layers may process information in different ways. The information passes from the first layer to the last one, eventually passing through each layer multiple times.

More specifically, a neuron receives inputs from some other neuron and from external sources and then combines them to produce some output (see Fig. 6.5). Each input x_i with $i = \{1, \ldots, m\}$ has an associated weight w_i, which expresses its relative importance to other inputs. The neuron produces output through a function $f(\cdot)$, sometimes called an activation function, combining the weighted sum of its inputs. If x_i, x_2, …, x_m are inputs and w_1, w_2, …, w_m their corresponding weights, and w_0 describes some external source, then a neuron produces output y through

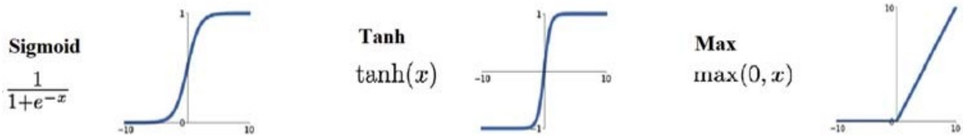


FIGURE 6.4 Different activation functions.

$Y = f(w_0 + w_1x_1 + w_2x_2 + \ldots + w_nx_n)$. The activation function $f(\cdot)$ is assumed to be nonlinear to allow for the fact that a certain threshold level of information is needed for the neuron to produce output. Such nonlinearity in the output generating process allows a neural network to model and to learn from information in a way that imitates the nonlinear behavior of real-world data.

Several activation functions have been proposed in literature. The most widely used are the sigmoid, the hyperbolic tangent, and the max function (Fig. 6.4).

The feedforward neural network was the first and simplest type of artificial neural network created (see Fig. 6.5). A feedforward neural network contains multiple neurons that are arranged into layers: nodes are connected to the adjacent layers by means of edges, and all connections have weights associated with them (see Fig. 6.6). It may contain the following three types of nodes: input nodes, hidden nodes, and output nodes. Input nodes provide information from the outside world to the network, and usually no processing of information is performed in any of the input nodes but the information is just passed to the hidden nodes. Hidden nodes have no direct connection with the outside world, and they process and transfer information from the input nodes to the output nodes; a collection of hidden nodes forms a hidden layer. Output nodes are responsible for processing and transferring information from within the network to the outside world (see Hewamalage et al., 2021; Shen & Khorasani, 2020; Smyl, 2020, for applications relevant to supply chains).

After setting the hidden structure, three different stages are implemented in the analysis of a neural network: training, testing, and forecasting. Training refers to the use of a subset of the available data to estimate the unknown parameters of the network through a training algorithm which tries to minimize the distance between forecast and empirical values.

In the development of AI applications involving very large datasets, the most common practice is to optimize a regression model, or more generally any prediction model, through the method of *gradient descent* on the *cost function*, usually the difference between the prediction and the expected value from the training dataset (see Fig. 6.7). The "cost function" of a prediction tool, both for regressor and classifier algorithms, helps in optimizing their performance.

The principle of gradient descent on the cost functions simply directs the algorithm to increment the weight's value *opposite to the gradient* of the cost function, where the cost here refers to the difference between the expected and obtained values (a prediction algorithm is "costly" if it performs poorly).

While artificial neural networks have proven to be accurate in classification and regression problems, their use of a complex algorithmic architecture to reach a prediction has given them the reputation of a "black box" method (Rudin &

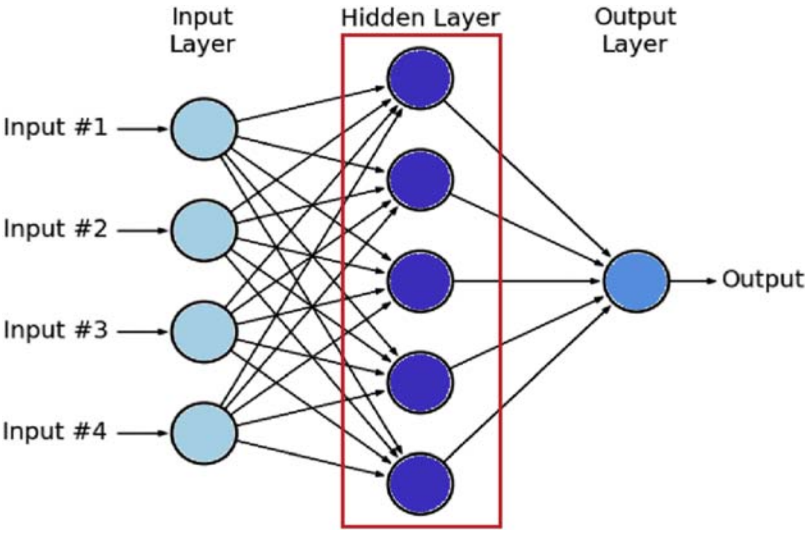


FIGURE 6.5 Multilayer perceptron.

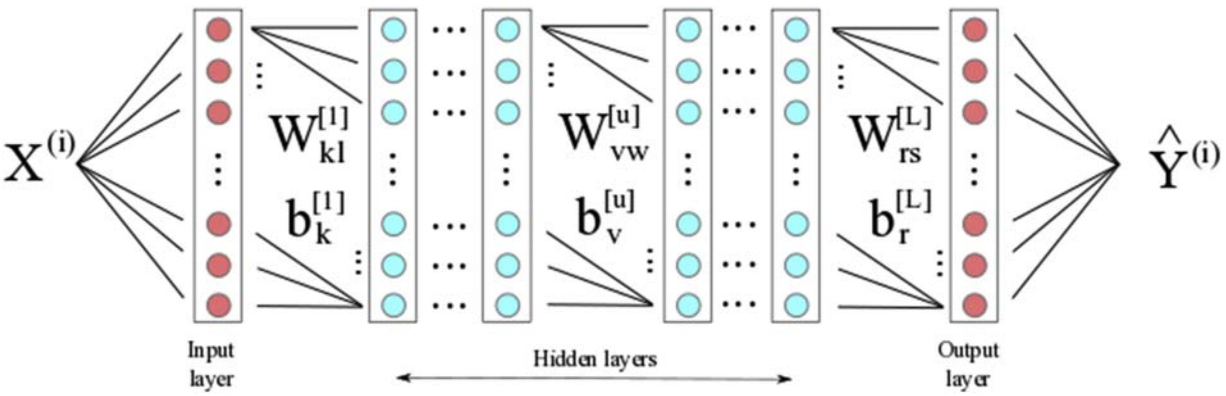
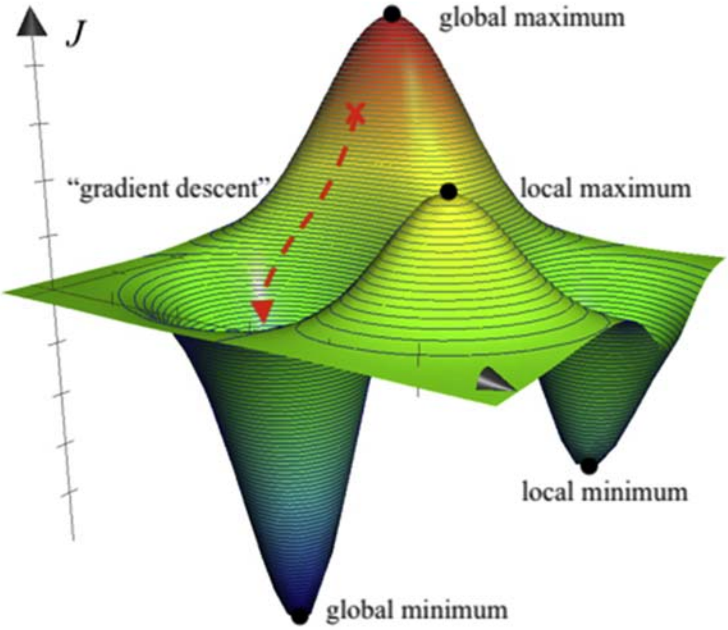


FIGURE 6.6 Deep neural network containing L layers of neurons, with respective weights $W_{vw}^{[u]}$ and biases $b_v^{[u]}$ where u, v, r are the number of nodes in the hidden layers, k and s are the number of nodes in the Input and Output layers respectively.

FIGURE 6.7 Iterative updating of neural network parameters to achieve a global minimum.



Radin, 2019). The optimal weights and biases may not simply translate into some easily explainable prediction function. In contrast, some nonparametric algorithms for regression and classification have been developed, which are more often thought of as "interpretable models." In a decision tree, a prediction—or decision—is obtained step-wise by checking a scenario for a few criteria. After checking such a criterion, the decision path branches off to the next criterion, to finally end up in the final node where the most optimal decision or prediction, such as a class label, is given (Kanungo et al., 2002; Liu et al., 2018; Wei et al., 2017).

Typically this multistep decision process is presented as a branched flowchart: starting from a root node with a first splitting criterion the cases are further down the branch on each node's criterion to end in a leaf node where the ultimate decision is formulated. These decision trees also rely on labeled data for their training, but instead of obtaining optimal weights and biases this method simply looks to reduce the impurity of the subsets after a criterion-based split. And it looks to reduce this impurity in the next split again, until sufficient accuracy has been obtained or the maximum depth of the tree is reached. This algorithm uses brute computation to find the best criterion at each instance; that is, the criterion that results in the next split with the greatest drop in impurity. The impurity metric of a set corresponds to the expected miss-classification probability following the realized proportions of classified items in the set.

Due to the consecutive conditional splitting in the decision tree, the subsets of cases in each node become smaller when progressing deeper into the branches. The decision tree algorithm is therefore prone to overfitting and hence may not generalize well in forecasting the outcome of new cases. This issue has been tackled by running several distinct trees in parallel: a decision forest. The predicted output corresponds to the majority vote of the individual trees. For regression, the average is taken over the individual predictions. However, the latter decision forest again resorts to a "black box" algorithm since averaging obscures the effect of explicit splitting conditions.

3. Current AI and algorithmic applications with the most impact

Here we provide our perspectives on the most impactful AI applications in operations and supply chain management. The dimensions of impact we consider are assessed by the increase in efficiency or value creation through a supply chain. The most interesting applications no longer just rely on *descriptive* algorithms but use *prescriptive* ones or may even make decisions *in lieu* of humans. Recent work in this area shows that, beyond the hype which characterized the field in the early 2010s, there are substantial improvements and even startling areas where AI is having an impact (Akter et al., 2022). We provide here a brief description of some of them. We hope that these descriptions will also spark interest to either try them out or begin a search for alternative or new avenues for development in the field of supply chain management and business and management more generally.

We distinguish here between the narrow applications of AI where the purpose is to apply a well-defined and well-behaved algorithm to perform a specific task such as image recognition (for example, identifying how a parcel is positioned on a conveyor belt so as to direct a robotic arm to pick it up), from the almost-human intelligent systems that have the ability to learn on the job to become smarter (and so not having to be reprogrammed or retrained by developers). These smarter AI systems are covered in the next section where we look into the future to provide some insights into what potential applications might appear in the next 10 years.

Currently, the applications of AI can enable the building of new kinds of functionalities in operations and logistics (Helo & Hao, 2021). AI can be implemented in the following ways:

- Learning systems that can adjust behavior based on dynamically observed data (Baryannis et al., 2019).
- Situation-aware systems that can detect and understand conditions (Singh et al., 2020).
- Autonomous decision-making systems that can execute decisions (and not just stop at making a recommendation) (Dwivedi et al., 2021).
- Processing and interpreting streaming images, video, and audio (Brynjolfsson et al., 2019; Mehta et al., 2020). In considering the supply chain from final consumer back to the raw material supplier, we find substantial applications where AI provides higher efficiency or value creating services previously unavailable or unaffordable. We list here some examples: fraud detection, routing self-driving inventory handling robots in a warehouse (Ahamed & Karthikeyan, 2020), finding the shortest path for replenishment of vending machines in a network, or measuring sugar consumption in Thailand (Kantasa-ard et al., 2019). Given the attention of shoppers to their smartphones, retailer smartphone apps can be made smarter so as to provide help to consumers in their choice without inconveniencing them in an omnichannel retail environment (Guha et al., 2021). There is also a substantial improvement if the smart "chatbots" are able to both understand the query and the tone of the caller (Luo et al., 2019). More generally what has been termed Customer Experience Analytics is breathing new life into the way companies interact with millions of customers in a personalized way (Abdollahnejadbarough et al., 2020).

In home delivery, the proportion of missed deliveries is high. New applications aim to link a delivery to the presence of the receiving party by the GPS position of her smartphone. So, if absent, the delivery person's route can be modified and new or modified rendezvous can be set up on the fly. Vendor Managed Inventories have long been a valuable way for manufacturers to ensure that the right inventory is in place when customers require it. Now, smart AI applications are able to compensate for the stochasticity of both production and sales so as to minimize production and inventory while maximizing the order fill rate (Giovanni, 2021).

When looking at the retailing—inventory interface, AI provides highly valuable applications in creating a knowledge-driven collaborative platform to collect production, logistics, warehouse, and marketing data and provide intelligent reports based on the corresponding data to supplement S&OP activities (Li et al., 2017). Other applications use the demand patterns store-by-store, based on both category information (about other product promotions, for example) as well as daily or weekly seasonal patterns by SKU to tailor replenishment orders and reduce out-of-stocks at store level. The same type of intelligent system can also make price recommendations down to the store level to help in reducing overstocked items or deal with a competitor's promotional activity (Gupta et al., 2020).

In the B2B environment, understanding customer behavior, their product requirements, specifications, and other customer relationship management issues and leveraging such knowledge with big data can yield enhanced knowledge creation for marketing–sales decision-making in areas such as customer segmentation, sales channel management, investment in marketing, and customer relationship management (Bag et al., 2021). In the manufacturing environment, production, assembly line management, and automation have all had highly relevant new AI developments (Dubey et al., 2020), which we only briefly describe as most are extensions of prior effort and hence are amply covered in other chapters of this book.

Since the movement of logistic units are highly dependent on external conditions from traffic in the case of road transport to other forms of congestion on rail networks and port operations, new algorithms using information from IoT sensors and past history are now able to forecast with high accuracy the Estimated Times of Arrival for the corresponding cargo and so enable the optimization of the schedules of the receiving parties' equipment (cranes, forklifts, etc.). In warehouses, interconnected IoT sensors enable predictive maintenance of forklifts and other equipment as well as forklift driver fatigue and other driving parameters and juggles schedules accordingly.[1] Transport hubs such as airports and ports are ripe for major revolutions, thanks to wider use of IoT and the corresponding connection of management systems of the various stakeholders (Boyles, 2019). A port is a meeting point for most of the common transport modes: overseas ships must be berthed (so booking a berth requires advanced knowledge of arrival time), cranes must be made available for unloading, railcars, forklifts, trucks, and barges must also be on hand to shift the goods inland. Such logistic units are brought up to the side of the ship because their GPS position, their owner, and their availability are known. All this information is brought together in a Digital Twin of the port (Yao et al., 2021). Algorithms arrange the corresponding schedules so that all these assets are used efficiently by reducing all of energy to move them, idle time, congestion in the port area and access ways. Such algorithms cannot be complete or ensure the maximum efficiency the first time: they rely on fine tuning, which, because of the amount of information, is done through Deep Learning.

The implementation of such analytics and algorithms using AI has been greatly facilitated by the replication of a network—or city, plant, equipment, or patients—in digital form. The advent of these *Digital Twins* is important as guidance and virtual test beds (Rosen et al., 2015). Combined with IoT, such digital twins in production systems enable agile and "intelligent" manufacturing through a simulation and test loop involving information exchange between the physical factory and a virtual twin to realize production control and optimization by machine learning based on big data (Min et al., 2019). In supply chains such digital twins enable testing and optimizing "real-time" activities and positions of various fleets, of logistic units or inventory (Baryannis et al., 2018). This enables identification of underutilized or idle assets, bottlenecks, and the reduction of pollution. Furthermore, the combination of model-based and data-driven approaches allows uncovering the interrelations of risk data, disruption modeling, and performance assessment (Ivanov & Dolgui, 2020).

4. Potential techniques and emerging areas of application for AI and algorithms

> *"The coming years might give rise to diverse ecologies of AI systems that interact in rapid and complex ways with each other and with humans: on pavements and roads, in consumer and financial markets, in e-mail communication and social media, in cybersecurity and physical security. Autonomous vehicles or smart cities that do not engage well with humans will fail to deliver their benefits, and may even disrupt stable human relationships."*
>
> Dafoe et al. (2021).

A major improvement in neural network architecture by Hochreiter and Schmidhuber (1997) provided a remedy to the "vanishing of the gradient" problem (of the cost function) when back-propagating through the layers of a deep neural network. The latter problem can occur in the learning phase of deep neural network training when weights, valued smaller than one, scale exponentially with the depth of the number of layers, the expression of the derivatives, and hence result in near zero values. In this situation the relationships between earlier and later activations in the forward flow of the network are lost, causing the network to not remember the relation between earlier events and later events. These temporal relations between longitudinal observations are essential in, for example, forecasting the output at each segment of the supply chain network. The introduction of a memory effect in the neural network by using LSTM modules (see Fig. 6.8) allows an efficient output prediction in time series—and also in natural spoken language, video, handwritten text, music, and all applications in which an ordered representation is appropriate (Smyl, 2020).

Computationally intensive AI technologies for supply chain management may be transformed further by emerging quantum computing technology. Essentially, quantum computation could deliver a substantial speed up for specific

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[1] SmartLIFT at Swisslog.com and Locoslab.com.

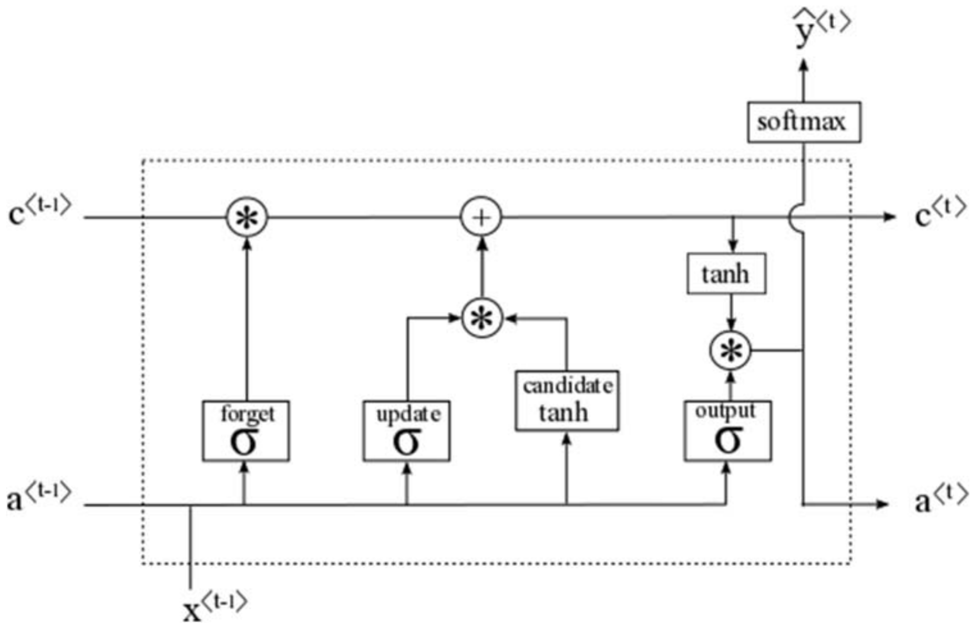

FIGURE 6.8 Long–Short-Term Memory unit with "update," "forget," and "output" gates, for Recurrent Neural Networks.

algorithms. Based on the properties of *qubits*, which can take any value on the complex unit sphere instead of just the classical 0 or 1, and which can organize in entangled configurations (in a very restricted environment), a system of simultaneous parallel computation would be feasible. While the available algorithms for true quantum computers are still limited, a quantum alternative has been developed in what is named a quantum annealing processor. The latter special purpose technique is specifically targeted at optimization problems (Boixo et al., 2014) and has been explored in industry applications by, e.g., ExxonMobile and BMW (Leprince-Ringuet, 2021a,b).

As indicated earlier, AI applications, if they are to contribute to a wider extent, have to provide truly intelligent solutions or recommendations which operators, managers and decision-makers will adopt. For this to happen, such applications must improve "on the job" by learning and, even better, learning how to learn while at the same time interacting and coevolving with human beings and their abilities and skills. Hence, in the future, the most successful AI applications will be those that mesh with operators and their processes by taking away the repetitive hard data crunching tasks and letting human operators adapt systems and solutions flexibly to uncertain and highly variable environments. In such combination, hybrid machine learning systems will, for example, establish fault-diagnosis strategies using embedded health information contained in the I/O sensor data and report back as to the best machine combination given the expected workload (Shen & Khorasani, 2020). As an example, take the case of the huge warehouses where conveyor belts, pallet lifting robots, and other identification devices combine with human operators (Wang et al., 2021). Human operators can deal with a wrongly placed or oddly shaped parcel as well as a pallet stuck in the wrong position or a machine functioning in degraded mode. In the future, such situations will be handled by machine learning systems (Dogru & Keskin, 2020; Guha et al., 2021).

Given the rapid strides in programming achieved today, programming robots will use existing libraries of code to help programmers when setting up new or modifying existing systems. Further advances in coding languages already help programmers and nonprogrammers dictate in a common language what they want a program or an algorithm to do. With these new abilities, building or incorporating a new algorithm into a system takes less time. This ease of use will help nonprogrammers (that is, most operators and decision-makers in a supply chain environment) to incorporate new features and rules into existing systems (Nguyen et al., 2021).

Recent advances in European-funded research projects have brought the Physical Internet, smart mobility, and collaborative logistic platforms beyond the proof-of-concept stage.[2] These and other initiatives demonstrate that the building blocks as well as the necessary knowhow are available and will slowly be embedded in logistic networks and

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[2] See the achievements from some recent projects at ICONET, SENSE, and FEDeRATED.

infrastructure so as to achieve seamless freight transport and logistics and, thus, increasing efficiency, reducing energy use, while ensuring high customer satisfaction rates.

The Physical Internet coupled to Internet of Things sensors and edge computing devices (devices able to perform computing tasks at the periphery of a network) will help to track events as they happen in real time. Algorithms will provide local intelligence to make the basic decisions required (Lin et al., 2020; Singh et al., 2020). Other layers will consolidate information on a wider scale to further elaborate plans and act with higher value adding intelligent services. In this way, production schedules at plants will take into account the expected deliveries of raw materials and components, the expected production rates will feed forward to the warehouse and logistic service providers. The hiccups and wrinkles in these plans will be worked around by other smart systems. The major events and accidents will be brought to human attention together with the right amount of consolidated information in a form understandable by a human for a human decision to be taken.

As can be understood from the preceding sections, the various layers of such systems and systems of systems will need also huge amounts of data collected by many sensors. This information will be transformed and aggregated through algorithms for further analysis and higher-level decision-making. Inherently, such systems will require that human operators understand the processes through which such decisions were made. This requires full two-way cooperation between AI and human operators. Once an AI system, as an infant, has learned its way around and understands its surroundings, it needs to be able to understand and interact with humans around it.

One last area in which supply chains will face major challenges is the security of the systems and data which are being created. Cybercrime has now come to the fore of most operations and supply chain managers (Zhang et al., 2021). In the latest poll of supply chain managers worldwide, cybersecurity is even the foremost issue (Balakrishnan et al., 2020). In this instance, AI will deal with the traffic between all applications, IoT sensors throughout the network of supply chain partners. Recent research combining blockchain technology, IoT and the latest developments in smart contracts (Puri et al., 2021; Xu et al., 2020), and edge computing (Lin et al., 2020) shows that these challenges are taken seriously and extend across the globe.

5. Conclusion and perspectives

Machine Learning is now a well-developed subject in the domains of manufacturing, automation, and robotics. However, it is still in infancy in the domains of logistics (except where warehouse management is concerned as robots and automated warehousing is involved) and more generally in supply chain management. This situation may be possibly due to a lack of familiarity, resistance to change, or unavailability of data (Akbari & Do, 2021). Other reasons could be the complexity of supply chains, control of information, and power, control, and governance issues in loosely connected supply systems.

AI is certainly enabling better decisions and actions, and facilitating a move away from ’gut feel’ decision-making. But, as more reliance is placed on algorithms, data, and analytics, the question of trust in systems and trust in technology is emerging as one important consideration. A number of works imply that a *trust frontier* still exists which technology cannot bridge (Altmann et al., 2019; Hawlitschek et al., 2018, 2020). Is technology enough to ensure that no opportunistic behavior can take place in a supply chain that might impact other partners or products? Another consideration is the understanding of such applications by the C-suite executives among large and not-so-large organizations. As noted in Henke et al. (2016) and Henke and Kaka (2018), “many companies remain in the starting gate. Some have invested in data and analytics but have yet to realize the payoff, while others are still wrestling with how to take the initial steps.”

As can be gathered from the preceding sections, the opportunities for applying AI in management and in particular in supply chain management are endless. Even as this chapter is being written, new ways of improving the efficiency of supply chains, of providing new or better services to the end-customers, of making supply chains resilient are being developed. Google has spun out a robots-making firm: Intrinsic will focus on industrial robots that are easier to customize for specific tasks than those we have today. “Working in collaboration with teams across Alphabet, and with our partners in real-world manufacturing settings, we’ve been testing software that uses techniques like automated perception, deep learning, reinforcement learning, motion planning, simulation, and force control.”[3] In the Computer Vision and Pattern Recognition conference in 2021, 3D vision garnered the most papers and presentations with focus on movement understanding and interpretation.[4] Such research is highly relevant in both smart-vehicles as well as robot vision in warehouses and in many industrial environments (such as docks and rail yards).

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[3] https://x.company/projects/intrinsic/.

[4] https://public.tableau.com/views/CVPR2021/Dashboard1?:language=en-US&:display_count=n&:origin=viz_share_link:showVizHome=no.

New technologies such as Quantum Computing will further enhance the decision-making abilities of managers, especially as the corresponding technical breakthroughs will be combined with new specific mathematical algorithms to harness the computing power (see Adhikari & Chang, 2021, for an example in improving hotel performance). Quantum annealing has shown that it could be much more efficient in solving hard combinatorial optimization problems. Recent advances open the possibility of testing it empirically against the most challenging computational problems arising in spatial optimization applications such as can be found in complex network optimization (Guo & Wang, 2020).

The striking features of the projects noted in the preceding section are the granularity of the system building blocks: because they can easily be upgraded separately and flexibly, new features can be added on a case by case basis. As new algorithms or new business requirements appear, they can be incorporated into the existing information system infrastructures without massive amounts of work. Legacy systems, the curse of information systems, will no longer weigh on the agility and resilience of supply chains. As noted in the introduction, we hope that this chapter has helped in aligning scholars and practitioners around a common vision of the scope and depth of what AI, Advanced Analytics, and the corresponding algorithms can do for supply chains.

New business models are being created to harness such new applications into new value propositions to be made at all levels of all supply chains across the world.

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Chapter 7

The impact of digitalization on contemporary and future logistics

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Abstract

Logistics as a sector has grown significantly in recent decades, both domestically and internationally. The digitalization of business systems and the use of Information and Communication Technology have had a major impact across the spectrum of logistics and supply chain management activities. A wide range of developments have already taken place and the pace of change is quickening. We chart the principal stages in the development of computer-based and digital logistics systems that have changed fundamentally how goods, information, and finance flow through the supply chain. Contemporary developments covered include cloud-based systems, digital platforms, Artificial Intelligence, the Internet of Things, Digital Twins, the physical Internet, and Industry 4.0. These technologies not only have the potential to support logistics operations but may also act as disruptors to established approaches, practices, and logistics systems. This chapter discusses how these technological developments, in parallel with economic drivers such as cost saving, the desire for speed and accuracy in delivery, and the imperative for sustainable logistics systems, are contributing to the rapid changes and adaptations taking place. Although there are significant hurdles to widespread adoption, digitally enabled logistics is likely to continue to improve supply chain transparency, operational efficiency, and responsiveness.

Keywords: Contemporary logistics; Digitalization; Future logistics; Information and communication technology; Supply chain management.

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1. Introduction

Logistics activities act as enablers for the global flow of goods. The steady increase in long distance sourcing stemming from the globalization of production and consumption has been paralleled by the increasing size, sophistication, and reach of major corporations. In order to facilitate the global flow of goods, logistics has grown as a sector both internationally and domestically. This has translated, in logistics terms, into steadily increasing volumes of goods being shipped and commensurate increases in cargo value. There is a corresponding need for tighter control of the physical flows themselves and of the transactional activities surrounding these flows, notably planning, finance, and security. At the turn of the century, global maritime trade stood at 5.23 billion tonnes, following continuous growth over the preceding 14 years (UNCTAD, 2000). Although there have been fluctuations in the volume of globally traded goods in the recent past due to the economic crisis of 2008/2009, trade policy tensions, adverse economic conditions, and social unrest, international maritime trade was still around 11.1 billion tonnes in 2019, more than doubling over the first 2 decades of the 21st century (UNCTAD, 2020). Although the global COVID-19 pandemic in 2020 will also have affected trade, it is likely that volumes will continue to increase. New forms of commerce such as omnichannel retailing have also emerged, which rely on a complex web of information exchange, enabling greater choice and improved market access for the consumer.

The digitalization of business systems and the use of Information and Communication Technology (ICT) within the logistics and supply chain management sector have already had a significant impact across the spectrum of activities in these areas. A wide range of developments have taken place in recent years, and the pace of development is quickening. Technological developments in parallel with economic drivers such as cost saving, as well as speed and accuracy of delivery, are all factors contributing to the rapid changes taking place (Klumpp & Ruiner, 2018; Nikitas et al., 2020).

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New business concepts, emerging business models, changing customer demands, and the need for "seamless integration" across supply chains means that organizations have had to leverage ICT to adjust to a radically different marketplace. These changes have meant that organizations that have adopted ICT and that have adapted to the needs of an increasingly automated/augmented world are those that have stayed agile and responsive to meet evolving customer requirements are most likely to be successful (Cirulis & Ginters, 2013; Youssef et al., 2019). In light of the rapidly changing landscape, this chapter shows how digitalization is affecting the contemporary logistics and supply chain management sectors, outlining key issues and highlighting practical examples. A range of technologies are discussed, some of which have matured and are in use, others which have reached only the early stages of deployment. These technologies both support existing approaches and act as disruptors to established systems. Contemporary developments include Cloud-based systems, digital platforms, Artificial Intelligence (AI), the Internet of Things (IoTs), Digital Twins (DT), the Physical Internet (PI), and Industry 4.0. These technologies, in parallel with demands for greater cost savings, higher supply chain speeds, and accuracy of delivery, are all factors contributing to the rapid changes and adaptations taking place in logistics.

2. Digitalization in logistics and supply chain management

Globalized manufacturing, distribution, and sales are commonly linked through ICT systems, which improve visibility within and across the supply chain. Such systems are used for forward supply chains for goods from the raw material state, through manufacturing processes to transport, distribution, and sales. Reverse supply chain systems cover end-of-use/end-of-life products that are returned through the supply chain for recycling or remanufacture (Cognizant, 2011). ICT has improved transparency, increased operational efficiency, and enhanced the responsiveness of supply chains. The quantity and quality of information has reduced uncertainty and facilitated significant reductions in inventory. Modern digital infrastructures, including satellite positioning technologies, and wireless networks, supplemented by mobile devices have enabled the implementation of systems that provide effective, rapid information transfer through the supply chain. It is now common practice for a customer accepting a parcel delivery to receive a notification from the courier or the retail company, or both, that the parcel has been delivered, often within minutes of delivery. This increase in the use of ICT has thus fundamentally changed how goods, information, and finance move through the supply chain (Cordon, 2021; Cordon & Buatois, 2020).

To best highlight the importance of digitalization in logistics and supply chain management, it is first necessary to recognize that in the last 2 decades there have been a variety of concepts developed. roughly sequentially, which frame our understanding of the digital business world. The development of these concepts is outlined in Table 7.1. Whether using ICT in a support role to fulfill online e-commerce orders (Joseph et al., 2004) or to support wider logistics activities (Gunasekaran et al., 2007), digitalization is critical for both business to customer and business to business relationships and practices.

There have been many stages in the development of digitalization for logistics and supply chain management. In the 1960s, systems were developed to rationalize business processes, although these were largely underutilized. Typically, although not exclusively, major manufacturers, e.g., in the automotive or retail sectors drove system advances. From the 1960s through until the 1990s, systems were still largely independent. Even as greater integration occurred, some organizations continued to use independent systems for specific logistics activities, for example, Warehouse Management

TABLE 7.1 Key concepts of digitalization in logistics and supply chain management.

Concept	Key Author(s)
E-business logistics	Auramo et al. (2002)
E-commerce	Rayport and Jaworski (2003)
Internet-enabled logistics	Dadzie et al. (2005)
Electronic marketplaces	Bakos (1991), Wang et al. (2007)
Electronic logistics	Wang et al. (2011)
E-logistics	Wang and Pettit (2016)

Systems, which are still widely used. The effectiveness of the integration of separate systems became a key competitive factor, for example, in Transport Management Systems (Wang & Pettit, 2016). The development of more open systems were early examples of a more integrated approach to information sharing to allow more effective interfacing between parties in the supply chain. In parallel, automation of cargo handling, for example, in the port sector, started to develop bringing benefits in terms of reduced costs and improved productivity (Chu et al., 2018) From the late 1990s, point-to-point systems were replaced by web-based platforms designed for participants to share data and information and allow for greater supply chain coordination and collaboration at lower cost (Fawcett et al., 2011; Wang & Pettit, 2016). Electronic Marketplaces (EMs) became more prominent in the 1990 to 2000 period with "Open" EMs improving the procurement process between buyers and suppliers. "Closed" Electronic Logistics Marketplaces emerged in the early 2000s and were used to enhance strategic alignment (Bakos, 1991; Wang et al., 2007). Such systems allowed multiple participants to have uniform visibility in contrast to "shared collaborative systems" which provided access only to supply chain partners of the system owner. These developments incrementally improved the effectiveness of logistics organizations. The principal stages are detailed in Table 7.2. By the 2000s, systems were largely moving to Internet (web)-based platforms, which allowed for the development of cloud-based applications which are discussed in the next section.

3. Cloud-based systems

The expansion of web-based technologies predicated the development of on-demand "cloud computing" whereby computing power, data storage, and software applications are distributed over the Internet, avoiding the need for companies to purchase hardware and software as a direct investment. One of the key advantages of cloud-based systems is that they provide flexibility in terms of both operational strategy and cost, with enhanced security features available. They also allow a wider range of organizations to join a cloud, should they be required to do so in order to achieve closer integration (Armbrust et al., 2010; Winkelhaus & Grosse, 2020).

Cloud-based systems for logistics are now widespread (Prang & Barba, 2021; Smith & Grossman, 2021). Third-party organizations often host ICT systems providing both flexibility and affordability for many organizations that might not otherwise be achievable (Winkelhaus & Grosse, 2020). This has reduced entry barriers and extended accessibility across the spectrum of organizations involved in logistics and supply chain management. For smaller organizations, Cloud computing provides higher security levels and scalable flexibility, allowing them to develop new services and products more quickly. In the logistics and freight transport sectors, Technology Service Providers facilitate more effective lease and ownership models, while telematics and the use of Global Positioning Systems (GPS) for vehicle and trailer tracking is well established. Other benefits of cloud computing include reduced capital expenditure and lower labor and power costs (Leimbach et al., 2014).

In the wider consideration of Cloud computing, systems have been developed to facilitate both logistics and cross-border stakeholder integration. Port Community Systems such as Portbase (a ports of Rotterdam and Amsterdam twin-port initiative) have been developed to allow port users to cooperate more effectively (Portbase, 2021; Yip et al., 2016). Single Window Systems facilitate integration between the range of organizations involved in international trade, easing friction in terms of cross-border administration and customs procedures (Han, 2016). Hence, digitalization can be seen to have been incorporated strongly into logistics and supply chain management practices, and a new stage of development is now occurring. More recent developments in digitalization have the potential to fundamentally change practice. Some of these are now considered.

4. Emerging technologies

It is clear that a new wave of digital technologies are emerging and that these will have significant ramifications for logistics and supply chain management. The organizations that will be successful in this new era are those that, as in previous eras, will be able to best leverage these new technologies for competitive advantage, some of which are already being incorporated into globe-spanning systems. A number of technologies are likely to play a significant role over the next decade including Logistics Platforms, AI, the IoTs, DT, 5G, Big Data, and Advanced Analytics. These have all been predicted to play important roles through the 2020s and beyond (Clarke, 2020; Garay-Rondero et al., 2020; Hall & Pesenti, 2017; Nasiri et al., 2020). In order to future-proof supply chains it is clear that key players will have to integrate such technologies into supply chains and wider networks and systems.

TABLE 7.2 Principal stages in the development of logistics systems.

Era	System type	Key aspects	Key references
1960s	Materials requirement planning	Independent, function-based systems, important in manufacturing sector	Bonney (1994)
	Inventory management	Important in retail sector	Bonney (1994)
	Distribution resource planning	Important in distribution	Feigin et al. (2003)
	Electronic data interchange	Developed to rationalize business processes	Gosain et al. (2004)
1980s	Electronic data interchange	Electronic Data Interchange (EDI) use expanded, US manufacturing companies such as General Motors began to require their suppliers to use EDI	Gosain et al. (2004)
	Felixstowe Cargo Processing System (FCP80, FCPS)	UK-based cargo control system developed to improve the efficiency of import and export activities	MCP (2021)
1990s	Enterprise resource planning	Systems developed to integrate transaction processing and other functions	Turban et al. (2018)
	Decision support	Aided [sic] decision-making	Turban et al. (2018)
	Warehouse management	Facilitated improvements in stock management	Richards (2017)
	Transport management	Skylark and Roadrunner, developed by Road Tech	Beevor et al. (2016), Falcon Tracking (2021)
	Internet-based EDI	Internet-based EDI more practical but requirement for interface software made the less attractive	Huang et al. (2008), Wang and Pettit (2016)
	Automation of port cargo handling	More efficient cargo handling, lower costs	Chu et al. (2018), Beresford et al. (2004)
2000s	Web-based platforms, development of electronic marketplaces (EMs)	Easier coordination, lower cost, improved linkages	McLaren et al. (2002), Daniel et al. (2004)

4.1 Platform logistics

The growth of globalized manufacturing and distribution has created a new set of challenges that require logistics providers to coordinate across multiple actors rather than just between shippers and customers. Choudary et al. (2019) identified three factors leading to the development of logistics platforms, which go some way to addressing the increasing demands for both functionality and cost reduction: new IT infrastructure and technology, richer logistics data, and the continuous pressure to reduce costs. Although there are various logistics platforms in existence, two systems that have come to prominence are those based on blockchain/distributed ledger (DLT) and network platforms, which are based on cloud technologies.

The emergence of DLT has enabled actors in the supply chain to share data on a single platform with data visible to all parties. For example, the use of DLT in the Tradelens-Maersk platform, which was developed from 2018 by a collaboration between IBM and Maersk, now claims to publish more than two million events per day and includes more than 175 organizations (Tradelens, 2021). While DLT will clearly play a significant role in the future, it is covered in greater detail in other chapters in this book, and so not in this chapter (Ahmed & Rios, 2022).

Other cloud-based platform systems include, for example, Singapore's Transport Integrated Platform (TRIP), Alibaba's Cainiao data platform (Alibaba, 2021), UPS's Ware2Go platform (Ware2Go, 2021), and Project44 (Project 44, 2021). These platforms are designed to connect relevant stakeholders in the logistics cycle and provide seamless end-to-end tracking of goods. They provide a single shared view across the range of activities where there is the need to exchange information, coordinate the deployment of assets, and harmonize cargo movement. As more logistics partners join such systems, their value increases through network effects, enhancing end-to-end shipment speeds, and optimizing routing. These systems can "learn" about various aspects of the shipping cycle helping to mediate volatility, decentralize trade flows, and improve tracking and logistics coordination (Choudary et al., 2019). Such platforms offer a variety of solutions with the common themes of connecting companies, managing end-to-end logistics, providing cargo tracking and cargo routing but without any one company owning all the assets. They are designed to overcome the problems created by the use of manual processes and disparate systems that are often incompatible with commensurate communication problems (Williams, 2017).

As well as providing operational services for logistics, platform systems are also used to provide real-time information on prices to allow benchmarking data for parties involved in the process of shipping goods. Such platforms support logistics activities and play an important role in supporting informed decision-making. When competing for business, a logistics company moving goods globally will need to be aware of a range of variables in order to be able to set charges that are attractive for both the carrier and their clients. Variables include, for example, freight rates across all modes of transport, schedule reliability, market prices, and company performance characteristics. Thus, in order to stay competitive, market intelligence data are useful for benchmarking an organization against its competitors, and importantly in determining the rates they charge (Xeneta, 2021).

4.2 Artificial Intelligence

Substantial increases in computing power and increasingly sophisticated computer programming have led to the development of "intelligent" algorithms, which have moved computer technologies into performing tasks that could previously only be performed manually. Such developments mean machines have gained a level of human-like cognition that has become known as Artificial Intelligence or AI. AI and machine learning are becoming increasingly embedded in the commercial world and, if used properly, will impact collaboration, innovation, and communication with commensurate positive benefits for productivity. In terms of transport, logistics, and supply chain activities, the utilization of AI is becoming more prevalent and is increasingly being used in conjunction with Robotics and Autonomous Vehicles (AVs) (Bughin et al., 2017; Hall & Pesenti, 2017).

While robots are commonly used in warehouses to assemble pallet loads, their movement is not derived from the machine learning. Rather, they replicate human motion. AI-based robotic systems are, however, far more sophisticated and rely on the robot to learn the activity it is undertaking. AI is now being adopted to run warehouses, pick stock, and reorder stock automatically when inventories run low, and run unmanned stores. Such systems have become prevalent in the operations of retail organizations such as Ocado and Amazon, which use AI-powered robots. These have led to increasingly ambitious "click to ship" targets of around 15 min (Cooper, 2018).

AI also has many applications beyond warehouse automation, for example, in retailing, that are likely to impact supply chains and logistics in the future. As the ability of AI technologies are extended, so the ability to anticipate demand trends, optimize product assortment and pricing, personalize promotions, and automate in-store checkouts all become possible

(Mimoun & Poncin, 2015). In 2014, Amazon patented a predictive analytics tool known as "anticipatory shipping," which analyzes an individual's shopping history to predict what they will need in the future (Kopalle, 2014). Previous purchasing history data along with other information, such as items in baskets and wish lists, are used to predict the products customers will need and then ship them automatically once they have been ordered. Amazon can thus package and move products to their hubs before an order is made, significantly speeding up delivery times (Kopalle, 2014). Such predictive analytics are advantageous because this allows Amazon to use standard rather than expedited shipping to deliver such items to the relevant hub, meaning that those items are closer to the customer and therefore less expensive to deliver but with fast order fulfilment times (Nichols, 2018).

The completion of deliveries using drones has also been explored by organizations including Amazon, Google, and Alibaba. Over the last decade, in the United States, Amazon has developed self-flying electric drones, which can deliver packages weighing around 2—3 kg over a range of around 25 km. The drones use computer vision and machine learning to detect and avoid obstacles and people (Associated Press, 2019). In a similar vein, in China, in 2018, Alibaba started using drones to deliver food from restaurants in Shanghai over a 58 square kilometer area (Tang & Veelenturf, 2019). A recent example of the use of such technologies at the customer-facing end of supply chains has been in Amazon Go (launched in the United States in 2018) and Amazon Fresh (launched in the United Kingdom in 2021) till-less shops. Customers purchase goods using a smartphone application without the need to interface with a till, picking their goods, walking out of the shop, and being automatically billed. The system involves the use of cameras, depth-sensors, and software underpinned by AI technology to provide "frictionless" shopping (Kelion, 2021).

While much of the development of Autonomous Vehicle (AV) technology has been based around private vehicles, the gradual introduction of such technologies into the commercial world is likely to have a major impact on how transport systems operate in the future (Abduljabbar et al., 2019). One example of where AI is being adopted in the commercial arena is in the automation of road transport where the application of AI for truck platooning has been extensive (SMMT, 2020). This is an AI-based system whereby several autonomous trucks operate and communicate with each other to form organized, identically spaced convoys. While the lead truck has a driver, the following vehicles are programmed to automatically undertake the steering and braking required to maintain a specified distance from the vehicle in front. The AVs rely on AI software to control all aspects of maintaining a safe operating environment, adapting to conditions as they develop in real time. This level of automation requires AI to process the large, real-time, and continuous data collected by sensors on each vehicle, for example, spatial recognition, road conditions, environment, and location. This allows the trucks to operate closer together, reducing air drag friction and fuel consumption, and cutting costs, bringing significant commercial benefits (Eastwood, 2017; Janssen et al., 2015; SMMT, 2020).

4.3 Pervasive computing and Internet of Things

As computing power has increased, smart devices have become smaller and more connected. Widespread connectivity enables real-time visibility across supply chains allowing organizations to more effectively manage uncertainty and complexity in multimodal environments. A key enabler for such technological development is "pervasive computing," whereby everyday objects gain context awareness, becoming "smart," "knowing" where they are, what has happened to them, and what else is nearby (Bibri & Krogstie, 2017; Wang & Pettit, 2016). Broadly, these technologies all contribute to an increasingly common concept known as the IoT (Atzori et al., 2010), which is discussed in more detail in Baziyad et al. (2022).

The IoT integrates a range of technologies to allow remote monitoring management and control of devices that are empowered to "hear, see, listen, interpret, and communicate at the same time" (Nikitas et al., 2020, p. 11). Optimizing transport and logistics will be a key area to benefit from the IoT. With its potential to connect millions of devices and items, it potentially allows the tracking of goods with more accuracy, in a more efficient way and more securely, as well as improving decision-making with real-time analytics (Ericsson, 2021a). The IoT complements the use of Intelligent Transport Systems (ITS) that have developed over the last 2 decades based upon object-to-object communication (Nikitas et al., 2020). ITS provides the hardware component of the IoT, for example, Radio Frequency Identification (RFID) devices are widely used smart objects in supply chains (Landaluce et al., 2020). RFID tags and readers, sensor technologies, and positioning systems allow freight operators to track individual assets (containers, individual items) allowing continuous monitoring of a wide range of data including, for example, location, temperature, humidity, mechanical and operational conditions, and driver activity. Thus, the IoT has a range of applications in a supply chain context including inventory management and control, real-time routing, dynamic vehicle scheduling, trailer and container management, and shipment tracking (Manyika et al., 2015), all of which are important, especially for international and intercontinental shipments.

4.4 Digital twins

Although people and organizations currently interface with digital technologies via keyboards, touch screens, and voice commands, these may not be needed in the future. Instead, interaction will be facilitated by two-way communication enabled by the IoT. The IoT, simulation software, machine learning, and predictive analytics systems are now being used to facilitate what are known as Digital Twins (DT). Underpinned by the IoT, AI, and machine learning, the DT concept is effectively the third member of this group of disruptive technologies. DTs are exact digital representations or replicas of, for example, physical devices, or ecosystems of connected things and are becoming an accessible option for many organizations. They provide the ability to explore and stress test systems, potentially answering "what if" questions, and evaluating potential business scenarios (BIM+, 2020; Clarke, 2020).

Communication between real-world physical devices (physical twins) and their digital version aids in the development and analysis of evolving systems. DTs are valuable in both telecommunications and transport where asset life cycle management is critical to its correct functioning. Engineers can analyze how something performs, not just in the immediate physical environment, but over its life cycle. The improved performance of AI algorithms, the availability of data analytics platforms, and real-time data being shared with the DT, enhance the performance of both physical items and systems. This allows for complex associations, patterns, and other actionable insights to be generated before a physical device is built or deployed. Such an approach can support tactical and strategic development and several business domains are embracing this concept (BIM+, 2020).

DT systems are likely to be key facilitators of Industry 4.0 (Raj & Evangeline, 2020; Raj & Lin, 2020). With the expansion of cloud environments, DTs of complex supply chains and the connections between computer systems, vehicles, AVs, instruments, drones, robots, among others that make up the supply chain become possible. Specifically, in the logistics and supply chain environment DTs could be used to enhance the value chain, including managing container fleets, monitoring shipments, and designing logistics systems (Highland, 2019). While DTs do not yet exist for entire supply chains, and in the near future DTs are only likely to be used for specific activities, ultimately it can be envisaged that a DT for a complete supply chain would allow for more sophistication in development and testing before implementation.

4.4.1 Ocado and the digital twin concept

Ocado is the UK's longest established pure online retailers for grocery products. The business was established in 2000, and over the last 2 decades it has developed physical fulfilment infrastructure, cutting-edge technology, and automated processes to transform the online grocery space. The technology required was developed from scratch to a position today where the Ocado Smart Platform is claimed to be "the most advanced end-to-end eCommerce, fulfilment, and logistics platform" (Ocado, 2021). The success of the platform has meant that Ocado have been able to sell it to other retailers both in the United Kingdom and overseas (Evans, 2018; Kahn, 2020).

When Ocado was in its early business development stage, it established its first Customer Fulfilment Centre (CFC) in Hatfield in the UK. From around 2006, the Ocado software team began to build a simulation model of the CFC using a discrete event simulation framework to represent a single pick aisle broken down into its individual aspects including, for example, conveyor components, pick stations, and barcode readers. Digital simulations for each physical component were combined into a model of a complete aisle. The model was then combined with additional statistical timing models and calibrated against real-time operation. Over time the simulation was scaled up to represent the complete CFC but, while being reasonably realistic, it was recognized that random variations in activity could provide slightly different outcomes each time the model was run, essentially creating an envelope of potential outcomes (Clarke, 2020).

The simulation model allowed for the testing of various operational aspects of the CFC from control algorithms to possible conveyor topologies. However, a way to test production software before deployment in real-time led to the simulation evolving into a higher fidelity emulation of the hardware. Ultimately, this was linked to a "wireframe" visualization of the entire warehouse, which allowed for real-time data to be incorporated and complete visualization of the warehouse and the operational context at any chosen time (BIM+, 2020).

As Ocado's business grew the existing simulation software was used for the second CFC. However, by the time of the third and fourth CFCs, the simulation software had been developed to such an extent that it had effectively become a DT of the prospective CFCs, allowing for a thorough visualization of how they would perform. The pressure to respond to increasingly tight customer fulfilment times meant that complete automation of future warehouses was becoming a necessity. The concept that Ocado developed was a fully automated warehouse using swarms of robots to assemble customer orders. Using a "hive" system of storage, columns up to 21 bins deep a robot can move to any column as requested and working in conjunction with other robots, pick up a bin and move it to a pick station as needed. Data from all movements taking place in the CFC are linked to the simulation system to provide ever greater accuracy (BIM+, 2020).

Thus, Ocado's warehouse simulation can be seen as having ultimately evolved into a DT, allowing the company to explore how AVs, drones, robots, and infrastructure interact with each other. Further, as the simulation programs have developed, Ocado also now simulates the delivery van routes in order to develop new routing algorithms. As time progresses it is intended that the ultimate outcome will be an end-to-end simulation of the entire business—effectively a digital Ocado twin. In this way, Ocado have used advanced digital technology to develop the DT concept and support their online grocery business (BIM+, 2020; Clarke, 2020; Kahn, 2020).

4.5 Physical Internet and Industry 4.0

Two potential facilitators of AI in transport are the PI and Industry 4.0. The PI is a more recent concept that aims to improve efficiency in the key areas of economics, environment, sustainability, and society (Montreuil, 2011). It is intended to be an "open, global logistics system founded on physical, digital, and operational interconnectivity" (Nikitas et al., 2020, p. 11). Using this approach, distributed multimodal networks aggregate and optimize modular units known as π-containers from multiple origins for onward movement (Montreuil et al., 2012; Pan et al., 2017). As the concept is still in a relatively early stage of development, it is likely that if it gained industry traction, it would be based around a smart IoT system and support the wider development of Industry 4.0 (Crainic & Montreuil, 2016; Maslaric et al., 2016).

While the PI would require major restructuring and the development of new infrastructure, Industry 4.0 builds on existing technologies including, for example, Additive Manufacturing, Robotics, AI, AVs, Distributed Ledger (Blockchain), Drones, and IoT. Industry 4.0 leverages these technologies in terms of their connectivity and communication capabilities to transform manufacturing, service operations, and global supply chain management, using digitalization to the maximum extent (Tang & Veelenturf, 2019). Within this concept companies can create value by exploiting the incremental, but recently rapid, advances in technology, rather than developing an entirely new way of operating as would be required for the PI. In the context of Industry 4.0, the logistics and supply chain sectors have the opportunity to reengineer their approach to ensure that the correct product is delivered to the customer at the right time for the best price.

While existing companies can take steps to incorporate Industry 4.0 technologies into their business models, such organizations are often burdened with high operating costs, high inventory levels, and infrastructure that newer businesses are not. The manufacturing and services sectors are littered with examples of organizations which did not fully engage with the digital aspects of their business, leading to short-term operational problems, and in the worst cases business failure. High Street food, clothing, and consumer goods retail businesses exemplify this problem. These organizations developed their business when the best way to supply goods to the consumer was to sell them through a physical site, usually a shop on the high street, or through out-of-town retail sites. While this model worked well for many years, once digitalization entered the sector more agile start-up companies were quickly able to utilize these disruptive technologies to their advantage, unburdened by high fixed and overhead costs. Recent examples of retail business failures in the UK include the Arcadia Group companies and Debenhams where these organizations did not adopt ICT effectively. While not in itself the reason for their failure, their slower adoption of online ICT ultimately contributed to their decline and to the growth of more recent innovative start-ups including Asos and Boohoo (BBC, 2021a,b). Such online retailers can sell goods more cheaply as they are not tied to the high-street and have been able to develop new centralized warehouse-based systems, using robotic technologies with high turnover and much lower costs.

4.5.1 Amazon and cyber physical systems

The development of Industry 4.0 technologies has facilitated significant improvements in logistics and supply chain activity. One example of a company that has leveraged the use of cyber physical systems is Amazon, which has pioneered the use of AI based robotics. Their innovative logistics and inventory management systems use AI and machine learning to gain an advantage over their competitors. Early investment in such technologies provided them with the opportunity to personalize products and target specific segments of the market (Marketing Club, 2019).

Amazon warehouses contain thousands of shelves filled with tens of thousands of products. In 2013, Amazon purchased Kiva for $775 million in order to utilize its mobile warehouse robot technology (Kucera, 2012). The technology reverses standard warehouse procedures with the robots picking up a shelf of goods and bringing it to the picker, who stays in one place to assemble the order, eliminating the need for excessive movement. Kiva robots are contacted with the location information of a product the moment a shopper presses "checkout." The robots are programmed to travel in four directions to reach their destination. Once at the desired shelf, the robot lifts it and then moves the entire unit to the queue line where operatives pick the appropriate item. Once the pick is complete, the robot returns to the storage area and finds a new location for the shelf. It has been suggested that the "goods-to-picker" concept can lead to as much as 50% savings in warehouse picking labor costs (DHL, 2020).

While Amazon's logistics network already involves AI and robotics, end-to-end automation within its warehouses is likely to be several years away. Robots are proficient at specific, repeatable tasks for which they are precisely programmed. To perform multiple tasks, operating in dynamic environments requires a robot to understand its surroundings but these are still in the research phase. However, such robots are part of the deep learning revolution that has accelerated the progress of AI research over the last decade (Statt, 2019).

Amazon is also leveraging the use of AI in other areas, for example, the Amazon search engine and Amazon Alexa. The Amazon search engine presents customers with a choice of products, and AI combined with machine learning uses these data to predict the specific products a customer may be interested in. Supporting their online sales platform are a suite of devices that use the AI "assistant" Alexa. Alexa uses a voice recognition system to detect voice commands and provides the answers using an electronic voice. Alexa is not only linked to Amazon's e-commerce activities but also, for example, its Prime video and music services. Alexa is now commonly built into other company's products to assist in their operation, and potentially providing Amazon with further strategic capability and competitive advantage (Marketing Club, 2019; Tracy, 2016).

4.6 Big data and Business Analytics

The multitude of devices linked through wired and wireless networks and continuously interacting with each other generate huge volumes of "sensor data," which are too large for existing database software tools to process. In order to make sense of these "Big Data" datasets, advanced predictive analytics tools such as cognitive computing systems are required (Atzori et al., 2010; Zikopoulos et al., 2015). Such analytical tools provide organizations in the logistics and supply chain sector the potential to fundamentally change how forecasting, inventory management, transport management, and human resource management are conducted (Waller & Fawcett, 2013; Zicari et al., 2016).

Big Data Business Analytics (BDBA) can provide insights into market trends, customer behavior, as well as cost reduction strategies and more targeted business decisions (Gang et al., 2016). As far back as 2013, DHL were predicting that Big Data would become a disruptive trend in logistics, identifying that BDBA can provide competitive advantage because of five key properties: optimization; tangibility; synchronization; network optimization; and global coverage. Logistics and supply chain operations require data to run efficiently and BDBA can optimize and improve delivery times, resource utilization, and geographical coverage. Data generated from customer interaction from order to delivery combined with product feedback or demographic data can generate tangible insights into consumer behavior and product quality, while synchronizing logistics systems with production and distribution processes can reduce supply chain risk and provide resilience against potential disruptions. DHL also implemented a risk management tool called "Resilience360" underpinned by Big Data in order to reduce risk in the supply chain. The company utilize the data collected from their supply chain partners, combining it with risk assessment and analysis tools to identify potential interference in their respective supply chains (Automotive World, 2014; Witkowski, 2017).

As digitalization has increased, so the supply chain network and its associated logistics and facilities infrastructure has become an important data source allowing greater network optimization and insights into the flow of goods. While decentralization is a necessity for logistics services, analysis of the "global" data from a network creates valuable information on a wide range of aspects (DHL, 2013). Such capabilities provide the opportunity to improve performance, obtain value, and gain competitive advantage through better visibility, increased flexibility, and greater integration (Gang et al., 2016).

Big Data is likely to have a profound impact on the logistics sector, with the European Commission suggesting worldwide savings of $500 billion from time compression and fuel cost reductions, as well as associated reductions in CO_2 emissions of 380 megatons (EC, 2020). With freight transport activities projected to increase by 40% by 2030, a 10% improvement in logistics processes could lead to cost savings of €100 billion for the European Union (EU). However, the EU has recognized that Big Data solutions only form part of business processes in around 19% of companies and there is significant scope for innovation. The EU therefore instigated a project named "Transforming Transport" (TT) to demonstrate the potential impacts that the use of Big Data could have through reshaping transport and logistics processes and services, increasing operational efficiency, and improving customer experience (EC, 2020).

4.6.1 Big data in ports

In a ports context, data management is essential for achieving greater efficiency. The use of Big Data can provide a significant step toward meeting such aims. The vast amounts of data of different types (digital, text, audio, video, etc.)

collected from sensors, GPS, and other port management systems provide the "fuel" for other technologies discussed in this chapter (Prosertek, 2020). Big Data underpins AI systems, which ports are beginning to use to automate cargo handling and movement. One of the test scenarios for the TT project of the EU is focused on the Port of Valencia, with the objective of optimizing the port logistics chain using specific measures such as crane programming (Valencia Port, 2021).

A further project known as DataPorts, also funded by the EU, combines technologies including Big Data, blockchain, and IoT to provide a Data Platform for port stakeholder companies to manage data as an asset, in order to create value from those data, and provide AI and cognitive tools to the port community. In existing data environments individual actors create their own data silos and many potential benefits are lost. The objective of DataPorts is to create a secure data platform, which will allow the sharing of information across all actors in the port environment. Ultimately, it is intended that the platform would allow the monitoring of goods moving through the supply chain (DataPorts, 2020).

4.6.2 *Fifth-generation communication technology and smart logistics*

The use of fifth-generation (5G) communication technology offers the potential for significant improvements in cargo handling processes within the supply chain. As communication technology has advanced from using radio frequencies through WiFi to 4G, so the associated speed of communication has increased. 5G infrastructure is a technology enabler. With the ever-expanding range of 5G technology—enabled equipment and machinery, it will make it very much easier for objects to communicate with each other, potentially making the IoT a reality.

5G technology increases the bandwidth available, improves latency, and significantly increases the volume of devices that can be connected (Thales, 2021). Regarding bandwidth, while the average speed of 4G networks is around 10 mbps, 5G networks will increase this to around 50 mbps, representing a step-change in the capability of mobile networks to transfer large amounts of data quickly. Latency, or 'ping' time (the speed a signal travels from a device to the network and back), for 4G networks is around 50 ms, which is too slow to operate high speed equipment remotely. However, the average latency of 5G networks is around 10 ms, making it possible to remotely operate equipment effectively. Further, while 4G supports around 4000 devices per square kilometer, 5G increases the volume to around one million, making it possible to connect hundreds of thousands of sensors. These improvements in bandwidth, latency, and capacity make "smart logistics" a realistic possibility. While the autonomous and remote operation of devices and machines has been limited by these factors, as well as the fact that networking equipment at scale over a large area has been expensive, the removal of these constraints will allow a step change in operational capability (Chubb, 2021).

4.6.3 *5G and smart ports*

Smart Ports have been described as those that use "automation and innovative technologies including Artificial Intelligence (AI), big data, Internet of Things (IoT), and blockchain" to improve performance (Port Technology, 2021). The use of 5G is making "smart ports" a reality. Several examples exist of its use in the ports environment, including remote control of machinery and automatic monitoring of the port space.

In 2018, the port of Qingdao, one of the largest ports in the world based on cargo throughput, successfully trialed the operation of automated ship-to-shore container cranes over a 5G connection, remotely from a control center (Ericsson, 2021b; Statista, 2021). While the port has been operating a fully automated harbor since 2017, this trial sought to increase the level of innovation by using 5G. The system used data from more than 30 high-definition cameras and control data for a programmable logic controller. In order for the system to work successfully, millisecond-level latency control signals, and stable, remote and real-time control were required. The trial confirmed both the feasibility and potential of 5G applications for the development of "smart ports," which have greater flexibility and higher efficiency levels. One of the key findings of the trial was that up to 70% of labor costs could be saved when a port uses 5G automation compared to a more traditional fully automated terminal (Ericsson, 2021b). Furthermore, the Qianwan container terminal at the port improved operating productivity from 26 containers per crane per hour to over 35 using an AI system underpinned by Big Data (Prosertek, 2020).

At the port of Antwerp, automatic monitoring of the port space is being trialed in a project known as "The Digital Schelde" comprising a network of 600 cameras using computer vision and AI. The system makes possible the automatic monitoring of berths and traffic flows around the port area. Underpinned by 5G, connecting this extensive camera array and other sensors to a network without the need for additional communication infrastructure has become a realistic prospect (Chubb, 2021; Port Strategy, 2020).

In the United Kingdom, the Port of Felixstowe is testing 5G technology to allow both remote-controlled crane operations and predictive maintenance. A 5G-enabled sensor and CCTV network installed across the crane fleet will replace an existing fiber-optic cable-based system. The desired outcome is improvements in the performance of remote control yard cranes, enabling increases in efficiency and improvements in safety (UK5G, 2021). At the same time, an IoT sensor network will be installed to underpin predictive maintenance for the port's 31 quayside and 82 yard cranes. It is intended that the use of 5G, combined with AI and advanced machine learning, and predictive data analytics will enhance asset management and maintenance, thus reducing unscheduled downtime (Maritime Executive, 2021). With thousands of containers in one yard, communication between the control systems and individual sensors can become a problem. The ability of 5G networks to handle hundreds of thousands of devices in a small area facilitates these increasing capacity demands (Chubb, 2021).

5. Concluding observations and future prospects

The trend toward increased digitalization in logistics and supply chain management over the last 4 decades has seen a progression toward connected systems and networks, with modular design and on-demand use. In addition, changes in ICT during this period include increased capacity for distributed storage and processing of data; greater reach and range of information transmission; and faster speeds and larger volumes of information transmission (Merali et al., 2012; Thales, 2021). It is clear that rapid and fundamental change is taking place in the sector that addresses the inefficiencies of existing systems that underutilize transport capacity and are confronted by delays and congestion. The developments in ICT, and digitalization in particular, outlined in this chapter will go some way to addressing the shortfalls in the existing systems. There are significant competitive and sustainability advantages to be gained as these new concepts are leveraged and exploited more widely.

The technologies discussed above will transform transport, logistics, and supply chain management in the coming decades and bring a number of benefits including higher service speeds, greater reliability, lower operating costs, and improved efficiency. However, while these opportunities exist, it is apparent that many organizations have not yet developed their ICT capabilities to meet the challenges ahead. There are significant adoption hurdles to be overcome, and questions remain as to how best to configure relationships and strategies to allow organizations to best respond to increasingly demanding customer requirements.

Rapid adaptation to changes in competitive commercial environments is a recognized issue and fundamental to the success or otherwise of many businesses. Thus, the sharing of data between logistics companies and shippers, combined with advances in ICT to ensure information flows are integrated between logistics partners and supply chains members, will provide the best conditions for organizations to remain competitive. It is important for logistics and supply chain organizations to first understand the strategic value of ICT for the management of their supply chains and logistics networks, and then to assess what the impact on business performance could be. Therefore, organizations utilizing ICT will need to develop sophisticated systems that enhance business performance and create value. Digital capabilities will need to be fit for the information processing needs of the key stakeholders involved.

Currently a wide range of ICT systems coexist and interact with each other, with varying degrees of interconnectivity and interdependence. This creates a level of complexity which introduces fresh uncertainty and unpredictability into the logistics and supply chain system, thus raising the stakes, and sharpening the edge between success and failure. Collaboration, transparency, and standardization remain key stumbling blocks. Fragmented software systems and varying standards, lack of interoperability between systems, and the time and cost of development and deployment are all issues which need to be addressed (Raj & Lin, 2020). However, technology is evolving rapidly and while not all emerging technologies will succeed, some will disrupt the status quo. ICT will continue to penetrate new areas, increasing automation and transforming the way businesses and their logistics systems operate.

The rate of advancement in IT capabilities in a range of logistics activities over the past few decades, as discussed in this chapter, points toward a series of grand challenges in the years ahead. Among these are several in the area of personal liberty and freedom. For example, will individuals, organizations, or machines be the ultimate arbiters of which technologies could or would be adopted in particular fields?, and which will be most appropriate for logistics solutions? A parallel challenge is the corporate capabilities of IT-based production, trade, and transport versus the emergence of ultra-large companies, which increasingly dominate the landscape. As networks, both actual and virtual, become ever more complex and connected, the stakes rise inexorably such that the cost of failure of such networks could become intolerable or even unimaginable. Companies growing ever larger may have the unforeseen consequence of disproportionately larger risk being attached to failure. This suggests that developing legal protocols, which themselves may be in danger of becoming exceptionally complicated, could be almost as important as developing a robust system for the future itself. Especially important will likely be the construction of ultra-robust warning systems and feedback loops to alert users as well as administrators that the performance of a given system is below required levels and perhaps even below permissible levels. Areas such as scenario building, e.g., in the development of DT for logistics systems, within the control and operations systems in order to cover extreme "what-if" consequences are likely to emerge as key issues for many logistics applications, not least those discussed in this chapter. Finally, the possibility of greater state control versus corporate power is likely to be a growing issue, particularly as companies based in market economies seek to expand into regions where business models contrast significantly, in some cases dramatically, with theirs. This could make the development of stable and reliable logistics systems increasingly difficult. Achieving a balance between competing ideologies and contrasting cultures will be a balancing act that global logistics companies will have to engage with and confront.

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Chapter 8

Blockchain technologies in the digital supply chain

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Abstract
The application of blockchain or, more generally, distributed ledger technology in logistics and supply chain management has created a huge amount of interest among academics and practitioners. Blockchain's inherent characteristics include immutable data, seamless information flows, and shared access to data. Also, the potential to deploy smart contracts (program code executed automatically) with blockchain has raised high hopes for improving the effectiveness, efficiency, and sustainability of supply chains. In this chapter, we clarify the meaning of terms used in the blockchain ecosystem and present the results from an extensive literature review from which we summarize current findings. We highlight the principal drivers influencing blockchain adoption—traceability, trust and transparency, supply chain integration, data security, privacy, and sustainability. We note technical, organizational, and regulatory barriers that may inhibit adoption of blockchain in supply chain applications, including scalability, investment costs versus perceived benefits, data sharing and interoperability challenges, and lack of standards or regulations. Although blockchain adoption is still in its early stages, an increasing number of applications are being reported. We identify reported supply chain applications classified by industry sector. This chapter equips scholars and practitioners with an understanding of how blockchain can provide value in contemporary supply chains.

Keywords: Blockchain adoption barriers; Blockchain adoption drivers; Blockchain technology; Distributed ledger technology; Literature review; Supply chain management.

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1. Introduction

Blockchain technology is predicted to disrupt a wide range of industrial and business sectors in the next decade (Clohessy et al., 2020). Previous research has indicated how blockchain can potentially impact modern supply chains in various ways. Queiroz et al. (2020) point out that blockchain-induced disintermediation has a huge disruptive potential and note that the integration with supply chain management (SCM) is still in its infancy. From a theoretical perspective, Treiblmaier (2018) shows how existing theories (i.e., principal agent theory, transaction cost theory, resource-based view, network theory) can be used to investigate blockchain-induced changes in the supply chain. In their investigation on how blockchain in combination with the Internet of Things (IoT) can potentially impact SCM, Rejeb et al. (2019) find various synergies of these technologies, such as the positive impact of blockchain on the scalability, security, and interoperability of IoT solutions. When it comes to the importance of blockchain for supply chain collaboration, Rejeb et al. (2021) identify three main success factors; namely, the streamlining of information sharing processes, support of decision and reward models, and strengthening of communicative relationships with supply chain partners.

However, there also exist numerous challenges when it comes to blockchain adoption in supply chains. Among those, Ghode et al. (2021) identify the necessity of developing inter-organizational trust, obeying governance rules, providing tamperproof data, improving coordination and information sharing among network partners, and training participants. Furthermore, it has to be pointed out that practical implementations have already illustrated that blockchain-based networks might lead to problems, such as power struggles within networks (Allison, 2018).

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In light of the diversity of previous findings and the numerous drivers of, as well as barriers to blockchain adoption that have been previously identified in the literature, in this chapter we strive to summarize and critically appraise existing research as well as highlight the current state of the art when it comes to the adoption and application of blockchain technologies in the supply chain. More specifically, we outline the functionality of blockchain, review and update previous research, present a framework of drivers and barriers of blockchain adoption, and enrich theoretical academic results with current examples from the industry.

2. Functionality of blockchain

Blockchain technology gained widespread public popularity as the technology that enabled the cryptocurrency Bitcoin. More precisely, however, blockchain is a combination of technologies, many of which are still under development. It combines previous solutions that pertain to linked timestamping and verifiable logs, proof of work, Byzantine Fault Tolerance, public keys as identities, and smart contracts (Narayanan & Clark, 2017). According to Treiblmaier (2018, p. 547), blockchain can be defined as "a digital, decentralised, and distributed ledger in which transactions are logged and added in chronological order with the goal of creating permanent and tamperproof records." Frequently, the term distributed ledger technology (DLT) is used to also include protocols that do not record data in a chain-like structure, but use a directed acyclic graph, such as IOTA or Hedera Hashgraph (Treiblmaier, 2019a).

Fig. 8.1 shows a simplified blockchain structure that is characteristic of Bitcoin. Several transactions are combined in a block, and then a hash function is calculated for each of them. This hash value is a number of fixed length that can be used to easily check the integrity of data (i.e., if the data have been changed, the hash value also changes). All the individual hashes are combined into a single hash (i.e., the Merkle root), which is then stored in the block header. Even a minor modification of the data will yield a completely different hash value, which makes it easy to immediately spot modifications of the underlying data. Besides the Merkle root, the block header includes information, such as a timestamp and a so-called nonce ("number only used once"), which is an arbitrary number that blockchain miners are searching for when they are trying to solve a cryptographic puzzle. Miners are highly specialized computers that validate transactions, put them in a block, and then add them to the blockchain network. In order to find a nonce that leads to a valid solution (in the case of Bitcoin, this is a hash value that starts with a specified number of zeros), the miners try out numerous nonces, and the first one that finds a valid solution is allowed to add a new block to the existing chain. In return, the miner receives some newly minted Bitcoin and transaction fees. This mechanism ensures that the ability to add new blocks only depends on computing power and is not granted by any central authority. Another important characteristic of a blockchain is the inclusion of the hash from a previous block into the header of the subsequent one. This creates a data structure that cannot be changed without corrupting the integrity of the chain of blocks following the modification. Further information on how a blockchain works and its characteristics can be found in Kravchenko et al. (2018), Morkunas et al. (2019), and Treiblmaier (2019a).

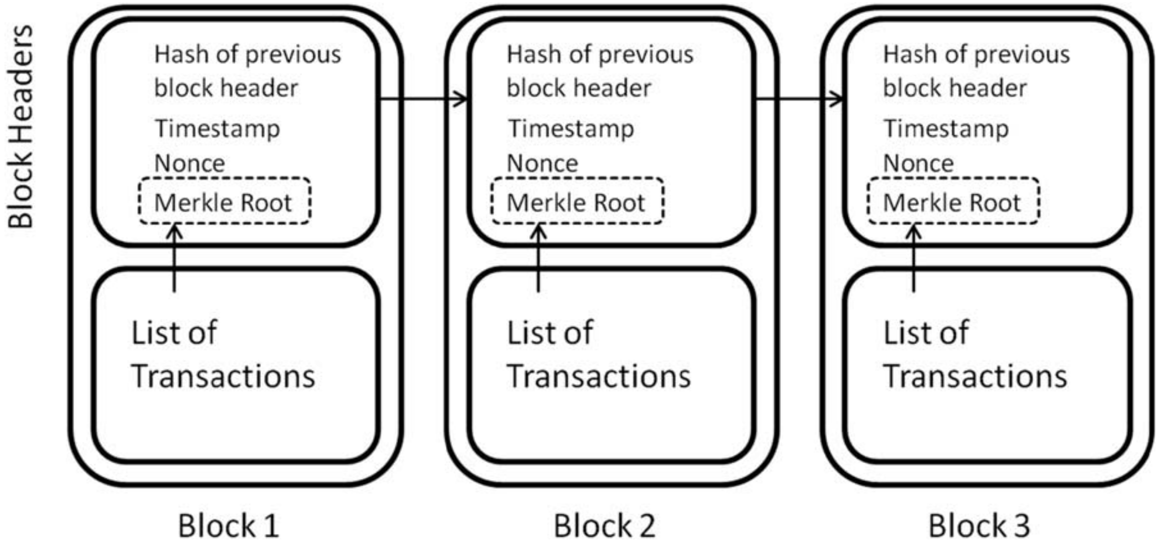

FIGURE 8.1 Simplified Bitcoin structure as an example for a public blockchain (Treiblmaier, 2020).

Various protocols exist that differ according to the respective rights of the participants. The first criterion to differentiate between the protocols is the ability to operate validator nodes that store a copy of the blockchain and confirm the correctness (i.e., validity) of the transactions. Permissionless blockchains make this possible for anyone, whereas permissioned blockchains restrict access to this role. The second criterion pertains to the ability to submit and view transactions. Public blockchains allow anyone to do so, while private ones require specific access keys (Lacity, 2020). Hybrid solutions exist that combine features of both private and public solutions to achieve a balance between openness and controlled access.

The main idea behind blockchain/DLT is to create a digital ledger of records, the veracity of which is based on the consensus of the network participants. The ledger can be easily shared among participants and provides a high level of trust due to its immutability, which is achieved by the chaining of blocks as outlined above. It has to be noted, however, that none of the existing blockchain/DLT protocols provides a perfect solution for all industry problems. For example, tradeoffs still exist between consistency, availability, and partition tolerance (i.e., the capability of a distributed system to keep working in spite of the occurrence of communication breakdowns), also known as the CAP theorem (Kannengieβer et al., 2020). Therefore, the immutability of a blockchain depends on the collective behavior and consensus of a group of validators. In private blockchains, which are the most prevalent type in most supply chain applications, this group might be relatively small and consist of actors that know each other.

It has to be noted that some features of blockchain might create new problems for organizations. For example, in order to account for the need to edit or delete data in order to be GDPR-compliant (General Data Protection Regulation), mutable blockchain solutions have been suggested (Politou et al., 2019), which contradict the original idea of blockchain immutability. Notwithstanding these limitations and potentially also the introduction of new vulnerabilities through additional cyber attack vectors (Katrenko & Sotnichek, 2020), blockchains offer a higher level of immutability, transparency, decentralization, and distributed trust in comparison to centralized databases (Treiblmaier, 2019a). Additionally, they enable programmability, which refers to the deployment of computer code that establishes rules that are executed automatically in case predefined conditions occur. This code is frequently referred to as a *smart contract* even though it is not a contract in a legal sense, and the resolution of sophisticated disputes cannot be fully automated. In any case, the development and deployment of such program code requires novel approaches in the design and engineering of blockchain-based business solutions (Sillaber et al., 2020).

3. Blockchain in the academic supply chain literature

In recent years, blockchain has gained increasing popularity in the supply chain literature. Consequently, scholars have conducted numerous review studies to provide an overview of the various research issues related to blockchain applications in SCM. For example, Queiroz et al. (2019) performed a systematic literature review to identify, analyze, and classify the literature surrounding the integration of blockchain in SCM. The authors concluded that the implementation of blockchain in SCM is still in its infancy, except for the electric power industry, which has exhibited a relatively mature understanding of blockchain's potential for SCM. Wang et al. (2018) investigated blockchain-related literature for academics and practitioners and found that the value of the technology lies in its ability to improve visibility through shared data access, traceability, supply chain digitalization, and disintermediation as well as data security and the deployment of smart contracts. Gurtu and Johny (2019) highlighted the growing applicability of the technology to several industries and its tremendous potential to eliminate intermediaries and increase supply chain efficiencies. Similarly, Cole et al. (2019) provided an explanation and analysis of blockchain to identify its implications for the field of operations and SCM. Their findings illustrate that the properties of blockchain can enhance product safety and security, improve quality management, combat illegal counterfeiting, and increase supply chain sustainability. In the context of the food industry, Feng et al. (2020) carried out a review of blockchain technology characteristics, and functionalities, and identified blockchain-based solutions for overcoming food traceability concerns and ensuring sustainability through enhanced information. In this chapter, we build on previous findings and update the current progress of blockchain research in SCM, which is a rapidly growing field. Additionally, we provide a link to reported industry applications.

3.1 Methodology

In order to identify the key areas of current blockchain research in logistics and SCM, we conducted a systematic literature review following the guidelines of Kitchenham and Charters (2007). The respective steps include planning, conducting, and reporting the review outcomes. In the following analysis, we explain the process of literature search and selection. The search was done in the title, abstracts, and keywords using the Scopus database. It was conducted in February 2021 using the following search query: Blockchain* AND ("supply chain*" OR logistic*). Scopus is recognized for its inclusivity and comprehensive coverage of a wide variety of scientific databases, such as Emerald Insight, Science Direct, Springer Link, IEEE Xplore, and Wiley Online Library (Roy et al., 2018). Studies with missing bibliometric data (e.g., abstract) were removed, and then the results were filtered using the inclusion and exclusion criteria listed in Table 8.1.

Fig. 8.2 illustrates the selection process. A total of 1545 publications resulted from the initial database search. After applying the suitability criteria, 226 publications were first read at a metadata level (title and abstract) and later in full in order to obtain more detailed insights. This process yielded 177 studies for the final review and analysis, which discuss the applications of blockchain in logistics and SCM from various angles. The data from each article were retrieved and classified into three categories:

TABLE 8.1 Selection criteria.

Inclusion criteria
• Articles must be written in English • Articles published in Q1 and Q2 journals based on the SJR ranking (SCImago Journal Ranking) • The subject areas of the selected articles have to be related to business with a special focus on supply chain management and production operations • Articles must present relevant discussions on the integration of blockchain in logistics and SCM
Exclusion criteria
• To ensure the high quality and academic nature of the retrieved studies, non−peer-reviewed literature as well as conference papers were not included (Ramos-Rodríguez & Ruíz-Navarro, 2004) • Articles exclusively focusing on financial applications of blockchain (e.g., Bitcoin and cryptocurrencies) were excluded • Articles with a purely technical focus were excluded

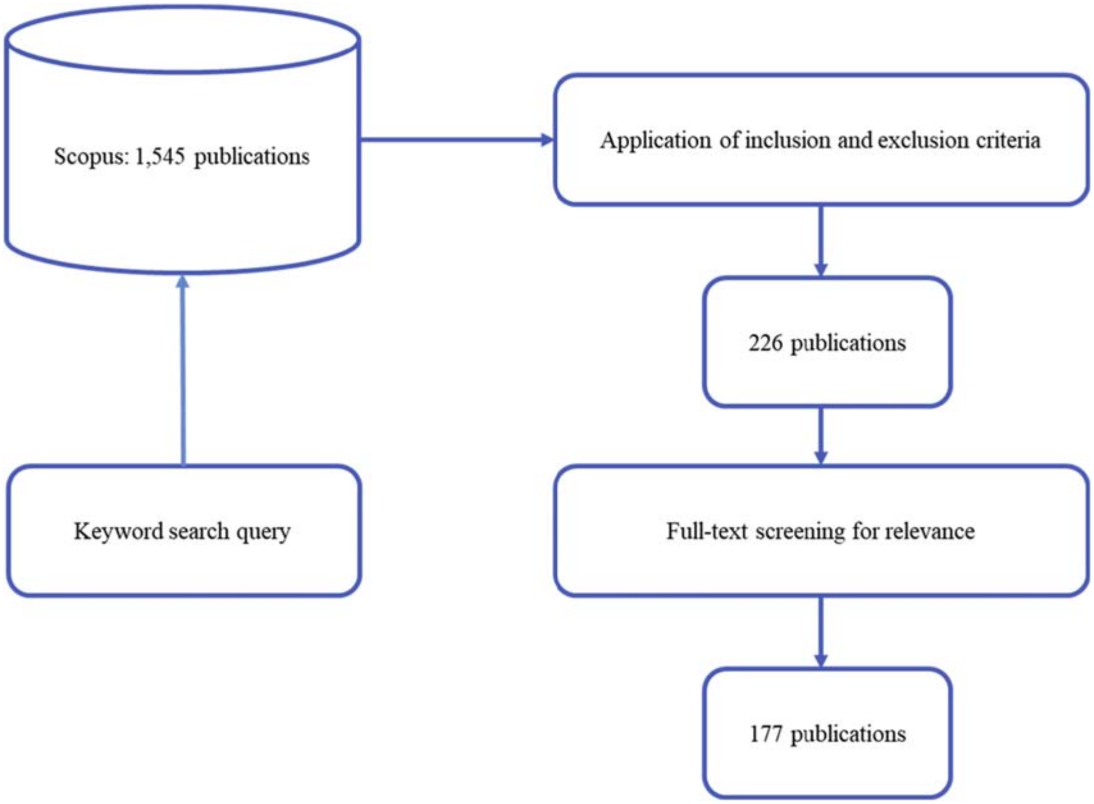

FIGURE 8.2 Literature selection process.

(1) Context data: The industrial context in which blockchain is discussed.
(2) Quantitative data: Descriptive analysis that includes the evolution of blockchain research and the main keywords used.
(3) Qualitative analysis: In-depth analysis using an inductive coding approach to identify important and common themes without being encumbered by predefined categories.

The temporal distribution of the publications is shown in Fig. 8.3, which illustrates a considerable increase in the number of articles published between 2017 and 2020 and shows how the idea of integrating blockchains in logistics, SCM, and related business enterprise applications has gained increasing attention within a relatively short timespan.

We conducted a keyword analysis across the 177 selected articles. Table 8.2 presents the frequency of author-supplied keywords used in the literature. "Blockchain," "supply chain," and "supply chain management" are the most frequent keywords in all articles. "Smart contracts," "DLT," and "Industry 4.0" are also frequently mentioned, all of which refer to concepts that are closely related to blockchain or the context of its application. Keywords used frequently in blockchain-related studies

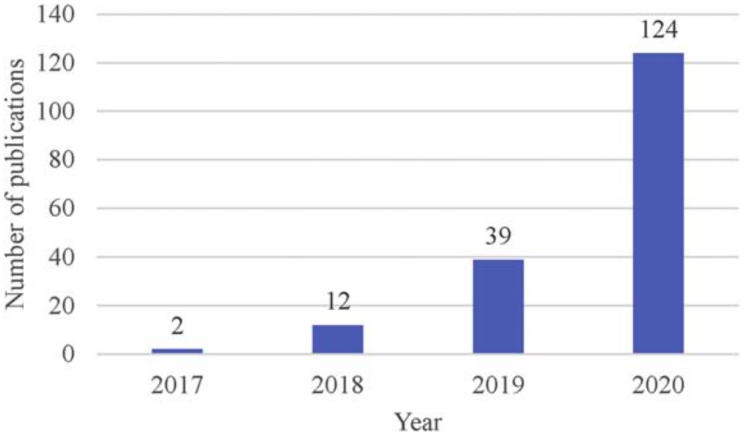

FIGURE 8.3 Number of journal articles published over time.

TABLE 8.2 Top 15 most frequent keywords.

Keyword	Occurrence
Blockchain	150
Supply Chain	49
Supply Chain Management	38
Smart Contracts	18
DLT	13
Industry 4.0	13
Sustainability	12
IoT	10
Logistics	10
Technology	10
Traceability	10
Transparency	9
Food Supply Chain	6
Trust	6
Big Data	5
Information Transparency	5

also include "sustainability," "IoT," "traceability," and "transparency." Further details related to these keywords and their relationships with blockchain are discussed in the following sections.

Each selected article was read in full and coded to identify the main themes discussed in the literature. During this process, the articles were categorized according to three main categories that were derived inductively: (1) adoption drivers of blockchain; (2) adoption barriers hampering the integration of the technology in logistics and SCM; and (3) examples of current industrial applications of blockchain. As can be seen in Fig. 8.4, the main drivers of blockchain adoption in logistics and SCM identified in the literature are *traceability, trust and transparency, supply chain integration, data security and privacy,* and *sustainability.* The hurdles to its adoption can be clustered into *technical, organizational,* and *regulatory barriers.* In the following sections, we first elaborate on these drivers and the barriers, followed by a selection of blockchain application cases.

3.2 Drivers of blockchain adoption in logistics and SCM

Traceability. Supply chain (SC) traceability is defined as the "ability to track a product batch and its history through the whole, or part, of a production chain […] through transport, storage, processing, distributing, and sales" (Moe, 1998, p.12). Traceability is a critical issue for supply chain partners, and it is challenging to ensure due to the enormous amount of information and high level of precision that it necessitates. Consequently, Jansen-Vullers et al. (2003) argue that traceability is an entrenched information issue that is still unsolved and that existing solutions are neither sufficiently effective nor efficient. It is a key differentiator in several industries (Martinez et al., 2019), and blockchain presents an opportunity to improve end-to-end traceability (Dutta et al., 2020) and bring about substantial operational efficiencies in this process. Organizations can benefit from the tamperproof nature of transactions recorded on blockchain and shared access to data to ensure real-time traceability, accountability, and increased performance (Fosso Wamba et al., 2020).

For example, Bumblauskas et al. (2020) posit that blockchain technology can be a promising solution in the production and supply of food products since it enables tracking products from farm to fork. According to the authors, the combination of the technology with the IoT facilitates the creation of a more traceable and transparent food chain, thereby supporting customer purchase decisions and satisfaction. In a similar vein, Prashar et al. (2020) proposed a blockchain-based solution that helps to assure food safety based on blockchain's ability to eliminate the need for intermediaries, simplify information

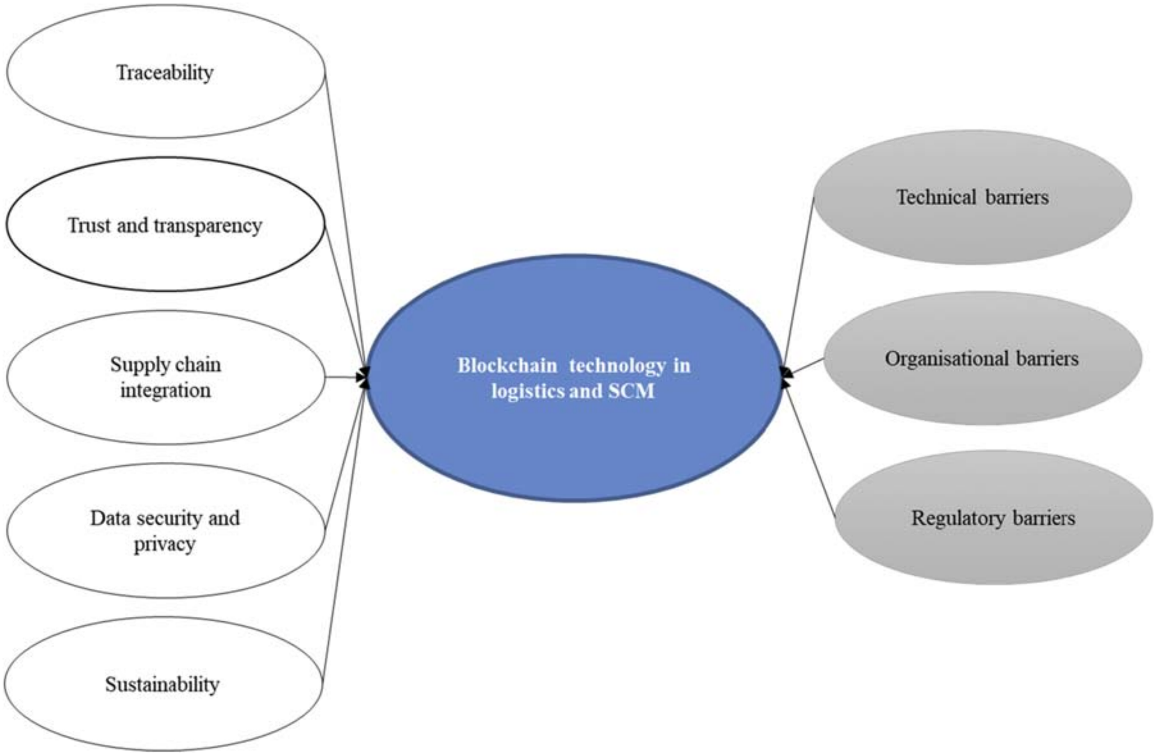

FIGURE 8.4 Blockchain adoption drivers and barriers.

sharing, optimize performance, and ensure compliance with a stringent level of safety and integrity. Moreover, blockchain can provide reliable and trustworthy data for product traceability in supply chains as diverse as foods, vaccines, diamonds, fashion, and services. This traceability information can support organizations to control the origin of their raw materials, their quality, and all information related to organizations and people involved in supply chain processes.

Trust and transparency. Trust and transparency are crucial factors for organizations to develop effective relationships and support logistics and SCM activities. As per Ireland and Webb (2007), trust is an important predictor of positive performance within inter-organizational relationships. Transparency is crucial for organizations because a supply chain network with higher information visibility is able to respond faster to market requirements, which in turn will result in increased turnover (Liere et al., 2006). Despite their importance, trust and transparency are hard to attain. Even though organizations may have systems in place to identify and evaluate potential risks, the overall effectiveness of risk management policies is determined by the quality and quantity of information obtained from exchange partners. To improve trust and transparency in the supply chain, blockchain constitutes a workable solution that may help to create trust through the open and transparent nature of its transactions as well as the immutability of its data (Qian & Papadonikolaki, 2020).

Decentralization, immutability, and disintermediation enabled by blockchain have shown demonstrable benefits in supply chain trust and transparency. In this regard, Cole et al. (2019) assert that data encryption and coding significantly enhance trust, transparency, and efficiency in supply chain sharing processes. Similarly, Tomlinson et al. (2020, pp. 1−31) point out that blockchain drives more trustworthy modes of governance due to its ability to self-adjudicate independently of a central authority and to provide customers with direct insight into how their goods and services have been produced. Blockchain thus eliminates the need for a single trusted authority that controls the validation and storage of transactions in the supply chain. Instead, its distributed consensus paves the way for the development of an environment protected by cryptography (Pournader et al., 2019). Furthermore, the adoption of blockchain leads to increased real-time transparency, which can achieve substantial cost savings (Ko et al., 2018), accelerate transaction time, and reduce fraud risks (Kayikci et al., 2020, pp. 1−21). Consequently, blockchain technology creates motivation for more trust and transparency in logistics and SCM and can serve as the basis of more trusting relationships among organizations and further collaboration (Rejeb et al., 2021).

Supply chain integration. The integration of supply chains is a critical strategic topic for enhancing business performance in competitive environments (Narasimhan & Das, 1999). Integration routinely involves several exchange partners, and it links primary business functions and processes within and across organizations. Maintaining effective information and supply chain integration is also a challenging issue due to conflicting interests. From a resource-based perspective, supply chain integration is recognized as a firm capability, which comprises a set of skills and incremental knowledge operationalized through business processes that aids organizations to coordinate activities and exploit their assets for numerous purposes (Lai, 2004).

Practical supply chain integration can be facilitated through the use of blockchain. According to Wang, Chen et al. (2020), the technology is appealing for firms that strive to work collaboratively with others, improve supply chain integration, and simultaneously enhance environmental performance. A key advantage of blockchain in this regard is its ability to achieve the integration of informational, financial, and physical flows among organizations, resulting in a better matching of demand and supply in the supply chain, more efficient processes, and higher customer satisfaction (Nandi et al., 2020; Treiblmaier, 2019b). More specifically, the creation of blockchain-based collaborative platforms promises significant benefits to all supply chain stakeholders, such as higher logistics efficiencies, streamlined business processes, optimal resource utilization, and better coordination of information (Papathanasiou et al., 2020). The positive outcomes of blockchain use in supply chain integration also include more effective financial operations, reduced working capital requirements (Sheel & Nath, 2019), and process automation (Wang et al., 2018). In short, it is postulated that blockchain contributes to the development of long-term strategic processes and relationships among organizations, thereby increasing the overall performance of the supply chain.

Data security and privacy. Data security and privacy policies can have a substantial impact on the security of supply chain systems and the effectiveness of business operations. Information security is an important issue for organizations and thus has garnered significant attention among scholars from various fields (Kim et al., 2011). Blockchain technologies are predicted to be able to resolve major data security concerns associated with supply chain information systems, including cyber-physical systems and the IoT. Nandi et al. (2020) argue that the chaining of transactions with their predecessors guarantees data integrity and facilitates the traceability of events. The increased data security stems from the basic features of blockchain, including immutability, decentralization, and its distributed nature. As such, blockchain can help to prevent data leakages and preserve confidentiality based on cryptographic protocols that ensure the protection of supply chain data and the mitigation of unauthorized changes (Bullón Pérez et al., 2020). By reducing the likelihood of security breaches and privacy violations, organizations will be able to better protect themselves against the disruption of information flows and the subsequent disturbance of product flows. Therefore, blockchain may help strengthen data security and to overcome cybersecurity attacks that threaten the information infrastructure of the supply chain without compromising the privacy of the involved stakeholders (Kamble et al., 2019).

Sustainability. In recent years, significant attention has been paid to supply chain sustainability by academic scholars, practitioners, and organizations (Saberi et al., 2019; Seuring & Müller, 2008). Supply chain sustainability necessitates a managerial attitude that places a high emphasis on the development of sustainable product designs and processes. The management of economic, social, and environmental performance and impact and the need to create effective governance practices throughout the product/service lifecycle are crucial objectives of organizations. In order to improve supply chain sustainability, organizations can use blockchain to support their competitive supply chain sustainability efforts and improve their supply chains with respect to the three foundational dimensions of sustainability (i.e., economic, social, and environmental) (Treiblmaier, 2019b). From the economic perspective, blockchain enables organizations to reduce supply chain costs (e.g., by streamlining processes), optimize operational efficiencies, and increase their performance within multi-echelon supply chains (Dutta et al., 2020). By means of its transparency, traceability, and disintermediation capabilities as well as the application of smart contracts, blockchain can substitute traditional transaction platforms (De Giovanni, 2020) and usher in the development of more market-oriented governance structures for customer—supplier transactions (Schmidt & Wagner, 2019). As a result, blockchain can play a key role in fostering economic sustainability, increasing organizations' profitability, supporting internal and external organizational processes, and strengthening resilience and competitive advantage.

From a social perspective, blockchain can help to improve welfare and supply chain profit by improving data quality (Choi & Luo, 2019), track potential social conditions that might pose health and safety issues, and facilitate collaboration among supply chain partners (Rejeb et al., 2021; Saberi et al., 2019). The positive social impacts of blockchain can manifest in the reduction of unethical business practices, including child labor, inhumane working conditions, extortion, protection of human rights, and the fight against social inequality and poverty (Kononets et al., 2022; Varriale et al., 2020).

Besides improving their corporate social responsibility, organizations can also make use of blockchain to better communicate the environmental quality of their products to the customer and improve supplier selection based on accurate green performance values (Kouhizadeh & Sarkis, 2018). Likewise, blockchain can increase environmental sustainability by reducing the rework and recall of products through enhanced information sharing, resulting in a decrease in resource use and greenhouse gas emissions (Saberi et al., 2019). As a result, organizations will be able to better balance their sustainability goals and face the increasing calls for holistically sustainable supply chains. To advance future research, Table 8.3 lists the previously discussed drivers of blockchain adoption and several related research gaps.

3.3 Barriers to blockchain adoption in supply chains

Technical barriers. Despite the manifold potential of blockchain for supply chains, several challenges still hamper its industry-wide implementation. For instance, blockchain has several technical problems that have yet to be addressed (Wong et al., 2020). These include scalability, security, and privacy issues. According to Choi et al. (2020), blockchain has been extensively criticized for its limited scalability, namely, the speed of transactions and the block size. Even though scalability issues mainly arise with public blockchains, organizations may also face this issue with permissioned blockchains. Behnke and Janssen (2019) argue that the implementation of blockchains may also be hampered by uncertainties, such as a lack of government involvement or resistance by a supply chain partner.

Moreover, blockchains can be subject to security attacks, such as botnets, illegal transactions (Kumar et al., 2020), or 51% attacks wherein a set of users gain control over the network's computing power and the ledger (Esmaeilian et al., 2020). These information security issues can impact the digital trust mechanisms of blockchain. Although blockchain transparency may be mostly beneficial for organizations, prior research also shows that this can create privacy issues (Fosso Wamba et al., 2020). As a result, sensitive and highly confidential business data are at risk of being stolen or infringed upon. To overcome the current limitations of blockchain, more scalable solutions are needed, as are efficient solutions that are compatible and tailored to specific supply chain settings. Furthermore, the financial losses associated with compromising blockchain security have to be quantifiable so that organizations can optimize the security of their blockchain-based supply chains, thereby minimizing the likelihood of system failure and privacy violations.

Organizational barriers. Since the implementation of blockchain in the supply chain is still in an early stage, numerous organizations are reluctant to integrate the technology in their own business processes (Bai & Sarkis, 2020). Bavassano et al. (2020) posit that organizations will face several uncertainties related to the costly investment in new and alternative technical solutions as is the case with blockchain. For risk-averse managers, blockchain may not deliver its perceived benefits in terms of profitability and usefulness. Blockchain is not a standalone solution and, according to

TABLE 8.3 Research gaps for future studies.

Potential drivers of blockchain adoption	Research gaps	Supporting literature
Traceability	The impact of blockchain-based traceability systems on supply chain performance The use of blockchain in the traceability of recipe-based food products The factors or variables determining the performance of blockchain-based traceability systems	dos Santos et al. (2019), Dutta et al. (2020), Kayikci et al. (2020, pp. 1–21)
Trust and transparency	The impact of blockchain-enabled trust and transparency on cooperation and collaboration within supply chains The rules and policies needed for information transparency in collaborative supply chain models The role of trust and transparency to reduce supply chain risks in the blockchain era	Ivanov et al. (2019), Rejeb et al. (2021), Saberi et al. (2019)
Supply chain integration	The influence of blockchain adoption on supply chain integration and performance The internal and external risks enabling or restraining supply chain integration in the blockchain context The need for an appropriate methodological framework to facilitate the use of blockchain for supply chain integration	Karamchandani et al. (2020), Wang, Wang et al. (2020)
Data security and privacy	The intersection of blockchain and information security risk management The relationship between blockchain and information security and privacy as well as e-supply chain performance Potential threats to information security and privacy in the blockchain era	Nandi et al. (2020), Pournader et al. (2019)
Sustainability	The impact of blockchain on the social and environmental performance of supply chains The impact of blockchain-enabled supply chain sustainability on supply chain resilience The incorporation of sustainability practices in blockchain-based supply chains	Dubey et al. (2020), Ivanov et al. (2019), Saberi et al. (2019), Treiblmaier (2019b)
Potential barriers of blockchain adoption	**Research gaps**	**Supporting literature**
Technical barriers	The impact of limited technical capabilities of blockchain (e.g., low scalability) on firms' resistance to blockchain adoption The integration of blockchain with other technologies (e.g., cloud computing, artificial intelligence (AI)) to improve network security and scalability The development of effective solutions for the "garbage-in-garbage-out" problem and improved security	Choi et al. (2020), Dutta et al. (2020), Fosso Wamba et al. (2020), Tang and Veelenturf (2019), Yadav et al. (2020)

Continued

TABLE 8.3 Research gaps for future studies.—cont'd

Potential barriers of blockchain adoption	Research gaps	Supporting literature
Organizational barriers	The organizational resources and capabilities necessary for blockchain adoption The impact of organizational designs and processes on blockchain-based supply chain performance The economic feasibility of blockchain technology	Caldarelli et al. (2020), George et al. (2019), Treiblmaier (2018)
Regulatory barriers	The impact of regulatory support on blockchain adoption The implications of regulations, industry standards, and guidelines on the design and implementation of blockchain security measures and policies The role of blockchain in supporting regulatory compliance	George et al. (2019), Wong et al. 2020)

Choi et al. (2020), implementing it alone is not practical. The authors argue that the technology requires the involvement of all related parties, the willingness to share information, and the development of good relationships. As such, blockchain needs to be interoperable in order to ensure efficiency and alignment among supply chain exchange partners.

At the organizational level, managers have to raise staff awareness regarding blockchain through the provision of workshops and training, which are necessary to upskill the employees and facilitate the smooth integration of blockchain (Choi et al., 2020). In this regard, future research needs to investigate the organizational mechanisms, practices, and processes that are prerequisites for blockchain adoption (Clohessy et al., 2020). Additionally, the enabling role of organizational culture has been mostly overlooked so far when explaining the adoption of blockchain (Treiblmaier et al., 2020). Thus, a further research direction is to ground future works on the theoretical conceptualizations of culture to clarify the values and beliefs necessary for the adoption of blockchain and how the technology can assist organizations in promoting creativity, employee satisfaction, and shaping managerial beliefs.

Regulatory barriers. Although blockchain has rapidly evolved since its inception, regulatory support for its integration in supply chain lags behind (Paliwal et al., 2020). According to Sahebi et al. (2020), regulatory uncertainty constitutes one of the important barriers to blockchain adoption. Apart from the technical configuration, the lack of regulatory measures can hamper the effective integration of blockchain in supply chains, thereby affecting both an organization’s perceived technology readiness and facilitating conditions (Wong et al., 2020). Hastig and Sodhi (2020) argue that in default of responsible institutions and a supportive regulatory framework, organizations will be left with opaque monitoring systems and thus struggle to sustain their supply chain operations. Therefore, the lack of regulations can result in several unwanted complications and outcomes (Dutta et al., 2020). Without a supporting regulatory system, there is also a certain risk that powerful supply chain actors may make use of their financial and technological capabilities to threaten smaller market participants, serve their own interests, and create entry barriers for future competitors (Hooper & Holtbrügge, 2020). Further research is also needed to examine the impact of regulations on interorganizational practices and firm performance in the blockchain era. Regulatory measures need to be identified that can tackle potential irregularities or disruptions when operating with blockchain technology. The lower-half of Table 8.3 summarizes the three types of barriers and related research gaps.

4. Industrial applications of blockchain

In addition to the drivers and barriers of blockchain adoption discussed above, we also strived to identify those industries that were explicitly mentioned in the studies. Most academic articles, however, are at a generic SCM level, which can be attributed to the fact that wide-scale blockchain implementation has yet to be realized. The most common practical application is within the food industry, which is mentioned in 24 articles (e.g., dos Santos et al., 2019; Kayikci et al., 2020, pp. 1−21). Several driving forces for blockchain adoption in this industry exist, including mounting traceability requirements, rapid quality degradation, and product perishability as well as the need to enhance productivity due to the low margins in the food industry as compared to other industries (Kittipanya-ngam & Tan, 2019). Several benefits can emanate from the implementation of blockchains, such as increased traceability and food safety as well as efficient data capture, management, and control.

A total of 15 papers discuss blockchain in the context of transportation, where its potential includes the increased traceability of the goods in transit, reduced paperwork (Batta et al., 2020), and the provision of a mechanism to verify the accountability of partners (Peronja et al., 2020). Nine papers focus on blockchain in manufacturing, where common use cases include the management of supplier contracts, the improvement of payment efficiency through smart contracts, and the solution for issues associated with security and intellectual property protection in an additive manufacturing marketplace (Chang et al., 2020). The apparel, humanitarian, and trade industries are discussed in five articles, respectively. Industries mentioned in four or fewer papers include services (e.g., tourism, entertainment, food service), luxury, construction, and healthcare. Even though these industries have experienced a significant rise in information and communication systems adoption, they still lag behind in terms of concrete blockchain implementation. Table 8.4 summarizes the opportunities of blockchain in each industry from a logistics and supply chain perspective, identifies current research gaps, and lists the relevant literature for interested readers.

Table 8.5 shows practical examples of prominent blockchain projects across different sectors that are related to logistics and SCM. It has to be noted, however, that blockchain adoption is still in its early stages and many firms and consortia have just started to explore its full potential. The use of blockchain technology for product traceability across the supply chain has been the main driver for numerous current blockchain applications (Kshetri, 2018). Leading companies such as Carrefour (2021) and Walmart (Hyperledger, 2019) in the food industry, the Lenzing Group in the textile industry (Lenzing, 2019), and Volvo (2019) in the automotive industry, have already experimented with blockchain to track

TABLE 8.4 Applications of blockchain across industries and pending research gaps.

Industry	Blockchain use case	Research gaps	Supporting literature
Food	Facilitate food traceability Increase food safety Improve management and transparency of food chains	Role of blockchain in faith-based food consumption Blockchain and food chain collaboration Consumer perception of food quality in a blockchain setting	dos Santos et al. (2019), Kayikci et al. (2020)
Transportation	Streamline transportation processes Ensure efficient logistical tasks Foster transportation sustainability	The role of blockchain to redefine transportation systems (design, planning, and operations) The cost performance of blockchain-based transportation systems	Peronja et al. (2020), Yang (2019)
Manufacturing	Assure manufacturing sustainability Ensure agile manufacturing practices Support automated workflows	The ability of blockchain to reduce manufacturing costs Blockchain as an enabler for agile manufacturing Barriers of blockchain adoption in manufacturing	Gunasekaran et al. (2019), Ko et al. (2018), Tozanli et al. (2020)
Apparel	Improve product information disclosure Enhance forecast accuracy Increase transparency and traceability	The impact of blockchain on the performance of apparel firms Blockchain and circular fashion supply chains The impact of blockchain on fashion consumption	Chan et al. (2020), Choi and Luo (2019), Guo et al. (2019)
Humanitarian	Facilitate donations and collaboration Support the building of swift trust	The role of blockchain in disaster prevention The impact of blockchain on emergency response Key issues related to integrating blockchain	Dubey et al. (2020), Ozdemir et al. (2020)
Trade	Optimize cross-border trade Replace costly financial services	The impact of blockchain on global trade policies Blockchain-based trade and sustainable development	Chang et al. (2020); Kimani et al. (2020)
Service	Strengthen service security Enhance service performance Improve customer performance	The impact of blockchain on customer satisfaction Blockchain and service automation The combination of blockchain and AI in service business models	Dutta et al. (2014), Karamchandani et al. (2020)
Luxury	Improve the authentication and certification of luxury products Enhance corporate social responsibility Combat counterfeiting of luxury products	The impact of blockchain and consumer spending on luxury products Blockchain and customers' purchase intention of luxury products The role of blockchain in branding and marketing	Chan et al. (2020), Choi (2019), Rejeb et al. (2020)
Construction	Support trust in the construction sector Increase transactional efficiency Promote the concepts of lifecycle asset management and circular economy	The cost of developing blockchain solutions The integrative use of blockchain with IoT, AI, and big data analytics The uncertainties and ambiguities of blockchain adoption	Qian and Papadonikolaki (2020), Wang, Chen et al. (2020)
Healthcare	Enhance healthcare supply chain and drug records Strengthen the security and privacy of patient data Facilitate the traceability of medical products	The impact of blockchain on healthcare data management and legal compliance The incorporation of blockchain in cross-institutional and cross-national healthcare contexts The integration of blockchain with medical AI, IoT, and drones	Dutta et al. (2020), Kshetri (2018)

TABLE 8.5 Blockchain projects.

Blockchain case	Industry	Description	Application area
Carrefour (2021)	Food and Beverages	Carrefour uses blockchain to store information about products' origins and production. The first product to trace in 2019 was chicken from Auvergne Filière Qualité Carrefour (FQC).	Product traceability
Walmart (Hyperledger, 2019)	Food and Beverages	Walmart uses blockchain to track products across their supply chain (e.g., traceability of pork in China to ensure its authenticity and of mangoes in the United States to ensure their provenance).	Product traceability
Lenzing (2019)	Textile Industry	Lenzing uses blockchain for its sustainable TENCEL fiber traceability downstream their supply chains up to brand retailers and final consumers.	Product traceability
Volvo (2019)	Automotive	Volvo uses blockchain for cobalt traceability across the supply chain to ensure ethical sourcing.	Product traceability
Block Aero (2019)	Aerospace	Block Aero develops a blockchain-based aircraft asset data management platform to improve engine overhaul times.	Aircraft asset data management
Modum (Rohr, 2019)	Pharmaceutical	In their pilot project, Modum, SAP, and Swiss Post use blockchain and IoT to monitor medicine temperature during transportation.	Product temperature monitoring
Maersk and IBM (TradeLens, 2021)	International Shipping and Logistics	TradeLens uses blockchain to ensure the security, privacy, immutability, and traceability of shipping documents. More than 17 million documents have been published through the platform.	Shipping documents management
Port of Rotterdam (2019)	International Shipping and Logistics	Several blockchain projects aim improve the efficiency of ports logistics. DELIVER, for example, uses blockchain to manage and track orders, shipments, and financial transactions.	Shipment tracking and data management
Arianee (2021)	Luxury	The Arianee project aims to enable the digital certification of luxury goods. Blockchain is used to securely and immutably store the digital identity of valuable assets.	Storage of the digital identity of valuable assets
Alibaba (BaaS) (Alibaba Cloud, 2021)	Retail	Alibaba provides blockchain solutions as a service. It enables the traceability of products across the supply chain and the integration of supply chain transactions to facilitate supply chain finance.	Product traceability Integration of transactions across the supply chain
SITA MRO Blockchain Alliance (2020)	Aerospace	The MRO Blockchain Alliance launched by SITA is an aerospace alliance that aims at developing blockchain solutions for aircraft parts traceability and maintenance data management.	Aircraft parts traceability Recording the history of aircraft maintenance

products across their supply chain with the goal of ensuring authenticity, provenance, and sustainability. In the pharmaceutical industry, a consortium consisting of SAP, Modum, and Swiss Post has used blockchain to monitor and track the temperature of medicines during transportation to ensure their quality and safety (Rohr, 2019). Other industry-wide blockchain consortia, including MediLedger and PharmaLedger, are currently experimenting with the technology for drug traceability.

Blockchain has the capability to transform business processes (Viriyasitavat & Hoonsopon, 2019), which is evident in the shipping industry that strives to overcome its longstanding inefficiencies, especially when the handling and processing of shipping documents is concerned. The two industry giants, Maersk and IBM, have developed TradeLens, an industry-wide platform powered by blockchain. TradeLens aims to provide end-to-end visibility of shipping processes and to enable the secure sharing and traceability of trade documents among permissioned parties (TradeLens, 2021). The Port of Rotterdam has been a pioneer in using blockchain to improve its ports logistics, resulting in a collaboration with BlockLab to develop DELIVER, a blockchain solution to manage and track shipments. In 2019, DELIVER was successfully deployed to process and track two containers from South Korea to Tilburg in the Netherlands via the Port of Rotterdam in a paperless and near real-time manner (Port of Rotterdam, 2019). In the aerospace industry, there is a growing interest in using blockchain in aircraft parts tracking and asset data management. The recently formed maintenance, repair, and overhaul (MRO) blockchain alliance aims at developing blockchain solutions and standards for the tracking and recording of aircraft parts, including parts manufacturing and MRO processes (SITA, 2020). The aerospace start-up Block Aero has developed an aircraft asset management platform powered by blockchain technology and is currently collaborating with Etihad Airways (Block Aero, 2019).

The immutability of blockchain makes it a potentially valuable technology for data protection. To protect luxury goods, the Arianee project combines blockchain with product identification technologies (e.g., RFID, NFC) to securely store the digital identity of valuable assets, ensure their authenticity, and fight the counterfeiting of branded products (Arianee, 2021). Moreover, Alibaba, the Chinese multinational technology company, developed a blockchain-as-a-service (BaaS) platform that provides solutions for product provenance, facilitating supply chain finance and data assets protection (Alibaba Cloud, 2021).

5. Conclusion and further research

Blockchain technology is predicted to revolutionize logistics and SCM and to create modern value networks that are characterized by immutable data, seamless information flows, and shared access to data. In this chapter, we briefly outline the main constituents of blockchain technologies and point out that these components are under constant development. Blockchain implementations in the supply chain will differ widely according to their respective characteristics and access models. There is no single blockchain technology and it has to be emphasized that it is not a silver bullet that solves all existing problems in logistics and SCM. Instead, it is another technical building block that is contributing to the increasing digitalization of supply chains, which also includes numerous other technologies, all of which are affected by many (inter) organizational and environmental factors.

Our literature review distils the findings from 177 academic articles published between 2017 and 2020 and yields the most important drivers and barriers that are currently discussed in academia. The former include traceability, trust and transparency, supply chain integration, data security, and privacy as well as sustainability, the latter of which can be clustered into technical, organizational, and regulatory barriers. Furthermore, we identify those industries that currently discuss blockchain the most, namely, the food, transportation, and manufacturing industries. Finally, we provide several practical examples of blockchain solutions for logistics and SCM that are currently being deployed or in development across various industries.

To inspire further research, we list numerous research gaps that pertain to the drivers and barriers of blockchain adoption in the supply chain across various sectors of the industry. Those gaps not only present challenges for academics but also pose major obstacles that the industry needs to overcome in order to improve their operations and strategic positioning. Given the steady increase in academic research and the proliferation of numerous industry projects, it is foreseeable that blockchain will play an important role in future value chains that span industry networks on a global scale. This chapter summarizes the state of the art of blockchain research and industry implementations, and we hope that it will help researchers and practitioners to identify best practices as well as areas that need further attention.

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Part III

Managing the Digital Supply Chain

Chapter 9

Digital architectures: frameworks for supply chain data and information governance

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Abstract

Advances in digitalization present new and emerging Supply Chain (SC) Information Architectures that rely on data and information as vital resources. While the importance of data and information in SCs has long been understood, there is a dearth of research or understanding about the effective governance, control, or management of data ecosystems at the SC level. This chapter examines data architectures through a navigation of the background of database management and data quality research of previous decades. The chapter unfolds the critical architectural elements around data and information sharing in the SC regarding the context, systems, and infrastructure. A review of various frameworks and conceptual models is presented on data and information in SCs, as well as access control policies. The critical importance of data quality and the management of data in the cyber-physical systems are highlighted. Policies for data sharing agreements (DSAs) and access control are discussed and the importance of effective governance in the distributed environments of digitally enabled SCs is emphasized. We extend the concept of data sharing agreements to capture the interplay between the various SC stakeholders around data use. Research gaps and needs relevant to new and emerging SC data and information ecosystems are highlighted.

Keywords: Data access control; Data flows; Data quality; Data sharing; Information architecture; Information flows; Supply chain.

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1. Introduction

Within the last decade, supply chain (SC) environments have evolved rapidly with the advent of cloud infrastructure and IoT, and developments in distributed systems and databases. Also, cyber-physical systems have emerged in production environments, and a wide variety of disruptive technologies are transforming factories, warehouses, logistics, and transport systems. A primary characteristic of these new SC landscapes is the use of data. Hence, the information architecture of these emergent, data-driven, and digitally enabled SCs needs to be explored, analyzed, and understood in order to identify the challenges and define the way data flows should be handled in data-driven SC environments. The governance, control, and management of data at the SC level is in its infancy. We discuss many of the challenges and the critical areas that arise in the SC data ecosystem, as well as the various data attributes and aspects associated with these issues.

The Information Architecture concept is a challenging one to define precisely (Rosenfeld et al., 2015). In general terms, Information Architecture is '*an emerging discipline and community of practice focused on bringing principles of design and architecture to the digital landscape*' (Rosenfeld et al., 2015, p. 24). In a business context, the focus is mostly on data as a resource utilized in organizations providing multiple advantages and capabilities for value creation and innovation for both customers and suppliers and also many other relevant stakeholders (Mikalef et al., 2019). Data extraction, generation, collection, and exploitation strategies can speed up and create value for the SC and the associated stakeholders. What is

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new in the SC environment is the digitally enabled capabilities introduced by the fourth industrial revolution. A radical change has emerged in the field of information sharing practices across SCs and the associated information and data architectures. The change lies because of the scope—data are shared across organizational boundaries not only in single in-house database environments. However, this gives rise to many challenges, ranging from data quality issues to the governance and management of data access and data sharing.

Motivated by the above manifestations of the fourth industrial revolution in the SC environment and the extensive use of data and information around the SC, we examine three main issues. This chapter responds to the following questions about the new forms of SC and the corresponding data and information sharing contexts:

1. Are there any information architectures available that can support data as a resource in SC environments and help to frame the ways data are shared among the various SC parties?
2. What are the various aspects we should consider in order to analyze the use of data and the management of data flows in the new digitally enabled and digitally supported SC environments?
3. What are the challenges in data management and data sharing for the SC context, and how can we address them?

This chapter initially defines data as a resource drawing on the pertinent literature on data and information management, while identifying the relevant data quality frameworks and information architecture designs. We then emphasize the information architectures for digitally enabled SCs and the vital structural elements to define them. Finally, this chapter discusses and analyses Data Sharing Agreements (DSAs), a model for data sharing practices among the various stakeholders. The subsequent sections describe the data attributes and data sharing aspects and the relevant actors and their relationships in the SC data sharing context.

2. Data as a resource—the need for data quality

Data and information are potential sources of competitive advantage in the SC world, exploited through Analytics for knowledge creation (Wang et al., 2016). While the transformation of SC from highly physical to cyber-physical systems requires knowledge and insights from data in decision-making, the challenging aspect is to realize value for relevant stakeholders including customers and suppliers (Sharma et al., 2014). Previous research has shown that customer value can be achieved through feedback and communication in various processes of the SC and from tailored offerings due to the use of data exploited through digital platforms (Giannakis et al., 2019, 2020). Value can be created through the knowledge derived from data and cross-boundary industry collaborations, forming data-driven and digitally enabled SCs in diverse and innovative ways (Karafili et al., 2018a).

The acquired knowledge created through information strategy transformation (Gandomi & Haider, 2015) can reshape fundamentally traditional SC operational models. There are various emerging new operational models, including omnichannel fulfilment that is transforming traditional retailing and digitalization of services in industries such as entertainment and leisure. Transformation of SC operational models and strategies focuses on the scope, scale, and speed of value creation (Bharadwaj et al., 2013), as well as innovative work patterns designed across boundaries of time, distance, and function, with new collaborative approaches (Spanaki et al., 2018). The collaboration of various stakeholders in a networked approach presents opportunities for innovative SC operational models that focus on the extraction of data as a resource.

Firms are investing in Analytics and data-driven innovation to optimize their processes and enhance their overall performance rates (Wang et al., 2016). Analytics practices have expanded the existing SC information exploitation schemes unprecedentedly, presenting new opportunities for companies to access meaningful and valuable information across the SC (Fosso Wamba & Akter, 2019; Kache & Seuring, 2017; Wang et al., 2016). However, SC data management gives rise to major challenges in terms of the frameworks used for data collection, data exploitation, and value creation from data (Jonsson & Myrelid, 2016; Kache & Seuring, 2017). We discuss the data management literature in the context of data and information being a resource for decision-making in SC strategy and operations.

Three paradigms are evident in the literature that considers data and information as a resource for competitive advantage: (a) the data manufacturing analogy, (b) the information quality path, and (c) information ecology (see Table 9.1). All three frameworks are interrelated. The frameworks were developed to explain how information could be extracted to generate applicable knowledge for a firm utilizing the full potential of the available data.

2.1 Data and information management frameworks

The concept of data as a resource was initially introduced using the analogy between product manufacturing and data manufacturing processes (Brodie, 1980), which highlighted data quality challenges in transforming data into valid

TABLE 9.1 Data and information management frameworks and elements.

Data management framework	Key elements
Data manufacturing analogy	Manufacturing process (input—process—output)
Information quality path	Information quality attributes (trustworthiness, accuracy, timeliness, completeness, consistency, current-ness, accessibility, intrinsic, contextual, representation)
Information ecology	Information architecture (content, context, users)

information and knowledge (Arnold, 1992). More generally, data management frameworks serve as a template for the data characteristics and attributes that can define the path to better data quality. The path to better data quality was a major concern in many studies in the 1990s (Ballou et al., 1998; Huh et al., 1990; Wang, 1998), and later studies, including March and Hevner (2007) and Madnick and Zhu (2006). Frameworks addressing the data quality problem sought to track the data manufacturing process and the steps in knowledge creation and data/information exploitation from in-house databases (Ballou et al., 1998; Ronen & Spiegler, 1991; Wang, 1998; Wang, Reddy, & Kon, 1995). The data manufacturing framework of *input—process—output* was developed based on the analogy with manufacturing processes (Wang, Storey, & Firth, 1995) and attempted to define, measure, analyze, ensure, and enhance data quality and hence to control the trustworthiness and reliability of the data used in decision-making. The data manufacturing analogy presented data as a resource/product similar to materials/products that flow through the manufacturing process and can be made available to consumers (data consumers in this instance).

The framework presenting the information quality path provides suggestions on how to build "better" database systems with a strong focus on assessment models of information quality (Ballou et al., 1998; Brodie, 1980; Huh et al., 1990). Data of poor quality used through the data production process will remain poor until the data are actively cleaned up or removed (Ballou et al., 1998). Applying criteria relevant to timelines, accuracy, and cost assessment of information quality was highlighted as a major data management problem (Ballou et al., 1998). The foundations for contemporary data quality, however, came from the positioning of the "data quality" problem in terms of Total Data Quality Management (TDQM). The initial view of Data Quality Attributes is presented in Table 9.2, including four major attributes to ensure the quality of the data used by the data consumers (Ballou et al., 1998; Wang, 1998; Wang & Strong, 1996)—accessibility, interpretability, relevance, and accuracy. The original view for data quality was extended in the framework of Wang and Strong (1996) and Strong et al. (1997), as depicted in Table 9.3, which presents a categorization of data quality. Four categories of data quality are highlighted in Table 9.3, where the seminal work of Strong et al. (1997) and Wang and Strong (1996) is summarized:

(a) intrinsic (data have quality in their own right—accuracy is merely one of the four dimensions underlying this category)
(b) contextual (the requirement that data quality must be considered within the context of the task at hand—data must be relevant, timely, complete, and appropriate in terms of the amount so as to add value)
(c) representational (the system must present data in such a way that they are interpretable, easy to understand, and represented concisely and consistently)
(d) accessibility (the databases and systems must be accessible and secure).

TABLE 9.2 Preliminary conceptual frameworks on data attributes.

Data attribute	Explanation
Accessibility	The data can be easily retrieved
Interpretability	The meanings enclosed in the data can be understood
Relevance	The data are relevant and timely for use in the decision-making process
Accuracy	The data are correct, objective, and come from reputable/reliable sources

From Ballou, D., Wang, R., Pazer, H., & Tayi, G. K. (1998). Modeling information manufacturing systems to determine information product quality. *Management Science*, *44*, 462—484; Wang, R. Y. (1998). A product perspective on total data quality management. *Communications of the ACM*, *41*, 58—65; Wang, R. Y., & Strong, D. M. (1996). Beyond accuracy: What data quality means to data consumers. *Journal of Management Information Systems*, *12*, 5—33.

TABLE 9.3 Data and information quality categories and dimensions.

Data quality category	Data quality dimensions
Intrinsic	Accuracy, objectivity, believability, reputation
Contextual	Relevancy, value-added, timeliness, completeness, amount of data
Representational	Interpretability, ease of understanding, concise representation, consistent representation
Accessibility	Accessibility, access security

From Strong, D. M., Lee, Y. W., & Wang, R. Y. (1997). Data quality in context. *Communications of the ACM, 40*, 103−110; Wang, R. Y., & Strong, D. M. (1996). Beyond accuracy: What data quality means to data consumers. *Journal of Management Information Systems, 12*, 5−33.

Wang (1998) proposed a methodology for TDQM where the key elements of data are identified in order to define the "quality" dimensions (Pipino et al., 2002; Wang & Strong, 1996). Data quality dimensions are applied in attribute-based models to serve as quality indicator identifications (Wang, Reddy, & Kon, 1995). Other applications of the dimensions are in the categorization of the data from a "data consumer" perspective as intrinsic, contextual, representational, accessible (Wang & Strong, 1996), or in the context of organizational processes (Pipino et al., 2002; Strong et al., 1997) or even as benchmarks and assessment metrics (Kahn et al., 2002; Lee et al., 2002; Pipino et al., 2002).

2.2 Data and information landscapes and information ecologies

The dimensions of data quality were extended in discussions about the "data consumer" (the users of the data) in the "information age" (Redman & Blanton, 1997), the challenges associated with poor data quality, and the operational, strategic, and tactical impacts in organizations (Redman, 1998). The impact of data quality in organizations was further explored through a data and information quality landscape (see Table 9.4), providing a framework for categorization of topics (Madnick et al., 2009), data semantics (Madnick & Zhu, 2006), and new uses of information (Zhu & Madnick, 2009). The seminal work of Madnick et al. (2009) classifies topics for future studies on data quality and also the various research methods that can be used to research data quality in organizations ranging from action research though to theory and formal methods. The impacts of poor data quality affect various organizational levels (Madnick et al., 2009): they appear as impacts in the functionality of various systems, economic/financial impact, impact in project management failure or success, or even through changes in processes, strategy, or policies.

The characteristics and attributes of data need to be defined in order to evaluate or assess data quality and also the context around the data is important in order to define the access control approaches for the data. To understand the context,

TABLE 9.4 Data and information quality landscape.

Categorization of topics	
1. Data quality impact **1.1** Application area (e.g., CRM, KM, SCM, ERP) **1.2** Performance, cost/benefit, operations **1.3** IT management **1.4** Organisational change, processes **1.5** Strategy, policy	**2.** Database-related technical solutions for data quality **2.1** Data integration, data warehouse **2.2** Enterprise architecture, conceptual modeling **2.3** Entity resolution, record linkage, corporate householding **2.4** Monitoring, cleansing **2.5** Lineage, provenance, source tagging **2.6** Uncertainty (e.g., imprecise, fuzzy data)
3. Data quality in the context of computer science and IT **3.1** Measurement, assessment **3.2** Information systems **3.3** Networks **3.4** Privacy **3.5** Protocols, standards **3.6** Security	**4.** Data quality in curation **4.1** Curation—standards and policies **4.2** Curation—technical solutions

From Madnick, S. E., Wang, R. Y., Lee, Y. W., & Zhu, H. (2009). Overview and framework for data and information quality research. *Journal of Data and Information Quality (JDIQ), 1*, 2.

the environmental factors around data should be identified so that appropriate access controls can be applied. In order to capture the wider context around the data, a new concept has emerged—the *information ecology*. The initial idea and the framing of *information ecologies* were presented by Davenport and Prusak (1997) as a holistic view of the information environment (endogenous and exogenous), distinguishing "data," "information," and "knowledge" as distinct aspects. An information ecology may be defined as *a system of people, practices, values, and technologies in a particular local environment* (Nardi & O'Day, 1999). Information ecologies illustrate the architecture around data and information in terms of users, content, and context and the complex dependencies in many information environments (Rosenfeld et al., 2015).

The data management literature related to SCs and SC processes has a major focus on SC Analytics (Karafili et al., 2018a). Analytics may be applied at strategic, tactical, and operational levels (Wang et al., 2016) to inform decision-making and enhance SC performance. SC Analytics topics usually explore strategic decisions around the management of SC (Dutta & Bose, 2015; Sanders, 2016), or at an operational level to enhance efficiency and effectiveness of the SC through informed data-oriented approaches (Fosso Wamba & Akter, 2019; Wang et al., 2016), and data innovation in service SCs (Opresnik & Taisch, 2015; Spanaki et al., 2018). The "data manufacturing" analogy and the "path to data quality" were revisited by Jones-Farmer et al. (2014) and Hazen et al. (2014) in an SC context, where they highlighted the need for continuous improvement in the SC management data production process. These two studies investigate the data manufacturing process using a data quality lens in the context of "Big Data" and SC Analytics. They suggest a framework for data quality control in an SC context.

The ways to process and evaluate the quality of the data used in contemporary operations and SCM contexts need to develop further (Karafili et al., 2018a). The previous scope of data management and data quality challenges has necessarily expanded to solve issues of interconnected data and the concept of a *boundary-less data environment,* which contrasts with the traditional archetype of a *single in-house database* from previous decades. The research agenda about data and information in SC management processes and the ways data are collected, processed, and used in various operations is a challenge that requires a holistic view of the ecology and the context of the data activities (Karafili et al., 2017a; Spanaki et al., 2018, 2021). An information architecture framing (Davenport & Prusak, 1997; Rosenfeld et al., 2015) supports the analysis of how data and information can be managed and exploited in an SC context, in terms of (a) context—overall business goals, technology, and constraints, (b) content—data types, dimensions, structure, and (c) relationships, access controls, and data sharing policies.

3. Data and information architectures

Designing frameworks for data management and exploitation is a crucial step and a necessary practice for the stakeholders in an information ecology (Nardi & O'Day, 1999). SC environments are dynamic, and the complexity of the relevant systems used for SC applications is increasing (MacCarthy et al., 2016). Hence, there should be a holistic view of how data and information are handled beyond the immediate boundaries of an organization, a single system, or an in-house database (Spanaki et al., 2018). The architectural aspects of data and information (Rosenfeld et al., 2015) should provide the backbone for managing and utilizing the data and data flows in digital SCs. The principal elements of an Information Architecture show how data are collected, exploited, and shared among various actors in a digital SC context.

The information architecture adopted here is based on the principles of *information ecologies* (Davenport & Prusak, 1997; Nardi & O'Day, 1999), where there is a categorization of the data and information flows in three interdependent core elements: *(a) the content, (b) the context, and (c) the actors* (Rosenfeld et al., 2015). In order to analyze the data and information flows, there should be a holistic understanding of the SC goals and resources, the types and formats of the data, and the relevant stakeholders so that information and knowledge can be acquired and applied for the benefit of the SC (see Fig. 9.1). The core elements are described in detail below and summarized in Table 9.5.

Context: Data and information in an SC are contextual. Specifically, the SC data and information flows are relevant to a specific context and characteristics (e.g., agricultural SC data differ from retail SC data). The overall SC goals, processes, and actions are determined by the specific sector's nature and requirements (Spanaki et al., 2021). The information architecture and the ways data can be handled and are expected to be used should match the SC technological infrastructure, the technology adoption maturity, and the mix of capabilities, resources, and requirements (Karafili & Lupu, 2017; Mikalef et al., 2019). Analyzing the digital SC context is vital in developing a successful information architecture to understand the requirements for data and information processing in the SC.

Content: The content in an SC information architecture refers mostly to the types of data and information and the frameworks that define the flow of information and data (e.g., multisource, multiformat), as discussed by Spanaki et al. (2018). In general terms, the information architecture content provides frameworks for the various data types based on their

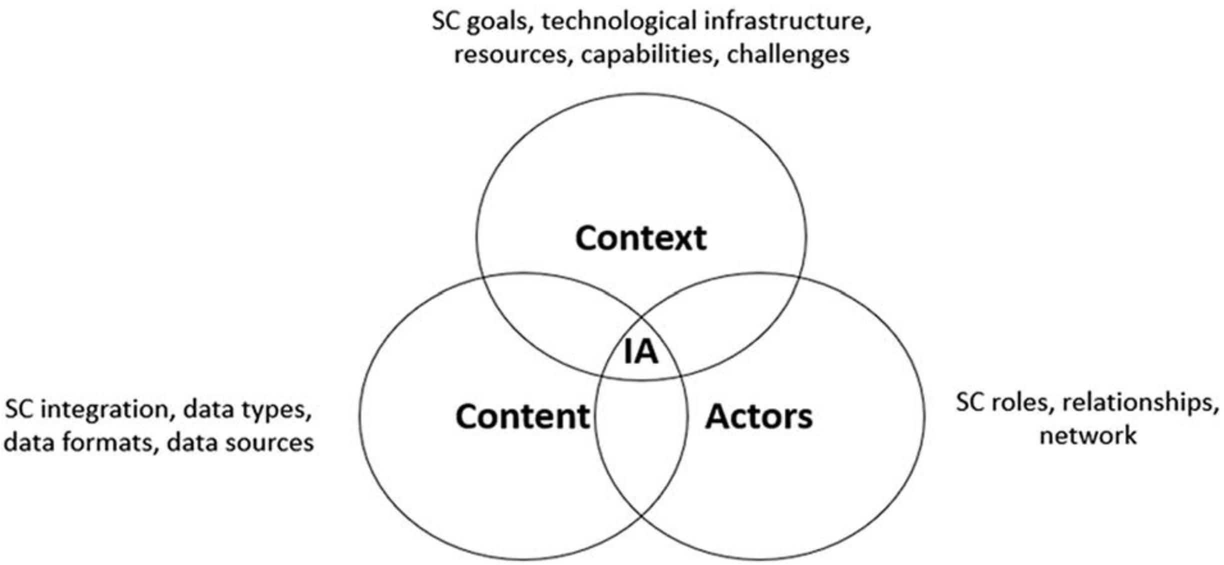

FIGURE 9.1 SC information architecture (IA) for the digital supply chain. *Adapted from Rosenfeld, L., Morville, P., & Arango, J. (2015).* Information architecture: For the web and beyond *(4th ed.). O'Reilly Media with adjustments adapted from Spanaki, K., Karafili, E., & Despoudi, S. (2021). AI applications of data sharing in agriculture 4.0: A framework for role-based data access control.* International Journal of Information Management. *https://doi.org/10.1016/j.ijinfomgt.2021.102350.*

TABLE 9.5 Information architecture elements and definitions.

Information architecture element	Definition
Context	The ways data should be handled and are expected to be used that match the SC technological infrastructure. The context also involves information about the technology adoption maturity and the mix of capabilities, resources, and requirements
Content	The types of data/information and the frameworks that define their flow. Data are considered as multiform (structured, unstructured, semistructured) and are gathered from multiple sources (multisource)
Actors	The interplay of stakeholders of the SC, also the various relationships in a specific digital SC context, as well as the associated interests and roles in the SC but also in data sharing activities

attributes and/or the associated metadata. Other areas covered in the content categorization of the information architecture are the integration of multiple data sources (internal and external to the focal firm), data collection, data processing and storage methods/tools, challenges of data ownership, provenance, as well as role-based and provenance-based access control.

Actors: The actors in an SC information architecture capture and explain the various relationships of the stakeholders in a specific digital SC context (Karafili et al., 2018a,b). The various actors are analyzed based on not only their interests and roles in the SC but also their roles in data sharing and usage activities. The role of each actor should be defined. The relevant roles in any SC collaborations and networks should also be defined so that data sharing rules and policies can be put in place for defining the correct access control rules (Spanaki et al., 2021).

3.1 Data management in cyber-physical SC environments

Value is created through the use, reuse, combination, purchase, and sale of data. The way data are accessed and used is therefore important. Smart devices and objects, Analytics, and data generation and collection techniques, and collaborative and integrated patterns of activities and processes play a critical role in analyzing data flows in SCs. Data flows across SCs present some unique characteristics (Spanaki et al., 2018).

Within an SC information ecosystem there is interplay between various actors out of the immediate boundaries of each SC. This is highly likely with SCs interconnected through various processes, technologies, and devices. Digitally enabled and cyber-physical SC networks may involve multiple new entrants in addition to the conventional SC stakeholders (e.g., cloud infrastructure and platform vendors, network providers, etc.). There may be conflicting interests among them when it comes to data sharing practices or such differences may emerge over time (Spanaki et al., 2021). The application of intelligent machines and sensors in the SC activities will continue to grow with a consequent increase in data quantity and scope (Ben-Daya et al., 2017; Xu et al., 2018). SC processes will become increasingly data-driven and data-enabled (Akter et al., 2019). In Table 9.6, we note the implications relevant technologies may have for the various stages of the SC and the associated information architecture elements in terms of context, content, and actors.

New and emerging digitally enabled SCs will be multiform and multisource. Thus, there is a need for new approaches for value extraction and creative industrial use and processing of this heterogeneous data (Karafili et al., 2018a; Spanaki et al., 2018). Data processing and manufacturing approaches need to be further investigated with regards to

TABLE 9.6 Indicative Systems and Technologies used in the cyber-physical supply chain.

Indicative systems and applications used in the cyber-physical SC	Implications	
	Supply chain	Information architecture (Context/content/actors)
Smart devices and platforms for SC Analytics	• Remote monitoring of the production, materials, machinery, and employees. • Obtaining statistics on processes, product quality, and production rates.	• **Context**—SC visibility and tracking • **Content**—data integration from multiple sources and platforms • **Actors**—data sharing and access control practices
IoT sensors (on the machinery, devices, buildings vehicles, etc.)	• Real-time data collection from a warehouse facility and other buildings, movements of employees/machinery, area and process condition variables. • Measuring the conditions within a warehouse/truck/vehicle and the routes of the machines/employees/materials. • Collecting and comparing information about the production and process steps. • Measuring and testing the performance of finished products.	• **Context**—identification of geolocational, chronological, and environmental specifics • **Content**—real-time data availability • **Actors**—data ownership and provenance
Autonomous robots and vehicles	• Obtaining detailed maps of the geographical conditions, topographical aspects, and resources of the area. • Improve labor by handling essential SC tasks such as operating at a higher volume and faster pace. • Higher productivity for more extended periods. • Remotely managing systems with a significant impact on managing the SC disruptions due to "work from home" mode.	• **Context**—automation in tasks and processes • **Content**—tailored services and operations based on informed insight • **Actors**—unmanned operations for inaccessible locations or during disruptions of the SC network
Drones for surveillance tasks	• Rendering maps processing spatial data, and applying analytical methods to geographic datasets, including the use of geographic information systems (GIS). • Surveillance of the SC tasks and simultaneously generating production data. • Calculating precise statistical predictions for the production. • Assisting in the delivery of various materials.	• **Context**—interconnectivity and easier access for multiple locations • **Content**—precision data available for better predictions • **Actors**—data availability and accessibility for definition of automated tasks

improving data quality and developing new frameworks to describe and track data manufacturing processes in different industrial applications (Hazen et al., 2014). An emerging concern around the SC design is data privacy, as often serious threats arise when data are shared among SC members and potentially third parties. Ways to prevent such issues open a new research agenda around trust and shared responsibility among the SC actors and entities (Janssen et al., 2020). Future research should also focus on new data collection, processing, and storage techniques and methods as this area is progressively expanding. Research is needed on the right tools and methods to exploit data generated from various sources through the SC stages, for example, in cases where the data provenance (the data lineage, as it is defined the origination of data) and ownership are not clear in SC processes (the data collected from smart machinery or autonomous vehicles in warehouses). A focus on organizational aspects of data generation and exploitation strategies and capabilities and skills (Mikalef et al., 2019, 2020) is required for the firms to build innovative SCs.

3.2 Data governance in the SC environments

Appropriate data governance is an enabler of data-driven change for the SC environment and a way to structure processes and acquire and manage the relevant skillsets necessary for analysis, prediction, and forecasting (Davenport & Patil, 2012; McAfee et al., 2012). Data governance encompasses a set of activities and practices relevant to decision-making (Mikalef & Krogstie, 2018). These practices are defined for the allocation of roles and responsibilities of the involved parties in data collection and processing mechanisms (Weber et al., 2009). Determining the key stakeholders and their roles, and the responsibilities for data ownership, value analysis, and cost management are crucial aspects for data governance and for compliance with policies and standards (Mikalef & Krogstie, 2018). Under data governance, developing internal and external data management rules about data retention, resource management, and data access are critical responsibilities within the firms (Rasouli et al., 2016).

Allocating the roles and setting access policies for data governance are practices applied on a *structural* level of the organization (in terms of the organizational hierarchical model); there are also data governance practices associated with *operational* and *relational* practices (Weber et al., 2009). Operational practices include data migration, data retention, data analytics procedures, and access rights (Karafili et al., 2018a; Mikalef & Krogstie, 2018). However, these practices are highly related to the data types (structured, unstructured, semistructured) and the type of insights that may be extracted from the data. Relational practices are concerned with HR-related matters on how employees are trained and educated for data governance practices and the knowledge sharing context of each organization (Kooper et al., 2011; Mikalef et al., 2020).

Applying appropriate data governance is a challenging task and depends on the information architecture of each SC (Tallon, 2013). The major challenges relate to the resources and capabilities of each SC (Mikalef et al., 2020) and the importance of defining a clear information architecture to achieve a blueprint vision for the way the capabilities and skills can be applied (Tallon et al., 2013). As data analytics practices for the SC rely on the governance frameworks defined for each SC context (relevant to the industry regulations and also internal organizational directions), well-defined data governance practices can result in better orchestration of the resources and capabilities within the firm, and value creation through data insights (Mikalef et al., 2020; Pappas et al., 2018).

4. Data sharing agreements

In these last 20 years, data have become a crucial factor in businesses and more widely in our everyday life. The increasing use of data has been energized by the increasing interconnectivity between users and devices. However, the increase of connectivity comes with its own challenges, including data and privacy breaches, cyber-attacks, and security properties violations. These challenges highlight the necessity to strengthen the security measures for all environments related to data, e.g., where the data have been collected, transferred (Kaufman, 2009), stored (Gertz & Jajodia, 2008), used, and shared (Karafili et al., 2015). Solutions dealing with these challenges focus on protecting the data and are called a *data-centric security solutions* (Bayuk, 2009; Kim et al., 2010; Zhou et al., 2010). These solutions are based on data access control and are linked to the role of the users (Ferraiolo et al., 1992), data attributes, and data Usage Control (UCON). The latter is based on *computational policy languages* (Pretschner et al., 2008) and is used in distributed systems contexts (Kelbert & Pretschner, 2013) for data flows across interconnected systems and multiple distributed systems contexts (Kelbert & Pretschner, 2015). They enforce a global usage control in a decentralized infrastructure.

Another interesting approach used to share and access data is the use of *sticky policies* (Pearson & Casassa-Mont, 2011). Sticky policies are machine-readable policies that present conditions and constraints attached to data, describing how data should be treated when they are shared among multiple parties. Sticky policies have been applied for enterprise privacy enforcement and the exchange of customer data, represented through a *privacy control language* (Karjoth & Schunter, 2002). A privacy control language is used for access control and authorization permissions in data administration tasks, extending the sticky policy paradigm for the cloud environment with additional features (Trabelsi & Sendor, 2012).

When managing data in an SC context, both the consumer of the data and the data provider should agree on the used and shared data, e.g., the data consumer needs to be assured about the required quality for the data, while the data producer needs to ensure that the data are protected appropriately. Therefore, before creating, sharing, and using any data, all the relevant actors need to agree on the rules controlling how the data should be treated (Swarup et al., 2006). These rules are called data sharing agreements (DSAs). The framework presented in Swarup et al. (2006) introduces the obligations between the entities to respect certain rules (called policies). DSAs also capture the compliance of the different sector rules and regulatory frameworks for data sharing (Karafili & Lupu, 2017; Matteucci et al., 2010). Conflicts can be generated by the heterogeneous nature of such agreements, especially between legal and business rules or legal rules and user requirements. Thus, DSAs need expressive language to represent the agreements (Craven et al., 2009; Karafili & Lupu, 2017; Karafili et al., 2018a,b).

The studies of DSAs propose a policy language based on logic programming that represents complex agreements and an analysis process for capturing the conflicts and the associated solutions (Karafili & Lupu, 2017; Karafili et al., 2018a,b). The analysis process is performed using AI techniques that apply human thinking and decision-making through formalism and argumentation reasoning (Kowalski, 2011). The DSA analysis provided in Karafili and Lupu (2017) uses preference-based argumentation (Kakas et al., 1992) and abductive logic programming (Kakas et al., 2001) that allow the identification of conflicting and incomplete rules. This analysis is particularly useful as it identifies when conflicting rules are applied to the same set of data or when there is no rule applied to a particular set of data. The analysis is crucial when different entities from various sectors are part of an SC network that deals with and encompasses heterogeneous data. The enforcement of the DSAs in Karafili and Lupu (2017) occurs using the sticky policies paradigm, where the DSAs rules and conditions are stuck to the data and are automatically enforced. See Fig. 9.2 for an example of DSAs using the sticky policies in the cloud environment. The various users can access the data that is in the Cloud through their Cloud nodes. Depending on the user's role, geographical location, and/or other attributes, access to the data is granted or denied. The access control to the data is enforced by the policies that compose the DSAs that are attached to the data in the cloud environment.

The structure of DSAs require already defined (a) the various data categories (data management aspects), so that the rules and conditions can be formed for the DSAs (Karafili & Lupu, 2017; Karafili et al., 2018a,b), and (b) the actors and roles in the data ecosystem under consideration. The two essential requirements (data attributes and the interplay of actors) that should be predefined for the development of DSAs are explained further in the following two sections, respectively.

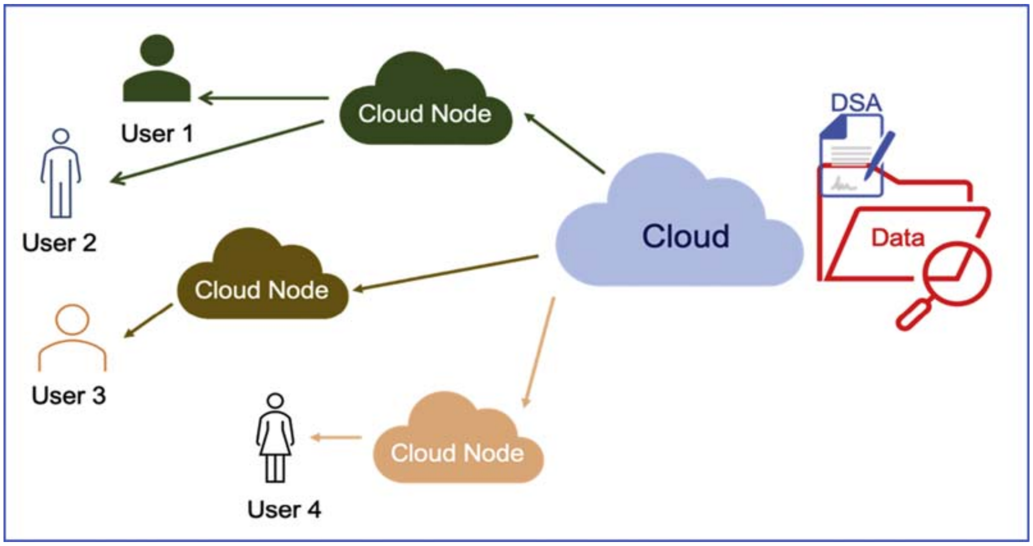

FIGURE 9.2 An example of a Data Sharing Agreement (DSA) usage in a Cloud Environment.

5. Data attributes, sharing, and access control

As noted in Section 2, the data manufacturing analogy has been explored in previous data management studies in the context of single in-house databases within the boundaries of an organization. However, in the last decade, SC data are shared through distributed systems and environments as well as across multiple databases (Karafili et al., 2018a; Spanaki et al., 2018). The main features analyzed by current data frameworks for SC applications are data quality, accuracy, and provenance (Karafili et al., 2018a).

Data attributes play an important role in data access control, as they are used to specify if a certain user can access the data or not in role-based control frameworks. The rules describing who can access the data and which data are provided in the form of rules are called policies (see Attribute-based Access Control by Hu et al., 2015). Data attributes are used widely by access control frameworks and allow data that require more restrictive access control rules to be identified and represented in order to preserve data privacy and other requirements.

Once the policy rules of the data sharing framework are constructed, they need to be enforced. These rules regulate data access, usage, and sharing, taking into account security requirements, business regulations, and relevant legislation (Bayuk, 2009; Karafili & Lupu, 2017). When data sharing frameworks are applied in the context of SCs, further aspects need to be incorporated in the data access control rules that are driven by the SC processes and their requirements. A critical requirement is the assurance of *data quality* (see Section 2). Data sharing frameworks can represent and enforce rules related to the collected, processed, used, and shared data (Karafili & Lupu, 2017) using a particular "*policy analysis language*" where the various rules are represented computationally (Craven et al., 2009). A data sharing framework combined with the use of an AI component (argumentation reasoning) can ensure that the quality of shared data respects necessary requirements and policies (Karafili et al., 2017). Two technical requirements for data quality can be enforced: 1. data accuracy, and 2. freshness, which refers to the timeliness of the collected data.

The main goal of a data sharing framework is to deal with the sharing of, and access to the collected data, not to process or enrich it. If the collected data are of low quality, then access control policies will work with that data quality and not improve it further. However, the quality of data can be lowered on purpose depending on who is accessing the data (Karafili et al., 2017). The same process is also applied for data timeliness, which can be lowered depending on the entities or processes accessing the data (Karafili et al., 2018a). The process of lowering data quality is based on data attributes (e.g., accuracy and freshness) and not on limiting the quantity of accessed data.

The use of a "policy analysis language" permits a data sharing framework to have a high expressivity in technical terms. Expressivity is a critical aspect of data access control. In an SC context, this restricts (i.e., expresses) how the different entities can process the data. The various rules enforced by data sharing frameworks can allow expressing

- *role and process-based constraints*, e.g., a wholesale employee can access specific parts of the warehouse data
- *time constraints*, e.g., an accounting employee can access the sales data only after a sale has happened for invoicing purposes
- *geographical constraints* (from geolocation attributes of the data), e.g., the wholesale employee can access only the data of the closest warehouse.

The expressivity of a policy analysis language represents the rules for data access control computationally, allowing the correct policies to be applied between the different entities and processes involved in the data sharing. As noted in Section 4, such rules are embedded in DSAs and are established between the entities involved in the data processing.

The data sharing framework for a digitally enabled SC requires the identification of the various actors and processes involved in the collection, use, and sharing of data across the SC. Identification of the actors and processes also comes with further constraints, which are combined with the SC processes and business requirements and legal regulations (Karafili & Lupu, 2017). The DSAs need to include all these requirements and regulations.

Raw data collection can be done manually or automatically; it can be collected from diverse actors—people, cyber-physical systems, IoT devices or drones, etc. Data can be collected continuously, at specified intervals of time, or for specified time periods, representing the level of freshness. The way the data are collected and the tools used influence the data quality. Data quality and freshness are also related to the type of collected data. With the use of AI techniques (Spanoudakis, Constantinou et al., 2017; Spanoudakis, Kakas et al., 2017), data access control frameworks can have the needed flexibility to deal with new components and can be enhanced when alterations in regulations, requirements, or legislation occur (Karafili & Lupu, 2017).

6. Actors, roles, and relationships in data sharing

In SC environments, there is a variety of data flows and associated processes of collecting, processing, and sharing data. The actors and their roles should be defined along with categorization of the data based on relevant attributes so that DSA and access control policies can be defined for the specific SC context (Karafili et al., 2018a). Here, we present the requirements in terms of actors, roles, and relationships for data processing at a high level. The representation of the roles in data processing respects the requirements of the interested actors and effectively suggests the access control policies and priorities of the rules associated with the contextual data that compose the DSAs (Karafili & Lupu, 2017). The following analysis of the roles and relationships of the data sharing participants is based on previous studies of role-based access control in contextual environments Spanaki et al. (2021) and Karafili et al. (2018a,b).

The *main actor* of the SC information architecture in any SC context is the owner of the SC activity and collects the data through the various operations, either manually (i.e., employees entering data in transactional systems of the firm) or automatically (via IoT sensors on machinery or vehicles, RFID devices, etc.). The *data owner* can collect, use, reuse, and share data of the relevant SC actions (as the data ownership is specifically defined). However, there are cases where the data ownership and provenance are more complex and cannot be specifically defined; such cases can happen when the data collection activity is conducted via an IoT device (e.g., the sensor on an intelligent vehicle, which may be part of the SC but a third party owns the vehicle). The main actor is also considered the *data subject*, as the collected data are part of the firm's operations and SC activity data. The data owner can also be the *data controller,* defining the purpose and means of processing the SC data. Sometimes, the main actor also relies on third parties that provide technical support for collecting the data. In this case, the main actor, who is the *data owner/subject*, is not the data controller, as there is a delegation of the control of the activity data to a third party; therefore, the data controller is a third party in this case.

The *data recipients* are the stakeholders involved in the data sharing process, acquiring and accessing the data, and need to comply with the data controller's rules. The data recipients can be third-party firms, collaborators, firms in the digital SC network, firms that provide technological services, infrastructure and technology, or even governmental stakeholders such as regulators. The reference activities where the data are collected can be part of *collaborative* SC operations. Through such collaborative activities, the SC partners can exchange information, knowledge, technology as members of the collaboration and can be considered as data recipients.

There are also other actors in data sharing activities; for example, the *data processor* is an entity (public authority, agency, legal person) processing the data on behalf of the data controller. If the collected/processed/shared data are stored in the Cloud, the cloud provider is considered the data processor as far as it respects the controller's instructions. The controller's rules should be respected by the processor and can also have a legal nature, e.g., if the controller is in an EU country, the cloud provider should be in an EU country as well and cannot share the data with countries outside the EU or EEA.

In the data and information architecture of an SC, often the data can also be shared with a *third party* who is an entity (public authority, agency, legal person) that is not the data subject, data controller or processor, and is under the direct authority of the data controller or processor. In our case, a company outside the collaboration that is granted access can be considered a third party. Once access is obtained, the third party becomes a data controller and has to comply with the data protection principles.

We provide an example within an online retail SC in Fig. 9.3 where the various entities are involved in data collection, storing, accessing, and sharing. The Retail Customer (Data Subject) is ordering products through the Retailer's Website (Data Owner) that collects the customer's data and stores them in a Cloud Environment (Data Processor and Controller). The Data Recipients are the staff of that Warehouse (Warehouse Employees) and even the Customer themselves. There are third-party entities like Marketing and Advertising Companies that collect the data for marketing purposes (if there is permission/consent provided from the customer during the registration in Retailer's website) or a Logistics contractor who uses the data to facilitate prompt product delivery.

Data collection can be performed either manually or through technological applications (IoT devices, drones, etc.) depending on the context of the SC. The data collection process may affect the accuracy and transparency aspects of the data and is highly relevant for the data quality; for example, data collected manually from the main actor may be more or less accurate compared to the data collected by a device. The reliability of data will depend on the efficiency, transparency, and the reliability constraints of the process steps. Data collection is also directly linked to the time (timeliness as it is referred to in data management literature); data collection can happen at various intervals of time, e.g., every hour/day/month, or a continuous collection (real-time). The collection time/period influences the timeliness of the data.

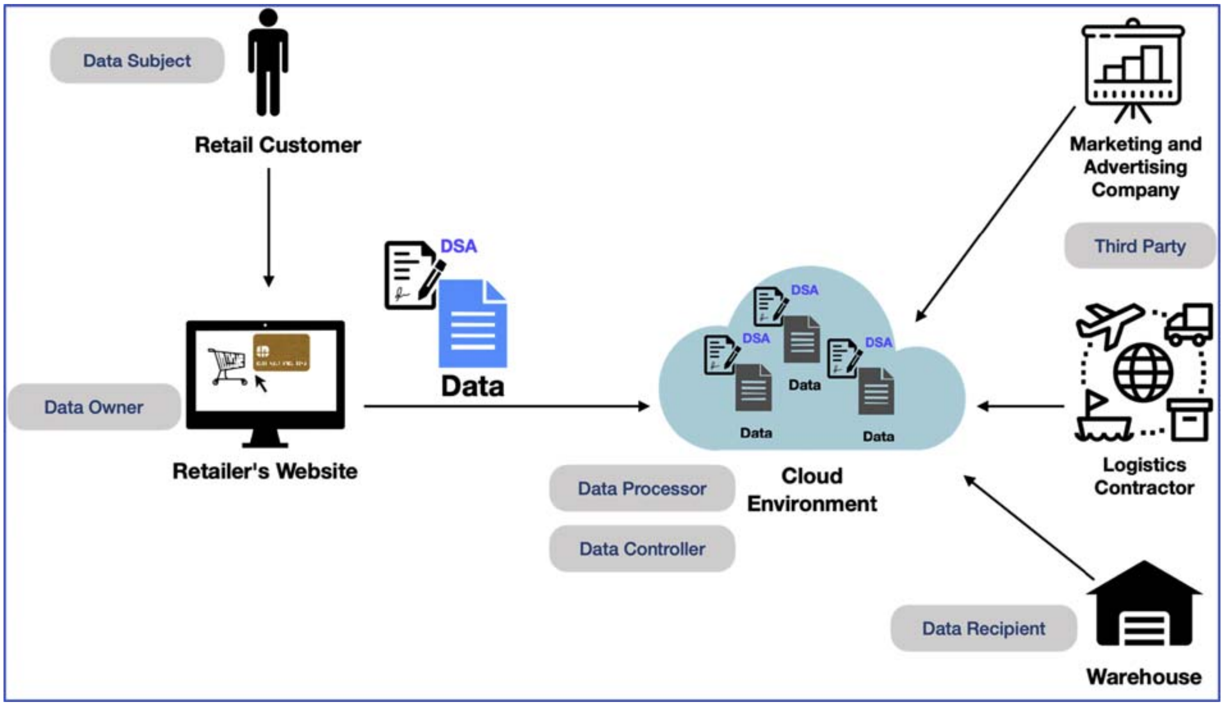

FIGURE 9.3 An example of data sharing in an online retail scenario.

7. Conclusions

In recent years, we observe many initiatives from vendors of SC technology (e.g., SAP, Microsoft Azure) that provide options for the SC customers to share their data to the Cloud (Hero, 2020). Data sharing practices alone open up a world of multiple potentialities. However, the data should be collected in a specified context from defined machines/devices, and the analysis of the data should consider all the issues we have highlighted and also consider the integration of the information available for materials, products, customers, inventory, assets, and more (Hero, 2020). Reference information architectures are provided as a template to customers to better realize the data sharing context around digitally enabled SCs (Titze et al., 2020). The integration of data resources from multiple collection points, in various formats and from various time instances, provides opportunities for better insight about the SC, enhanced decision-making processes, and improved tailored customer outcomes (Ng et al., 2015).

Through the background of data management and the various frameworks developed in previous decades, we have considered the challenges and problems identified in previous research but have examined them in the context of the SC information ecosystems. The concept of Information Architecture has been developed here as a framework for analyzing data and information flows in SC, in regards to three key elements: (a) the context, (b) the content, and (c) the actors in SC data sharing practices. The analysis of data and information flows provides a rich research agenda for further exploration, with many implications and challenges around the use of data in the digitally enabled SCs.

An important challenge is data filtering and clustering. We have moved in less than 2 decades from a shortage of data to an oversupply of data. These data need to be stored, analyzed, cleaned, and clustered; all of these processes require time and resources. Therefore, we expect the continuation of the Big Data Analytics trend, which allows such data to be filtered and analyzed in a focused and thrifty manner.

Another interesting aspect is the transition of the user from data subject to data owner and controller. Thus, the user may not simply provide their own data, but they may want to be in complete control of them and gain benefits (also monetarily) from the shared data. Further interdisciplinary research needs to be conducted in this area, as future digital SCs will also have citizens as possible data providers.

One of the main challenges in the future is how to protect data from cyber-attacks and data breaches. This is a challenge not only for SCs but also for all the industries dealing with data. An important aspect is the human component, as the majority of data breaches have occurred due to human errors or social engineering attacks where information is extracted through social media interactions (Evans, He, Maglaras et al., 2019, Evans, He, Yevseyeva et al., 2019). Therefore, we expect the business owners (as well as industry and governments) to invest and develop further security training for their employees, invest in cyber-security and breach protections, and cyber-security insurances.

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Chapter 10

Supply chain traceability systems—robust approaches for the digital age

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Abstract
Traceability systems play an important role in the digital transformation of the supply chain. This chapter examines the principal issues on the what, why, and how of achieving digital supply chain traceability in relation to data and technology. We consider the overlapping definitions of visibility, traceability, tracking, tracing, and transparency. We highlight factors driving the need to achieve higher levels of traceability, including regulatory demands, business incentives, and customer concerns and preferences. The emergence of global standards related to traceability is noted. The types of information required to successfully track and trace products in a digital supply chain are explained, as well as the technologies applied to collect, follow, and share information, including radio frequency identification, Internet of Things, and blockchain. The challenges around cybersecurity, standards, data quality, integrating new technologies, and potentially competing interests among stakeholders are discussed. We examine the traceability of wood products, which are important globally and raise significant sustainability challenges. The case illustrates how technical solutions can be incorporated into the traceability system to respond to the needs and challenges of stakeholders. Further research is needed on the technical, policy, and business strategy solutions to address common data and technology challenges for effective traceability systems.

Keywords: Data; Digital; Supply chain; Technology; Traceability; Track and trace; Transparency.

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1. Introduction

Traceability systems are increasingly critical to instill trust in consumers (Bateman & Bonanni, 2019) and enhance business operational efficiency (Morgan et al., 2018). The COVID-19 pandemic has roiled global supply chains, driving calls for greater traceability and transparency (United Nations Global Compact Academy, 2021). Kemp (2020) notes that from the onset of the pandemic, "It wasn't just the physical toilet rolls, face masks or pasta. It was the digital information about where to find them. Who could provide them fastest?". Traceability systems allow access to such data as they, " … show the path of a particular product from suppliers through intermediate steps to consumers" (International Trade Center, 2021). The pandemic has also brought a surge in counterfeit products, spanning garments, food, and medical devices (International Chamber of Commerce, 2020), and even COVID-19 vaccines (Hopkins & de Córdoba, 2021). Traceability systems make it possible to trace the origin of counterfeit products and put a halt to their production. Traceability also allows unsafe products to be tracked and recalled, enabling important consumer protections (Uddin, 2021).

Alongside the growing focus on traceability, digital technology innovation is rapidly changing the way we live, with fundamental implications for supply chains (Melumad et al., 2020). Much of the retail sector has moved online and transactions are increasingly executed via electronic payments systems (McKinsey & Company, 2020). Technology and innovation are key factors driving the transformation of supply chains, including their size, configuration, and ways in which stakeholders coordinate (MacCarthy et al., 2016). Businesses have begun to incorporate digital technologies into traceability systems to make possible a new level of supply chain transparency and traceability (Sodhi & Tang, 2019). With COVID-19, this trend has intensified such that companies have " … accelerated the digitization of their customer and supply-chain interactions and of their internal operations by three to four years," according to a survey by McKinsey and Company (2020).

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This chapter articulates fundamental elements needed for a traceability system, in terms of data and technology for the digital era. The following four sections cover the "what," "why," and "how," as well as common challenges, for achieving digital supply chain traceability and transparency. In particular, Section 2 defines traceability systems and other key terms, including visibility, transparency, and traceability. Section 3 discusses the motivations for different actors in the digital supply chain to maintain and transparently operate a traceability system, covering regulatory demands, business incentives, and customer needs. Sections 4 and 5 highlight implementation approaches, starting with the type of information required to successfully track and trace products in a digital supply chain. Section 5 then reviews some enabling technologies such as radio frequency identification (RFID), internet of things (IoT), and blockchain. Section 6 discusses common challenges across sectors including cybersecurity, standards, data quality, integrating new technologies, and competing interests among stakeholders. To demonstrate these issues in practice, Section 7 examines the specific case of wood supply chains where the needs to track and trace information are acute given legal compliance needs as well as growing attention to environmental and social impacts of illegal logging. At the same time, this is an area where countries are reporting challenges in tracking and tracing information in their supply chains. The case illustrates practical data and technology challenges as well as potential solutions for establishing digital supply chains that enhance transparency and traceability. Section 8 concludes with recommendations for further research on technical, policy, and business solutions to address some of the common data and technology challenges.

2. Visibility, transparency, and traceability

To lay the foundation for discussing incentives and implementation approaches for traceability systems in relation to data and technology, this section first defines a traceability system and other key terms, including supply chain visibility, transparency, and traceability, as well as how these interrelate.

2.1 Being visible and transparent

The term supply chain *visibility* generally denotes the ability of stakeholders within the supply chain to have timely access to relevant and accurate information (Dubey et al., 2019). For examples, Barratt and Oke (2007) describe supply chain visibility as " … the extent to which actors within a supply chain have access to or share information which they consider as key or useful to their operations and which they consider will be of mutual benefit." Francis (2008) explains supply chain visibility as "the identity, location and status of entities transiting the supply chain, captured in timely messages about events, along with the planned and actual dates/times for these events." Visibility throughout the supply chain, commonly referred to as end-to-end visibility, makes it possible for internal stakeholders in the supply chain to identify and share relevant information from the point of origin of a product to the end users (Wei & Wang, 2010). Supply chain *transparency* builds upon supply chain visibility (Brandon-Jones et al., 2014). Information collected from external parties can fill gaps in visibility within supply chains (Barratt & Barratt, 2011). The concept of supply chain transparency has expanded beyond visibility by extending the focus beyond internal supply chain stakeholders to include external parties (Gold & Heikkurinen, 2017). Supply chain transparency is today considered the practice that " … involves communicating with key stakeholders about the firms' current activities and incorporating stakeholder feedback for supply chain improvement" (Morgan et al., 2018).

2.2 The usage of terms—traceability, traceability system, tracking, and tracing

Though definitions vary, the term *traceability* is a widely used in supply chain management. The International Organization for Standardization (ISO) first used the term in 1996 in its 8402 standard on quality assurance and management (Walaszczyk & Galińska, 2020). The ISO (2021) provides a commonly referenced general definition of traceability for quality management as "the ability to trace the history, application or location of an object." In relation to products or services, traceability entails "the origin of materials and parts, the processing history, and the distribution and location of the product or service after delivery." In a more specific context, the United Nations (UN) Global Compact, with the mission to encourage businesses to embrace sustainable and socially responsible supply chain policies, defines traceability as " … the ability to identify and trace the history, distribution, location and application of products, parts and materials, to ensure the reliability of sustainability claims, in the areas of human rights, labor (including health and safety), the environment and anti-corruption" (UN Global Compact, and Business for Social Responsibility, 2014). The European Union's (EU) general principles and requirements on food law, with the objective of supporting food safety practices, defines traceability as the "ability to trace and follow food, feed, and ingredients through all stages of production, processing and distribution" (European Commission, 2021).

In summary, the term traceability generally signifies the ability to access relevant information about an object as it moves along a supply chain. An object is typically in the form of products or logistic units such as containers. The set of methods and practices used to achieve traceability in a supply chain is generally referred to as a *traceability system*. For example, this includes standards and technologies used to identify objects, record object attributes, and log the joining and splitting of objects as they travel along the supply chain (GS1, 2017; Olsen & Borit, 2018). The applications of technology to support supply chain traceability are well documented (Dubey et al., 2021; Panetto et al., 2019; Zhu et al., 2021). A traceability system helps keep track of relevant information as the object transforms and travels from end-to-end across a supply chain (Barratt & Oke, 2007; Brandon-Jones et al., 2014; Fawcett et al., 2011; GS1, 2017). As explained by Ivanov, Dolgui, and Sokolov (2019), a supply chain constitutes "a network of organizations and processes wherein a number of various enterprises (suppliers, manufacturers, distributors and retailers) collaborate (cooperate and coordinate) along the entire value chain to acquire raw materials, to convert these raw materials into specified final products, and to deliver these final products to customers." Thus, end-to-end supply chain traceability combines information from multiple parties, with objects categorized into those that are internal to the organization and those that are traded among organizations (GS1, 2017; Behnke & Janssen, 2020).

Traceability parties in a traceability system are the actors "who play a role in the chain of custody or ownership of supply chain." They capture, record, and share relevant information about the objects under their custodies (GS1, 2017). Those who can affect or are affected by the implementation of the traceability system such as traceability parties, regulators, and nonprofit watchdog organizations are considered stakeholders of the traceability system (Morgan et al., 2018).

In seeking to follow information across a supply chain, the terms "track" and "trace" have been used to provide additional details depending on the direction of the information flow along a supply chain from point of origin to end user (Bechini et al., 2008). *Tracking* refers to following information along a path as it moves forward or "downstream" through the supply chain from origin to the end users. Conversely, *tracing* refers to following information backwards or "upstream" in the supply chain toward the original source of a product (Musa et al., 2014). In some instances, the terms forward traceability and backward tracing have been used in place of track and trace (Karlsen et al., 2013). In the context of food safety, forward tracing is applied to examine the distribution and sale of potentially contaminated products and is a typical process used to support product recalls. Backward tracing helps to locate and stop the source of contamination, for example, at a particular farm or other supplier (McEntire, 2019).

The definitions show that, while distinct concepts, supply chain traceability and transparency mutually support each other. The success of supply chain traceability relies on being able to capture and see relevant information. Whether supply chains are transparent, such that stakeholders can have timely access to accurate and relevant information, hangs on the ability to follow information. What information is relevant will depend on the particular objectives that the traceability system is designed to achieve. The next section discusses some of the motivations to maintain and transparently operate a traceability system.

3. Motivations for traceability and transparency

The preceding section noted that the ability to follow relevant information throughout the supply chain makes it possible for businesses to know what is happening and to share this information with internal and external stakeholders. This in turn allows for more informed decisions, including by enabling timely identification of deviations and formulation of effective strategies to mitigate negative impacts from disruptive events (Ivanov, Dolgui, Das et al., 2019). In addition to managing such risks, what are some of the motivations for practicing traceability and ensuring transparent operations? This section categorizes and discusses these under four groupings (see Fig. 10.1).

3.1 Increasing operating efficiency

The UN (2021) highlights traceability as key to improving efficiency. The ability to capture and follow information throughout a supply chain and share this with stakeholders has clear implications for evaluating and monitoring operating processes and solving problems when they arise. Supply chain traceability and transparency can provide businesses with improved operating insights on batch sizes, throughput time, and level of work in progress (Morgan et al., 2018), as well as enhance operating efficiency through better inventory management (Hasan et al., 2020). For instance, when working with perishable products there is intense pressure for timely distribution and sale. These products have short shelf lives so having relevant and timely inventory information helps to maximize freshness and avoid spoilage (Visconti et al., 2020). It also makes it possible for retailers to automate price markdown as expiration dates approach or inventory levels change (Annosi et al., 2021; GS1 US, 2012). Traceability and transparency can also increase operating efficiency by enhancing procurement processes (Hastig & Sodhi, 2020). For example, supply chain visibility can reduce errors in order fulfillment, lowering costs from invalid quality claims and delivery mistakes (Southhall, 2019).

FIGURE 10.1 Motivation for traceability and transparency.

Globalization has intensified supply chain complexity and raised operational challenges (Shih, 2020). Systems for traceability and transparency can enable Total Quality Management and Just-In-Time strategies to enhance operations (Shou et al., 2021). Hastig and Sodhi (2020) and Wowak et al. (2016) suggest Internet-based traceability systems improve organizations' abilities to address challenges such as cross-border product recalls in global supply chains.

3.2 Meeting legal compliance

Many supply chain actors are required to adopt traceability and transparency practices to meet legal requirements. Failure to meet legal compliance could potentially lead to fines and/or being barred from conducting business, among other negative consequences. For instance, missing certificates of origin can translate to containers being held up or turned away at shipping ports overseas (Ringsberg, 2015). Businesses also often face regulatory or other legal requirements to practice traceability and transparency, especially in food and pharmaceutical industries. Such regulations have become increasingly common in the wake of health crises, including the severe acute respiratory syndrome outbreak in 2003, and bovine spongiform encephalopathy, commonly known as "mad cow disease" (Zhou & Piramuthu, 2015). Regulations that require traceability and transparency are also on the rise across a range of industries. Absent and incomplete traceability and transparency have been linked to product poisoning and human rights abuses in the toys, mineral extraction, and apparel industries (Busse et al., 2016). Such incidents have triggered a sweeping set of regulatory requirements in terms of traceability and transparency. For example, the California Transparency in Supply Chains Act (State of California, Department of Justice, 2021) and the UK's Modern Slavery Act 2015 (The National Archives, 2021) demand transparency and traceability in supply chains to tackle modern slavery, while the US Conflict Mineral Rule requires organizations to obtain supply chain data on minerals from conflict regions (The National Law Review, 2021). Businesses are increasingly required to disclose the extent of their efforts to meet these legal requirements in five areas: verification, audits, certification, internal accountability, and training (World Bank Group, 2019).

3.3 Managing risks

Over the years, scholars have proposed adopting traceability as an essential approach to manage risks across global manufacturing and supply systems (Skilton & Robinson, 2009; Stranieri et al., 2017; Tsang et al., 2018). The ability to track and trace through supply chains helps prevent disruptions and reduce their impacts (Timmer & Kaufmann, 2017).

Traceability systems provide access to information such as accurate levels of capacities and inventories across the supply chain, making it possible for stakeholders to take mitigating actions and develop recovery strategies (Dolgui et al., 2018; Ivanov, Dolgui, Das et al., 2019).

The Dow Chemical Co.'s Railcar Shipment Visibility Program is an early example in terms of adopting traceability and transparency practices throughout a supply chain to prevent disruptions. The company tracks the location of rail cars and uses GPS trackers to provide "geofencing" when transporting high-risk mobile assets such as hazardous chemicals. The company informs other stakeholders of potential risks if railcars deviate from scheduled routes or move into a heavily populated area (Sheffi, 2015; Tate & Abkowitz, 2011). There are now much greater opportunities for the deployment of such systems in digitally enhanced supply chains, for example, to identify counterfeit drugs (Zhu et al., 2020) and textile products (Agrawal et al., 2018) before they reach consumers.

Some problems, such as food contaminated with *E. coli* (U.S. Food & Drug Administration, 2020), may not become apparent until after products have reached customers. Under these circumstances, other types of risk management are needed to address the ex-post impacts. Being able to identify, track, and trace relevant information and communicate it to stakeholders allows the affected businesses to quickly withdraw unsafe products and inform the public to lower consumers' chances of exposure (Dai et al., 2021; Roy, 2019).

3.4 Building trust and confidence

Consumers are becoming more demanding of product safety as well as corporations' roles in social responsibility (Deloitte, 2020). Many buyers are seeking organic, fair trade, and environmentally conscious products (Latham, 2021). Consumers are also increasingly seeking disclosure of human right conditions embedded in supply chains, across both domestic and international labor markets (Paton & Maheshwari, 2019, p. 8). Research from the MIT Sloan School of Management reported consumers would potentially be willing to pay between 2 and 10% more for products from sellers demonstrating better supply chain transparency (Bateman & Bonanni, 2019).

A well-functioning traceability system is essential to meeting the increasing demand for socially responsible products (Norton, 2019). Supply chain visibility could help overcome skepticism on claims about social responsibility. Brown (2020) points out that "Supply chain visibility matters … sharing information about the supply chain overcomes consumers' inherent lack of trust or makes prosocial customers feel like they are patronizing a socially responsible company." Others have also explained that supplier transparency increases customers' perceptions of value and trust with the supplier (Kappel, 2019; The Consumer Goods Forum, 2016).

4. Information requirements for traceability systems

The information that is considered relevant for a traceability system will depend on the objectives that the system is designed to achieve and is affected by factors including industry structure, legal requirements, and strategic goals. Even within a specific industry, there is no common theoretical framework for supply chain traceability (Karlsen et al., 2013; Marconi et al., 2017). Although there is agreement that a one-size-fits-all approach is not optimal, scholars and practitioners have worked to identify common pieces of information and processes that are required to form the foundation of a robust traceability system for digital supply chains (Garcia-Torres et al., 2019; GS1, 2017). The quality of a traceability system depends on collaboration among the different parties that participate in activities throughout the supply chain. Lack of data access, data quality, and linkage of relevant information from any one party affects the reliability and robustness of the entire traceability system (Schrage, 2020). The next section discusses some of these crucial processes, standards, and pieces of information necessary for building a robust traceability system.

4.1 Traceability standards

Supply chain traceability standards create system compatibilities and make it possible to share information more effectively by avoiding a situation where stakeholders are using different measurement units or different names for the same product unit or supply chain process (Byun & Kim, 2020). Standards related to traceability have begun to emerge around the world (McEntire et al., 2010; Vander Stichele et al., 2021). These standards cover a range of areas developed by international organizations, regional governments, and industry associations (Dabbene et al., 2014; DNV, 2021). Examples of industry-specific standards include the food safety standard linked to traceability from the International Organization for Standardization (ISO, 2007), as well as the Solar Energy Industries Association's "Solar Supply Chain Traceability Protocol 1.0" adopted in support of corporate social responsibility (SEAI, 2021). A sector and product neutral example is the GS1 Global Traceability Standard (GTS). GS1 is a not-for-profit organization, working with public, private, academic, and other not-for-profit entities, that seeks to develop standard-based solutions to address the challenge in traceability practices. GTS " … does not aim to compete with other international standards that address traceability requirements … but rather complements and completes them. Where these standards define 'what' should be done, the GTS helps companies and organizations to understand 'how to' meet these requirements using standardized traceability data" (GS1, 2021c). These standards provide definitions of uniform pieces of information that are part of the foundations of a robust traceability system and a common set of language terms to identify, capture, and share this relevant information.

4.2 Common information building blocks

In general, among the different standards, the common pieces of information that are fundamental building blocks for a robust traceability system fall under one of five different dimensions. These dimensions capture "what," "why," "who," "where," and "when" for each relevant object to be tracked and traced.

1. *What* denotes the identity and additional attributes of primary and related objects that are being tracked and traced. Additional relevant attributes will depend on the objectives of the traceability system. For example, if temperature control is needed to avoid spoilage of certain vaccines or other products, such attributes would likely include the temperature associated with each relevant object (U.S. Department of Health and Human Services, 2021; Vander Stichele et al., 2021).
2. *Why* indicates the business process or event associated with a relevant object as it moves along a digital supply chain, for example, the different stages in a manufacturing process or changes in chain of custody or ownership.
3. *Who* captures the parties involved in different activities.
4. *Where* shows the location of a relevant object as it moves along the digital supply chain.
5. *When* explains the timeline of a relevant object as it moves along a digital supply chain (GS1, 2017; IOS, 2007; Schrage, 2020).

For instance, in the case of the canned tuna industry, the tracing begins with the catching of the tuna, followed by various processing and shipping events before it arrives at the cannery. The "tuna, quantity, and unit of measure" could capture the *what*, "wild harvest" could capture the *why*, "vessel operator" could capture the *who*, "catch area and vessel ID" could capture the *where*, and the "date, time, and zone" could capture the *when*. These types of information allow stakeholders to keep track of the parent—child evolution of products along the supply chain. For example, it could reveal that a can of tuna is manufactured using fish from a specific harvest location (Global Dialogue on Seafood Traceability, 2020).

4.3 Working with information in a common language

A common language facilitates identification of relevant information. Traceability standards such as GTS make use of identification keys. These identification keys make it possible to assign relevant information such as product type, parties, and locations to an object in a way the information is understandable among traceability parties. For example, a stakeholder records its company identifier to show in the traceability system that it is involved in a specific activity related to a trace object. No company around the world will have the same company identifier. Identifiers such as product type reveal whether the product is, for example, a bag of coffee, and the location identifier provides the location of the trace object, such as a manufacturing plant or warehouse. Unlike the company identifier, such identifiers are not necessarily unique to a specific party as, for example, many parties harvest, pack, and ship their products around the word (GS1, 2020b).

Identifiers are based on preagreed standard vocabularies to enable parties to communicate in a common language. For example, the GS1 Core Business Vocabulary offers a list of terms for business events such as "packing" and "shipping" and the disposition of products such as "expired" and "retail sold." In addition, GTS uses identification systems such as Electronic Product Codes to identify uniquely each relevant object by combining identifiers with serial numbers. A Global Trade Item Number (GTIN) is a GS1 identification key for identifying trade items. However, by itself it will only identify a specific bottle as a "1-liter brand x bottled beer," while an identification number that combines a GTIN and a serial number will identify the specific beer bottle (GS1, 2021a). The process of applying identifiers is relatively complex because the identification needs to be adjusted as the relevant object progresses through processing steps, such as picking, storing, packing, transporting, and selling, along the digital supply chain (GS1, 2020a).

As noted, one of the factors underlying the trend for businesses to adopt traceability and transparency practices in their supply chains is that consumers are becoming increasingly demanding over corporations' roles in social responsibility. In other words, consumers are seeking a traceability system with the capacity to support business practices that support sustainable development (Bush et al., 2015; Marconi et al., 2017). To this end, basic pieces of information and processes that are part of the foundation of a robust traceability system need to be expanded, including with information on policies and commitments, as well as on social and environmental impacts from production, transport, and other business operations. The commitment data provide information on businesses' sustainability pledges, while the impact data make it possible for stakeholders to see performance on these commitments (Gardner et al., 2019). For example, by collecting data on greenhouse gas emissions together with the five dimensions of "what," "why," "who," "where," and "when" for each relevant object discussed in the earlier section, the climate footprint of a trace object can be assessed (Rocky Mountain Institute, 2020).

5. Enabling technologies

Effective enabling technologies and networking environments are needed to collect, follow, and share information related to traceability (Ivanov et al., 2016). This section discusses some of the essential enabling technologies including laser, RFID, IoT, and, blockchain. This discussion is not exhaustive, and other information technologies such as cloud and natural language processing technology also play key roles in enabling stakeholders to collect and share information along supply chains (Büyüközkan & Göçer, 2018; Das, 2019; Dolgui & Ivanov, 2020; Gupta, 2018).

5.1 Laser and camera-based system with barcodes and QR codes

Technologies that enable labeling make it possible for stakeholders to tag an object with a unique identifier and other relevant information. In general, tagging an object involves encoding and printing. Barcodes and QR codes are two common and robust encoding formats used to represent unique identifiers and other relevant information for each individual object. Barcode uses a combination of one-dimensional black and white bars to represent different text characters (Abdelnour et al., 2018) and has become ubiquitous as a relatively low-cost way to increase inventory speed compared to traditional manual identification methods (Thanapal et al., 2017).

QR codes provide a two-dimensional image and have expanded the capacity of relevant information that can be collected relative to barcodes. Information being tagged could be either static or dynamic. A label tagged to an object with only static information remains the same throughout the supply chain (Qian et al., 2017). Information that is tagged to an object label and that is added to it as it moves along the supply chain is referred to as dynamic information. A common practice is to leave a blank portion of the label, allowing information to be added dynamically. Printing methods for barcode and QR codes can generally be grouped into traditional, digital, and direct marking methods. Traditional methods include flexography and offsets, while digital methods include thermal and laser and direct marking includes etching and engraving (Wasule, 2017).

In order to follow a tagged object along a digital supply chain, technologies are needed that enable stakeholders to read the tags, see the relevant information, and provide relevant comments. Laser and camera-based system technologies are used to read barcodes and QR codes labels and send the information to a host computer system and store it in a database (Li et al., 2013). However, both barcode and QR code readers can generally only identify information on the codes within a relatively short distance from the labels. The Line-of-Sight technique adopted in reading devices requires them to be placed within a few tens of centimeters from the labels (Thanapal et al., 2017).

5.2 Radio frequency identification and near field communication

RFID technology helps to address the distance restriction imposed by Line-of-Sight technique. RFID labels can be read at a distance up to tens of meters (Fraga-Lamas et al., 2016). RFID technology uses radio waves. RFID labels are made up of integrated circuits and antennas that are used to transfer information on the labels to the RFID reading devices. The readers send information to a host computer system and store it in a database. Furthermore, RFID technology has evolved over time to capture light, speed, and temperature (Fowler & Amirian, 2021). For example, RFID technology has been applied to trace temperature-sensitive products to monitor freshness to ensure quality and safety of food products (Oskarsdottir & Gudmundur, 2019).

Near Field Communication (NFC) technology is a subcategory of RFID technology that operates in the high-frequency range of the RFID spectrum. NFC makes possible two-way interactions among electronic devices. It has been broadly incorporated into mobile devices including smartphones to collect and follow information links to end users (Pigini & Conti, 2017). NFC is widely used in contactless payment systems (Fortune Business Insights, 2020). A downside of NFC technology is that it supports sharing information within a relatively shorter distance as compared to some of the other RFID technologies (Paret, 2016).

5.3 Internet of Things and blockchain

In recent years, emerging technologies have advanced supply chain transparency and traceability to make it possible for electronic devices and infrastructure to communicate and disseminate information to stakeholders in real time (Green et al., 2016). Industry Internet of Things (IIoT), designed for industrial use, is a subgroup of IoT (Ehret & Wirtz, 2017). Zelbst et al. (2019) suggest digital supply transparency and traceability could be strengthened by combining the use of RFID, blockchain, and IIoT. IoT, in its simplest form, can be viewed as enabling electronic devices to gather and transport information through the Internet (Chen et al., 2019). It attaches technology to devices such as smart phones, security cameras, and drones and links these online (Fernández-Caramés et at., 2019). Using RFID as IoTs allows scanning technology to improve on a conventional system by collecting and transmitting more than one piece of data at a time (Prakash, 2016). Adding these infrastructures to blockchain technology, information could be shared among stakeholders with a high level of visibility, strong security, and fast processing time.

Using blockchain technology to support transparency and traceability across digital supply chains is rapidly gaining attention. Blockchain offers a tool to enhance information flows and accessibility (Dolgui et al., 2020; Ivanov, Dolgui, Das et al., 2019; Pan et al., 2020). Blockchain is an encoded decentralized digital ledger, which is made up of data blocks. Each block contains relevant information on a transaction and is linked to its predecessor by a cryptographic pointer. Individual data blocks can be traced back to the first block (Dinh et al.,2018). Under public blockchain, no one party controls the data or infrastructure, while under private blockchain, only authorized parties can do so (Lai & Chen, 2018). Information is maintained by users via a network of computers and secured by cryptography (Swan, 2015). The technology has high level visibility, strong security, and fast processing time (Crosby et al., 2016) and has been tested for its potential to track shipments and trace product inputs along the supply chain (Van Hoek, 2019).

Success stories of leveraging blockchain technology for traceability systems include Walmart's use of IBM's Blockchain Platform to identify contaminated products (Lacity & Van Hoek, 2021). However, as can be expected with any new technology, the application of blockchain to support digital supply chain transparency and traceability still faces significant hurdles. Various efforts to date in leveraging blockchain to track, trace, and share information remain at the pilot study stage (Kouhizadeh et al., 2019; Wang et al., 2019). One reason is the application requires complementary tools to identify and share relevant information, in a timely manner, on labels of objects, which may not be a part of the participants' current networking infrastructure (Abeyratne & Monfared, 2016; Saberi et al., 2019). Cloud technology provides a potential solution to address some of these challenges (Novais et al., 2019). The technology enables businesses across the supply chain to collaborate and share information in real time (Ivanov et al., 2020; Shen et al., 2019), and supports real-time visibility and traceability across a multitude of actors (Kochan et al., 2018).

6. Challenges

Limited access to technology and essential traceability tools are only some of the data and technology challenges faced by stakeholders to track, trace, and share relevant information. This section considers some of these hurdles, particularly challenges associated with security, standards, data quality, integrating new technologies, and competing interests among stakeholders.

6.1 Cybersecurity—supply chain cybersecurity and multiple-party authentication

Safeguarding data privacy and preventing cyber-attacks are key challenges among entities transforming toward digitalization (Colicchia et al., 2019). Supply chain digitalization heightens such challenges, as it involves collaboration among diverse external partners who share access to data and data infrastructure (Boone, 2017). Exposure to data privacy and cyber risks can multiply as the volume of external partners working with the supply chain stakeholders increases. While an entity may have very strong cybersecurity measures in place, it may often fail to keep bad actors from infiltrating its data system through external partners' access to the system (Relihan, 2020b). This is commonly referred to as a third-party or supply chain cyber-attack. Example of supply chain cyber-attacks include unauthorized access to a stakeholder's data system using hidden algorithms embedded into software serviced by external vendors. Some of these incidents involve loss of customers' data, while others involve alterations to design blueprints so as to compromise the launch of new products (Zhang et al., 2019).

6.2 Standards—building standards and harmonization of guidelines

As discussed in Sections 4.2 and 4.3, standards create preagreed approaches for stakeholders to collect, follow, and share information. Some traceability standards have emerged around the world in recent years as a result of extensive public−private partnership efforts. However, establishing new standards only goes part way toward catching up with the needs of increasingly complex global supply chains if the diverse standards are not aligned (Brunckner et al., 2015; UN/CEFAC, 2021). For example, Willette et al. (2021) found unaligned standard definitions among guidelines led to inaccurate tagging of seafood products along the digital supply chain. Effective collaboration among stakeholders is essential in working toward a harmonized standard (WHO, 2020). The ISO, with members from over 160 national standards bodies and proven success in issuing international traceability standards, could potentially lead such an effort (ISO, 2020).

6.3 Data quality—unsynchronized data and signal corruption

Maintaining data quality along the digital supply chain is essential to ensuring the accuracy and timely delivery of shared information. Many factors can impact data quality. Some common challenges faced by stakeholders include duplicate records across different databases, collisions of signals generated by tags, and environmental factors that can corrupt information captured by reading devices.

Global digital supply chains often involve entities with facilities at multiple locations worldwide. When multiple entities hold copies of the same document, including certifications and transaction records, this complicates the data synchronization process (Leong et al., 2018). The auditing process to ensure timely and accurate data synchronization across many different databases can be costly. If any deviation in information is found in records that are expected to contain the same information, the system must be reconciled. The reconciliation process can be time consuming since it involves identifying prior versions and judging the accuracy of information contained in them. In addition, most reconciliations involve manual processes (Rao et al., 2021).

As discussed in Section 5.1, the success of digital supply chain transparency and traceability greatly hinges on stakeholders' ability to identify and follow tags such as QR codes. Collisions of signals generated by tags and environmental factors can both influence data accuracy during the data transmission process. Signal collisions occur when the placement of a reading device over a tag simultaneously activates multiple tags in the proximity. This means that various tags try to send their information to the reader at the same time. Various signals can overlay with each other and damage data quality (Tan et al., 2018). Environmental factors could also deplete data quality during the information transmission process. For example, Kumari et al. (2015) report that water and extreme temperatures can obstruct the accuracy of information carried by signals.

6.4 Integrating new technology

The rise of complex global supply chains has intensified the challenges in supporting transparency and traceability practices. This is because these supply chains often involve stakeholders across different geographic regions worldwide. A portion of the supply chains located in an industrialized country could be fully digitized, while another portion located in a developing country could still be using manual paper-based recording methods. Supply chain stakeholders often use different technologies for collecting, following, and sharing information (Agrawal et al., 2021). The need to integrate new technologies with current systems creates challenges. For example, many supply chain stakeholders are planning to leverage the use of the cloud technology in updating their traceability system to collect, follow, and share information (Schrage, 2020). However, there are various hurdles in migrating legacy software systems to the cloud. Some legacy systems were not built to support dynamic scaling of cloud resources (Fahmideh et al., 2017).

People with relevant skillsets to use the new digital technologies and infrastructure are critical in driving transparency and traceability in digital supply chains. Currently there is a significant deficit of digital skills among the workforce (Høyer et al., 2019). The challenges include attracting talent, as well as developing, managing, and retaining talent. Ruiz-Garcia and Loredana (2011) demonstrate that insufficient or poor training of employees in using the tracking and tracing technology could lead to breakdowns in supply chain traceability, including by collecting inaccurate data.

6.5 Competing interests among stakeholders

Collaboration among traceability parties who are custodians of trace objects at different points along the supply chain is essential to achieving supply chain traceability and transparency (Dubey et al., 2020). However, stakeholders will often have competing interests around enhancing traceability. For example, Relihan (2020a) describes how suppliers can have pressures to maintain big-name clients with large volume orders through unauthorized subcontracting: "If they take on too many orders to try to keep the client happy, they find that they need to subcontract some of the work out to stay on schedule. Those subcontractors may not adhere to the same labor standards." For the buyers, the unauthorized subcontractors may be blind spots in their traceability systems, and the suppliers may benefit from keeping it that way.

Stakeholders' lack of trust in each other and concerns over such blind spots are challenges for building a traceability system. "A supply chain partner's skepticism poses a threat to the adoption of traceability solutions across the supply chain" (Hastig & Sodhi, 2020). Group decision support approaches, which facilitate effective engagement among participants in a decision process, could play a key role in building trust and collaboration among stakeholders (MacCarthy & Pasley, 2020).

7. An illustrative case: the wood supply chain

7.1 Motivation and challenge

Annual global exports of forest products reached $244 billion in 2019 (UN FAO, 2020). The United Nations Forum on Forests reported that, "over 1.6 billion people depend on forests for subsistence, livelihoods, employment and income generation … but it is significantly higher in low-incomes countries" (UN UNFF, 2019). Concerns over climate change and biodiversity conservation, along with mounting concerns over links to deforestation and risks of pandemic outbreaks of zoonotic diseases, have brought increasing attention to global forest conservation (Brancalion et al., 2020). For over a decade, regulators worldwide have established regulations and policies such as The Lacey Act in the US and the EU Timber Regulation (EU Communication, 2019; United States Department of Agriculture, 2008) that make illegal timber trading punishable offenses to curb environmental degradation and negative social impacts caused by deforestation. In addition, there is increasing demand for companies to supply and use fair trade and environmentally sustainable wood products. Businesses are searching for solutions to meet legal, and customer demands while maintaining operational efficiency in the wood market (Kaakkurivaara, 2019). Digital supply chain traceability systems take on a critical role to meet these needs.

Economic incentives can be high to falsify information including the origin of wood products and the associated claims on sustainability. Countries have found falsified and tampered data in their timber traceability systems (Fraser, 2019; Mukul, 2014). To address this challenge, a traceability system with the capacity to identify illegality is crucial to ensure accurate information. Over the years, stakeholders of the wood supply chain have worked together to expand the traceability system to incorporate data and technologies that support the verification of legality claims. The case of wood product digital supply chains serves to illustrate the practical data and technology challenges in traceability systems as well as potential solutions in establishing digitally supported supply chains.

7.2 Relevant information

Wood product traceability systems collect, follow, and share information among stakeholders covering permitting, extraction, transportation, processing, and commercialization activities along the supply chain (Gaworecki, 2016). The harvest inventory associated with extraction activities is usually the starting point of wood product traceability. The harvest inventory consists of a list of trees that are expected to be extracted. The list generally contains, at a minimum, a unique identifier, location, diameter, species, and permit information associated with the trees in the harvest plan. Subsequently, each phase of the extraction such as felling, delimbing, skidding, and transporting needs to be recorded and linked in the traceability system. Depending on the final wood product type, the logs produced by the felled trees will be further processed, transported, commercialized, and relevant information for tracing the product back to the felled tree would be generated, by different stakeholders along the supply chain (Food and Agriculture Organization of the UN, 2016). Along the supply chain, information recorded by stakeholders could be for separate product units such as felled trees, logs, and other wood products or associated containers. Generally, information related to processing facilities, time arriving and leaving the facilities, environmental permits or other authorization requirements, as well as physical and chemical measurement of the products are recorded. These types of information allow stakeholders to keep track of the parent−child evolution of products along the supply chain. It reveals that a wooden doorframe is manufactured using a board sawn from a log that is linked to a specific felled tree at a particular forest location (Sirkka, 2008; Muller et al., 2019). To verify the accuracy of legality claims reported by the traceability system, additional data to support the verification process, such as images of harvesting or forest clearing activities would need to be incorporated as part of the relevant information.

7.3 Enabling technology

Digital supply chain traceability technologies for wood products can be divided into those technologies that leverage inherent features of the product and those that do not (Ng et al., 2020). Technologies that focus on noninherent features aim to collect, follow, and share information through the use of tags. They aim to identify information associated with *what*, *why*, *who*, *where*, and *when* for each relevant object at a particular point along the supply chain such as the date when an object arrives and leaves a processing facility.

Laser and RFID are two technologies being applied to tag, track, and trace data along wood product digital supply chains, though challenges remain as a result of competing interests among stakeholders, particularly in areas of poor forest governance in developing countries. The traceability process involves externally marking the trees with tags such as barcodes or RFID labels. Information on the tags, together with other relevant information associated with the extraction activities, is stored in an online database. Upon extraction, the tag remains on the tree stump and the corresponding tag is attached to the log linked to the felled tree. This process repeats at each point when a new activity takes place. A reading device like an RFID scanner is used during some of these activities. For example, at retailers, tags are read to capture information related to the sale to final consumers. Different authorized stakeholders are given access to information in the databases that are relevant for them at different points in the digital supply chain (Björk, 2011; Kaakkurivaara, 2019; Saikouk & Spalanzani; 2016). In some instances, blockchain technology has been applied or proposed to build a decentralized registry to share information among stakeholders (Costa et al., 2016; Figorilli, 2018).

Scholars and practitioners have warned that external tagging brings the risk of data tampering but this could be prevented with technologies that can examine inherent features of the wood products (Dormontt et al., 2015; Godbout, 2018). Technologies used to examine inherent features collect, follow, and share information leveraging scientific features of wood structure, molecular biology, and chemical composition. Nanotechnology and DNA technologies are two common technologies where inherent features are applied to trace a wood product unit in supply chain (Jasmani et al., 2020). These technologies recognize key characteristics contained in the wood used to make the product, to pinpoint the origin of the source wood (Schraml et al., 2020).

Technologies supporting remote sensing have also been applied to capture relevant information needed to verify legality claims and to ensure the accuracy of data shared in the traceability system. Technologies include satellite imaging and Light Detection and Range technology. These technologies make it possible to remotely capture data on forest land changes that may have involved illegal logging and to validate tree height measurements without having to take measurements on the ground (Ganz & Adler, 2019). This case demonstrates that incorporating digitalization into traceability systems leads to a greater level of transparency and traceability in supply chains.

8. Conclusion

Traceability systems play an important role in the supply chain digital transformation process. Stakeholders have incorporated digital technologies to collect, follow, and share relevant information and greatly increase the level of transparency and traceability. This chapter reviewed some of the principal issues on the what, why, and how of achieving digital supply chain traceability and transparency in relation to data and technology, as well as highlighting the most common challenges. The case of wood products illustrates technical solutions added into the traceability system to respond to the specific needs and challenges of stakeholders.

Although data and technology challenges vary across different supply chains, there are common challenges such as cybersecurity, standard setting, data quality, integrating new technologies, and competing stakeholder interests. Future needs to address these challenges include technical, policy, and business strategy solutions. A priority area for research on technical solutions is the development of infrastructure and processes to enable alignment and engagement of stakeholders for an end-to-end digital supply chain traceability system. To this end, innovations such as multi-party authentication systems are needed to keep up with the rising complexity of supply chains. More exploration of practical applications of blockchain technology would also help to understand and advance scalability.

Another area for research is linking policy and regulatory requirements. This could potentially resolve standards challenges caused by misalignments in definitions across different legal guidelines. Studies on developing policy and regulations to minimize blind spots in supply chain traceability systems are also important as blind spots can prevent identification and timely responses to unsafe products or violations of child labor laws. Research on requirements and protocols for auditing of reported information is also needed to stop reporting of falsified information.

In terms of business strategy, the rapidly growing amounts of data generated as supply chains move toward digitalization have greatly increased the size of digital information that could be considered as relevant to support supply chain transparency and traceability. To help manage these volumes, it is important to prioritize the capture of truly relevant information. Studies on aligning data needs along the supply chain to organizations' business missions would help avoid potential information overload and help guide the development of new technologies and policies to realize the greatest value from traceability systems for digital supply chains.

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Chapter 11

Digital purchasing and procurement systems: evolution and current state

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Abstract
This chapter investigates and charts the evolution of digital procurement systems. Digitally supported procurement has developed in tandem with the widespread adoption and deployment of ERP technology. Digital procurement has accelerated with the increased digital capabilities now available in contemporary organizations. Current digital procurement systems enable the automation of repeatable Purchase-to-Pay (P2P) processes. Improvements in digital technology are also supporting some strategic sourcing activities such as spend management, supplier selection, and category strategy development. These are helping to incorporate Source-to-Pay (S2P) functionality into digital procurement systems. A case study shows how digital procurement has supported a large complex tendering process in the rail industry. We look ahead to examine how future digital procurement systems may drive significant changes in the procurement landscape. The next generation of digital procurement systems will be boosted by the capture of reliable data in real-time, enhanced Data Analytics, Cognitive Analytics driven by advanced machine learning algorithms, and developments such as Artificial Intelligence and 5G enabling remote viewing. We note that research on digital procurement has focused on adoption and implementation, mirroring previous studies on technology acceptance and adoption. There are significant research opportunities to examine more fundamentally how digital procurement will change the procurement discipline.

Keywords: Digital procurement; Enterprise requirement planning (ERP); Procurement 4.0; Procurement automation; Purchase-to-Pay (P2P); Source-to-Pay (S2P).

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1. Introduction—the rise of digital procurement systems

Procurement is now established as a critical function in modern organizations with C-suite representation at boardroom level (Groysberg et al., 2011; Ramirez et al., 2020). Procurement processes bridge the gap between the upstream supply chain landscape and the downstream customer environment. Positioning the procurement function to sit at the center of an organization's value chain is becoming more common in leading global organizations (Chopra, 2019; Cox, 2015; Gattorna, 2009; Millar, 2021; Porter, 2004). Effective procurement can help organizations become more resilient to volatile, uncertain, complex, and ambiguous environments (Bennett & Lemoine, 2014) by focusing on cocreating "constellations of value" with suppliers rather than focusing on financial efficiency of simple supply chains (Ramirez et al., 2020). According to Bienhaus and Haddud (2018), "The disruptive and fast-changing business discipline 'Digitisation' is on the top-level management agenda of organisations, research institutes, politics as well as non-profit organisations." Digital procurement is major part of this agenda.

Makgill et al. (2021) estimate that global public procurement spend is currently upwards of $13tn dollars, led by governments who procure goods and services from the private sector. Bosio and Djankov (2020) note that it represents 12% of global GDP and that 77% of the total public procurement spend is spread across 17 countries with China being the largest procurer at $4.2tn per year. The market research platform, Statista (2021), predicts that the procurement software

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1. Adapted from internal Hitachi (2017) presentation.
2. Adapted from internal Hitachi (2020) presentation.

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applications market revenues worldwide will increase from $5.9 bn dollars in 2021 to $6.3 bn in 2024, a modest compound average growth rate of 2.3%, but as Radell and Schannon (2018) noted in their Bain & Company white paper, “digital technologies pave the way for procurement teams to play a larger role in accelerating business innovation.” Global ERP software providers like SAP S/4HANA, Oracle, and Intuit enjoy greater levels of year-on-year growth than the pure digital procurement software providers (Pang et al., 2021) but such systems often support some procurement processes with digital capabilities.

Rapid advances in digitalization have led major industrial organizations into a new era of global manufacturing, commerce, and trade. The new digital landscape has been called the fourth industrial revolution or Industry 4.0 (Glas & Kleeman, 2016). Adoption and successful integration of digital technologies capable of seamlessly merging business management systems into the “Digiverse” and connecting to e-commerce markets have now become a source of competitive advantage. The collective aim is to reduce intermediation and strongly improve organizational efficiency.

Digital procurement systems seek to incorporate all procurement processes, enabling the user to fully immerse in a digital environment with the aim of identifying and reducing bottlenecks to improve performance in procurement. As highlighted by Kosmol et al. (2019), “Leading companies have obtained significant process efficiencies and cost savings from the use of digital technologies in procurement. For example, BASF has done so by using IBM Watson’s artificial intelligence (AI) system to catalogue and evaluate its suppliers.” Digital procurement processes have the potential to act as enablers for companies to achieve financial objectives and reduce risk by providing seamless and wide access to accurate and relevant real-time data. Net gains can be passed on to the customer with competitive pricing or used to improve an organization’s profit margins. Improvements achieved in overall procurement performance through digitalization by some organizations may result in other organizations being pressured to react to ensure they are not left behind by the introduction of disruptive digital procurement processes.

However, adoption by industry of digital procurement systems has been relatively slow, considering that some of the early digital purchasing and procurement technology started to gain momentum in the late 1990s. A combination of technology still evolving and the readiness of organizations to digitalize their processes has subsequently slowed the pace of adoption until now (Hogel et al., 2018). The amount of data, the access to data, and the speed with which data can be processed have each greatly improved over the two last decades to the point where digital procurement systems are a viable value proposition, offering increased functionality and outputs that will become critical to procurement and business leaders. It is therefore timely to examine the current state of digital procurement system capability and functionality and understand the potential that these technologies may create for all industries and organizations. The motivation for investment in digital procurement is also influenced by the desire of many contemporary organizations to support and drive environmental improvements, sustainability, and social innovation (Kannan, 2021).

This chapter charts the evolution of digital procurement systems from early computer-enabled process functionality and supplier information repositories through to integrated dynamic systems capable of providing reliable sourcing information in real-time, enabling fast and effective decision-making, supplier segmentation, supplier evaluation, and performance analysis. Key stages in the development of digital procurement systems are examined, followed by an overview of themes investigated in current empirical research on digital procurement. The chapter then highlights the impact of digital procurement systems in practice by presenting a case study that focuses on the Hitachi Rail Group’s adoption and implementation of a digital procurement system. Finally, a discussion of the future of digital procurement systems and their potential impact on organizations is given. Conceptually, this chapter seeks to investigate how digital procurement systems have evolved (and could develop further) to help organizations fulfill all the requirements of the procurement process and embrace technology in the most efficient, frictionless, and “touchless” ways.

2. The development of digital procurement systems

Lysons and Gillingham (2020) note that “Procurement is a wider term than purchasing which implies acquisition of goods or services in return for a monetary or equivalent payment.” Eminent management strategists (Barney, 1991; Phahalad & Hamel, 2003; Porter, 2004) have argued that organizations need to focus on their internal capabilities and outsource the rest to the supply chain, shaping the way modern corporations structure their organizations. This has expanded the range and diversity of activities managed by the procurement function in contemporary organizations (Borg et al., 2019). The procurement function is now required to seamlessly integrate with both ends of the supply chain from suppliers through to customers. Aligning the end-to-end supply chain in an effective way has become critical for organizations to achieve strategic fit and retain and improve competitiveness (Slack & Brandon-Jones, 2019). A further essential requirement is the adherence to relevant internal and external purchasing and procurement rules, regulations, and compliances (Puschmann & Alt, 2005). Digital procurement systems now have the capability to bring all the key process elements together into one integrated system and help to manage compliance requirements. However, despite advances in digital procurement technology, many procurement functions still live in the analog past, performing tasks manually (Hogel et al., 2018).

The journey towards achieving fully integrated digital procurement systems has been a long one, fraught with many challenges. Progress can be charted alongside other significant computing advancements over the past 50 years.

2.1 Early computer-assisted purchasing with MRP and spreadsheets

Procurement processes were initially developed in an era when computational power was limited and basic operations such as calculating demand requirements and spend were carried out manually. Basic demand and inventory management concepts were used as early as the 1940s by UK aerospace manufacturing companies (Geary et al., 2006). Motivated by the urgent need to support the war effort, engineers performed manual calculations of dependent demand items to categorize, control, and manage stock levels. Calculations were created by exploding the Bill of Material of the aircraft design and giving each component a part number and corresponding stock unit. Agrawal et al., 2016 noted that around the same period, Lyons Teashops used early computers to plan material requirements, make orders, and manage their distribution. Each time stocks fell below a designated reorder point or quantity, more items were purchased to replenish stock.

These early procurement practices did not evolve further until computer technology became robust enough to provide a template for computer programmers to simulate procurement processes digitally (Bag et al., 2020). Developed within the same timeframe as MRP/MRPII systems (Mabert, 2007), the journey toward software enabled procurement systems coincided with the introduction of spreadsheet applications like Lotus 1-2-3, SuperCalc, VisiCalc, developed between the late 1970’s early 1980’s and finally, Excel, which entered the market in 1985 (Busch, 2016). Initially, procurement processes were developed in tandem with the outputs from MRP/MRPII systems by transferring key information on purchase requirements onto spreadsheets such as the scheduled demand requirements (usage rates) for production. The data were then manipulated to show the buyer how many components to order, what the component lead-time was from the manufacturer and other critical details on component specification and cost. According to Busch (2016), spreadsheets were used to collate the required information and buyers would procure items when instructed. There are still organizations that continue to manage procurement activities using spreadsheets and are reluctant to change from the basic functionality that they afford.

2.2 The integration of procurement and supply chain management through Electronic Data Interchange (EDI) and ERP

According to Nazemi et al. (2012), Gartner initially used the term “ERP” in 1990 when discussing the next generation of MRP systems. During the 1990s, ERP systems began to enable the integration of all core business activities including procurement (Katuu, 2020). Schoenherr (2019) notes that ERP systems often formed “the backbone for digital procurement systems.” ERP started to support procurement tasks and supplier performance management by converting demand data into requisitions and purchasing schedules. Indeed, a very first digital procurement capability came in the form of raising purchase orders, prompted by data extracted from a built-in inventory management module of the MRP/ERP system. Demand information was then exported and manipulated in Excel, prompting buyers to replenish the stock. The buyer would then raise a purchase order from the ERP/MRP procurement function and send to the supplier by fax with delivery instructions. Gradually, as the technology improved and started to be adopted within manufacturing and service industries, computer-supported procurement systems also began to develop.

Multinational (MNC) manufacturing organizations started to change their business models during the 1990s to focus on core competencies (Gottfredson et al., 2005; Mutambi & Venzin, 2010; Prahalad, 1993). That meant pushing manufacturing and service requirements upstream into the sub-tier supply chain (Sraia & Lorentz, 2019) and integrating suppliers’ digital systems with the prime manufacturer. However, organizations found that outsourcing component manufacture into the supply chain was complex and challenging, especially when customer demand profiles were unstable and volatile (Pereira et al., 2014). Coordinating the delivery schedules of multiple components with the lead-time of a final product often proved unmanageable resulting in either stock outs and production delays or excess inventory (Min and Yu, 2008). The issues caused problems for procurement when managing supply contracts and had damaging knock-on effects on the operating efficiency for organizations (Benton, 2020). To mitigate against potentially catastrophic failures, improved supply chain visibility of demand and stock requirements was needed.

The introduction of electronic data links (EDI) helped to increase integration and connectivity between both buyer and suppliers in the supply chain (Croom & Brandon−Jones, 2005) by improving the transparency and visibility of production demand requirements and supply in real time. Existing ERP systems have sought to digitalize these operational level procurement processes over the last 2 decades (Brandon-Jones & Kauppi, 2018) and in doing so have laid the foundation to enable the introduction of digital procurement systems that focus on the integration of supply chains from customer requirements through to demand planning and inventory management. However, in the early days, sharing demand information through an EDI link was often done by extracting data out of the prime manufacturer's MRP/ERP system and configuring it using excel spreadsheets. Hence data flow was neither dynamic nor seamless. Purchasing activities were also beset with further problems. Before the widespread adoption of barcoding, goods or services still required manual booking in on delivery, despite being managed through a digital system. Likewise, keeping a digital record to demonstrate that goods or services were satisfactorily delivered or completed still required manual data entry into the procurement system. Manual activities meant that reports had to be regularly updated to avoid inaccuracies in stock quantities and demand requirements, which proved to be very labor-intensive.

The emergence of the worldwide web in 1989 prompted the beginning of a new era of procurement and supply chain management due to the increased proliferation of, and access to, potentially relevant data on products, materials, parts and components, and on suppliers. As the volume, variety, and relevance of data and information on the web increased exponentially, it quickly became a valuable resource for purchasing personnel with developments such as e-catalogues (Baron et al., 2000), the integrated procurement of built assets in the construction industry (Cartlidge, 2003), and web-based e-procurement systems (Tai et al., 2010). Today's super information data highway, providing easy access across the globe for anyone with a smart device, has become an invaluable resource for purchasing and procurement functions. The implications for supply chain visibility and connectivity are profound. It has not yet, however, facilitated a widespread adoption of digital procurement systems but this reality is slowly changing.

2.3 Characteristics of contemporary digital procurement systems—P2P and S2P

The aim of the contemporary procurement function is to contribute to an organization's overall strategy while making procurement processes as smooth as possible to support effective supply chain management, i.e., to make them "frictionless," as described by Radell and Schannon (2018). For integration and collaboration to work seamlessly and add value throughout the supply chain, a robust, compatible, and flexible digital procurement system is needed. The technology needs to ensure that all sourcing requirements are met for the procurement stakeholder and that the processes enhance the procurement function's ability to not only buy the correct product or service at the right time and supply or deliver to the correct location but to ensure that robust sourcing decisions are made that will endure successfully over time. Digital procurement technology currently supports some but not all the requirements necessary for robust procurement decisions. Strong digital support is available for the operational and transactional aspects of procurement.

Operational procurement involves managing the day-to-day transactional activities of the procurement function. The Purchase-to-Pay (P2P) process supports routine operational procurement activities. Schnellbächer and Weise (2020) define P2P as "operational processes that begin with a decision to buy a good or service and end with delivery and payment." A detailed P2P activity involves formalizing demand requirements based on minimum/maximum stock levels, replenishment through order placement with receipt of goods triggering the invoice payment process. Generic P2P processes concentrate on the transactional process of acquiring goods and/or services as shown in Fig. 11.1—an example P2P process.

The activities highlighted in Fig. 11.1 demonstrate how modern-day procurement functions are often structured. The P2P process does not consider strategic sourcing activities each time there is demand for goods and services. The first two steps represent the link between the category management and strategic buyer domain with operational procurement activities. In P2P, the buyer will select from already approved suppliers for sourcing activities rather than investigate new suppliers. When completed and approved, responsibility is handed over to operational procurement personnel who are then required to manage the day-to-day operations and key relationships with chosen suppliers. Typically, each supply contract will be negotiated, awarded, and then, in most situations, handed over to an operational buyer to manage and monitor periodically throughout the duration of the contract from point of purchase to invoice payment. Purchase requisition to purchase order (PR to PO) is a similar process to P2P and is another term used to show how the procurement process is managed at an operational level from raising a requisition through to sending out the PO (Schnellbächer et al., 2018). Digital P2P systems automate this process, avoidng reliance on human personnel in purchasing. Such systems also enable non-purchasing personnel to request or initiate orders for the procurement of routine goods and services.

The need to develop an integrated end-to-end category planning and supply management strategy within the procurement process is the domain of strategic procurement. This entails categorizing products and developing a procurement strategy that fits with the overall objectives and future direction of the business (Nicoletti, 2020). Source-to-Pay (S2P) is the terminology now used for digital procurement technology that seeks to support strategic procurement and sourcing decisions. SAP Ariba (2021) define the S2P process as "a process that starts with finding a supplier, negotiating with, and

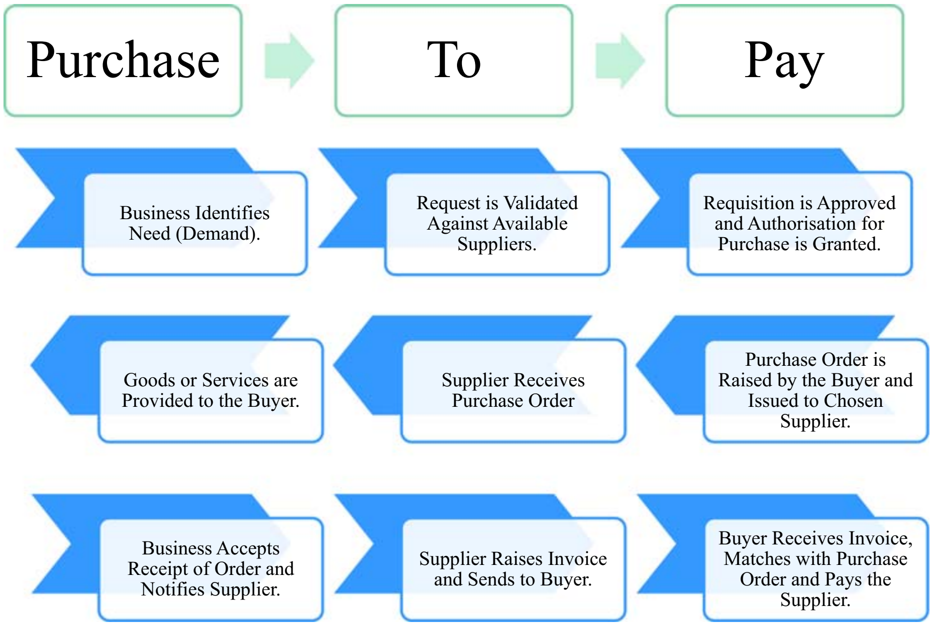


FIGURE 11.1 Example purchase-to-pay process configuration (P2P).

contracting, and culminates in final payment for those goods." A key part of the S2P process is to obtain accurate and visible analytical procurement data that support the category strategy development process. The S2P process gives the buyer a solid framework to deliver the best solution for the organization with input and critical review from chosen stakeholders at key stages of the sourcing process to ensure it fits with the goals of the organization (Jain & Woodcock, 2017; CIPS, 2020). Contemporary S2P processes tend to cover spend management, supplier selection and vetting, risk management to identify and manage supply risks in the sourcing process, and category strategy development. They may supply market research as a prerequisite to developing a sourcing strategy that could lead to a transactional relationship with a supplier (Basware, 2021). Fig. 11.2 is an example of a generic S2P process configuration.

New capabilities were being discussed by McKinsey and Company Inc. in 2016 in describing emerging solutions that could guide procurement category management through the strategic sourcing and category strategy process. They describe procurement platforms and software that helps managers to understand demand patterns, analyze the supply market, and generate savings (de la Bouleye et al., 2016). Understanding the functionality needed to facilitate category managers represents a barrier to entry for developers as each industry/supply chain may have unique supply characteristics that define them. Digital S2P capability is still treated with caution by organizations and not considered advanced enough to create and justify a category management strategy without some form of manual intervention and explanation (Schnellbächer et al., 2018). It is still common practice for category managers to have to provide adequate justification for the proposals made within the sourcing strategy. Sourcing strategies still need to receive approval and sign-off by senior management before being formally agreed with suppliers by strategic buyers and then handed over to operational procurement personnel. Reliable interpretation of data often requires an individual's accumulated experience and ability to ensure alignment with the operational requirements and context of the business. Those sets of capabilities remain closely associated with a category manager and a buyer's individual skillsets.

The latest digital procurement packages such as Jaggaer, Oracle, Allocation Network, and Bonfire (Sommers et al., 2020) do offer software that is becoming more capable in supporting and guiding the sourcing strategy and category management processes. Collaboration platforms offer greater connectivity and access to real-time data sources (Jonas, 2019), helping category managers and buyers in strategy development through to implementation, and the transition into the operational procurement domain.

The ability to digitally integrate supply chains has paved the way for access to a far greater volume of accurate digital information that is now helping to extend the digitalization of procurement processes (Schoenherr, 2019). Some of the processes have grown to encompass both strategic and operational procurement activities to support organizations achieve strategic fit and alignment with their customers and suppliers. The potential diversity of these process steps requires digitalization of the activities to have advanced data analytical and cognitive functionality. Current technology typically

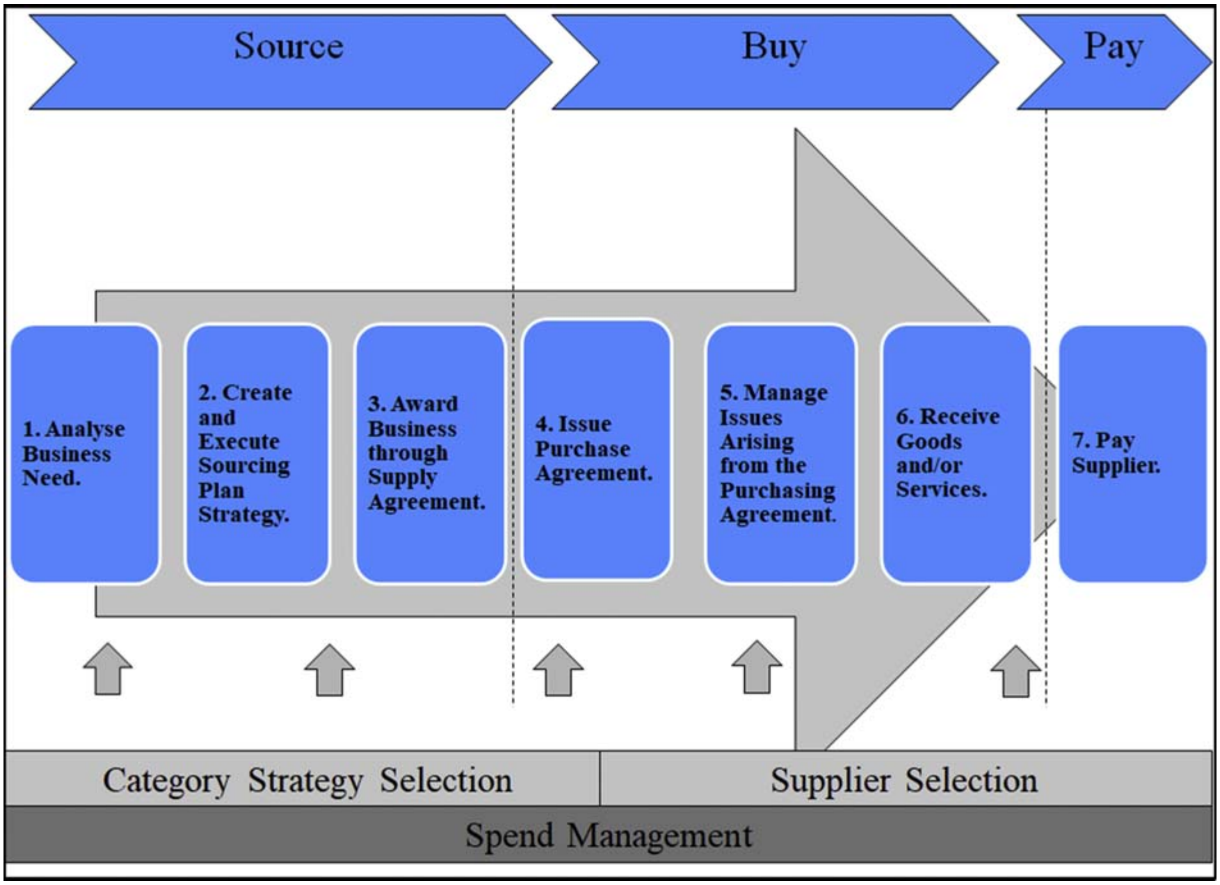


FIGURE 11.2 Example source buy pay process configuration (S2P).

only enables systems to carry out very basic decision-making tasks (Schnellbächer et al., 2018). Digital procurement software used for guiding strategy still needs to have a high level of human intervention at certain stages of the process, which may account for the slow growth rate of the digital procurement market, i.e., there is a perceived lack of return on investment when procurement personnel are still required to carry out many critical aspects of the process. For example, segmenting a product category helps to guide the category manager to define the structure and resources needed for the sourcing activity. Such decisions require cognitive decision-making by the category manager to manage significant differences between the characteristics and context of each category or commodity. Supplier management processes help to create plans for the existing subtiers and determine criteria for selecting new suppliers. Defining business requirements is context specific and so requires a level of experience and knowledge to position core products accurately should they have noticeably different supply characteristics when aligning a sourcing strategy process with the goals of the business (Chopra, 2019).

Real-time data and data integrity provide the framework that underpins analytical digital procurement software packages, enabling senior managers to interpret data more effectively. Handfield et al. (2019) suggest that the ability to capture and utilize real-time data is a key form of added value. Current technology can assist the category manager by using data analytics to collate key information and capture characteristics of a supply market in real time. Existing digital procurement systems can consolidate all the required information and convert it into analytical data that may be more easily interpreted by category managers. Example software includes services such as Smart-Cube, Compass, and E2open. Each platform offers an integrated end to end cloud-based supply chain management solution (Compass, 2021; E2open, 2021; Smart-Cube, 2021) and other business intelligence systems including supplier vetting. The E2open platform has been referenced and evaluated by Gartner's magic quadrant on an annual basis (Johns et al., 2021). The information gathered is a key component used to finalize the details of the category management strategy.

2.4 State of the art in practice

Nicoletti (2018) suggests that "Procurement 4.0" is driven by collaboration both inside and outside of the organization. State-of-the-art digital procurement systems have focused on the quality of data being managed, integrated, and interpreted, leading to real-time data driving procurement cybernetics technology (Rejeb et al., 2018). However, a study conducted by Bain & Company on digital procurement found that "Fewer than 10% of companies have deployed procurement solutions based on key technologies such as Big Data, the Internet of Things, Serverless Architecture or Block Chain Technology" (Radell & Schannon, 2018). The reality for prospective digital procurement system suppliers is that only a small number of large corporations have managed to align their systems and processes well enough to take advantage of real-time data and other state-of-the-art e-procurement capabilities.

An example of an organization that has strongly embraced digital procurement system technology is Wal-Mart, the major US retail supermarket chain. The Coupa business spend management (BSM) tool is a cloud-based system, which was implemented to streamline Walmart's companywide S2P processes (Scane, 2020). The competitive advantage created by Walmart has been achieved by successfully utilizing existing technology. Another example of how digital procurement system has been used to create competitive advantage is highlighted by one of the largest construction companies in the United States, the Bechtel Corporation. They operate a global supplier portal procured from and implemented by Oracle EBS. The supplier portal has enabled Bechtel to manage their global supply chain to support a far-reaching and diverse construction project portfolio. Once prospective suppliers progress through a rigorous approval process, the EBS system allows successful suppliers the opportunity to register, communicate, and participate in negotiations via RFI, RFQ, and/or Auctions on projects across the globe (Bechtel, 2020). All supplier information is stored and managed through the EBS data repository, providing access to buyers throughout the group. EBS provides information on all existing and upcoming construction projects across the globe, enabling qualified suppliers to bid for contracts in advance via e-auctions and tendering activities. As a result of implementing a centralized procurement system, Bechtel have the capability to consolidate multiple data streams, enabling procurement leaders to seamlessly manipulate real-time information, reducing their exposure to key commercial risk factors such as exchange rate fluctuations. Using EBS allows Bechtel's suppliers to contract in an agreed currency depending on the region. Reducing the risk on currency fluctuations through real-time exchange rate information allows senior procurement leaders to decide whether the currency strategy for a region is beneficial to Bechtel. Global currency market visibility is most effective when contracting with critical high spend suppliers who deliver products to multiple sites across the globe. Risk can be removed by hedging the currency for the duration of the contract. Thus, Bechtel's digital supplier portal supports senior leaders in making the right decision during contract negotiations.

3. Research perspectives on digitalization of procurement

Research on digitalization in supply chain management has focused on organizations' capabilities and appetite to adopt new technology for improved efficiency and its potential for achieving greater profit margins (Autry et al., 2010; Shee et al., 2018). The rapid advancements in automated technologies and the onset of hybridized digital and traditional procurement processes have left a large gap in the empirical literature. There is little literature that reports on the progress of digital procurement systems implementation in industry and the effect such systems have had on purchasing and supply chain management functions (Glas & Kleeman, 2016). Empirical research on digital procurement systems is limited as a result. Strohmer et al. (2020) note that the difficulties experienced by industry in adopting digital procurement technology has created challenges for software providers. They found that three-quarters of the companies researched were still focusing on problems identified in the early 2000s, namely spend visibility, supplier rationalization, and basic sourcing processes (Strohmer et al., 2020).

3.1 Research on digital procurement systems adoption: technology readiness

Theoretical frameworks that capture the evolution of technology and digital procurement systems were designed to identify how organizations coped with changing technological paradigms and their readiness to embrace new innovations and move into the digital age. Researchers have tended to focus on the required business environments and corporate structures that were most likely to embrace the technological functionality and operability of digital systems to gain advantages over their competitors. Implementation models were developed such as the early Technology Organisation Environment framework developed by Tornatzky and Fleischer (1990) and the subsequent Technology Readiness Index by Parasuraman (2000). Research into digital procurement systems has sought to adapt these frameworks to identify what is needed to encourage key stakeholders both downstream and upstream of the supply chain to adopt new supply chain technology (Kosmol et al., 2019).

As digital system capability in industry has become more widely adopted due to enhanced software functionality, improved data integrity, and greater computational speeds, the attention of researchers has switched from identifying the conditions needed to promote technical readiness for implementation (Spina et al., 2016, p. 18) to the characteristics and functionality of a system's usability (Brandon-Jones & Kauppi, 2018). To capture the required functionality and characteristics of widely adopted digital procurement systems, researchers have adapted the Technology Acceptance Framework (Brandon-Jones & Kauppi, 2018; Davis et al., 1989), which is a cognitive framework explaining how perceived ease of use and perceived usefulness impact on individual usage intentions.

3.2 The need for wider research on contemporary digital procurement systems

There are numerous studies that focus on the potential of digital supply chain technology in the extant literature, but these are mostly from the early to mid-2000s (Attaran, 2020). Recent case evidence is largely confined to single cases of positive experiences by niche and bespoke customers with nonrepeat procurement profiles as described by Papadopoulos et al. (2016) when conducting research on procurement in the construction industry. There is a significant amount of practitioner literature available, but the findings are often anecdotal. However, these may provide insights to ground future academic research studies. At present, Gartner's Business Information System Magic Quadrant is widely used by industry as a benchmark to compare rival systems (Schoenherr, 2019).

There are few studies, articles, or industry reports that compare successful digital procurement systems implementation versus examples of investments that have not gone according to plan or that have failed to deliver expected benefits. Investigation of successes and failures of adoption, implementation, and the performance of digital procurement systems more broadly are ripe for future academic research. Does digital procurement software functionality align with the needs of different types of industries and with the specific requirements of users in purchasing and procurement functions? Issues around "off-the-shelf" versus bespoke and customized digital procurement systems are also critically important, reflecting older debates on ERP system adoption, implementation, success, and failure (Kumar & Van Hillegersberg, 2000). There are many aspects of the digital procurement system adoption journey that would benefit from rigorous academic research including the barriers to adoption, the costs of implementation, and critical factors in achieving successful outcomes. Historically, research on adoption of technology and usage has focused on the individual user. However, it has been identified that firms display similar characteristics at the organizational level with regards to fundamental acceptance and adoption of new supply chain technology (Autry et al., 2010). More fundamentally, research is needed examining how digitalization is changing the procurement function itself and its role in contemporary organizations.

Notwithstanding the challenges in adopting digital procurement systems, their capabilities and potential are now slowly being recognized by major corporations across the globe in sectors that procure goods and services with vastly different demand profiles and levels of complexity. Hitachi Ltd is one such case, which we discuss below.

4. Hitachi case study

Hitachi Ltd was founded in 1910 starting life as a machine repair shop at Kuhara Mining company in Hitachi City, Ibaraki Prefecture, Japan. The company was incorporated in 1920. Since its incorporation, Hitachi Ltd has continued to follow a set of values on which all company actions are based - Harmony, Sincerity, and Pioneering Spirit - known as the Hitachi Founding Spirit. The set of core values drives the need to ensure that any new and innovative solutions should seek to improve social value through the development of superior, original technology and products. They strive to contribute toward environmental values, for example, by helping rail operating companies to manage rolling stock movements more effectively and reduce carbon dioxide emissions, as well as economic value by adding value for customers in the transport sector. Hitachi Ltd seeks to improve the lives of everyone through democratization of technology for the benefit of society (Von Hippel, 2006). The Hitachi Ltd 2021 global strategy is for growth through social innovation to power good. Any innovation strategy for Hitachi group companies needs to incorporate the core values and contribute to a company that has a global reach and annual revenues of £57bn.

4.1 Start of Hitachi's digital procurement system journey

Prior to 2015, it was made clear to the Hitachi Ltd board (led by four major business units forming the structure of the company) that a reform of procurement was needed. The desire for change was driven by the need to implement an S2P process on a new digital procurement platform. A fundamental requirement for the new system was to significantly improve the supplier management process by integrating procurement data used throughout the company. The initiative was motivated because of the huge amount of time and money being consumed annually by the company because procurement support systems were not integrated effectively.

Fig. 11.3 summarizes the types of problems being reported by procurement and supply chain personnel throughout the company before the new digital procurement system was implemented. They range from differences in basic operational processes around quotation activities to strategic processes around supplier selection and supplier management, and the diversity evident in approaches and systems used across Hitachi at the time. In the worst cases, it was recognized that major suppliers to multiple Hitachi business units were trading simultaneously with group companies on different commercial terms using different rates. The amount of waste generated had a serious effect on the ability to meet challenging PBIT (profit before interest and tax) targets and the specified objective to make Hitachi a leading company in the world in reducing its carbon footprint.

It was decided that work was needed to identify a digital procurement system that could digitally integrate all Hitachi group companies effectively to meet the needs of the business. To identify a system capable of integrating the supply chain of circa 800+ group companies, Hitachi Ltd conducted extensive market research to find the best fit fully integrated digital procurement system capable of interfacing with a multitude of legacy and new corporate information systems. Hitachi Ltd tasked their Value Chain Integration Group (VCIG) with the job of finding the right system for the company. With the help of a third-party research agency, the VCIG began by reviewing the Gartner Magic Quadrant ranking for Strategic Sourcing and Sourcing solutions (Gartner, 2017).

On every occasion, Bravo Solution was identified as a market leader but, most importantly, it remained as a top choice by industry peers in 2017. Bravo was viewed as the best organization to work with to engineer a bespoke system that could cater to Hitachi Ltd.'s requirements. With 650 organizations across 70 countries in both the public and private sector, Bravo Solution acts as an online data lake/storage repository, providing information for strategic sourcing projects and

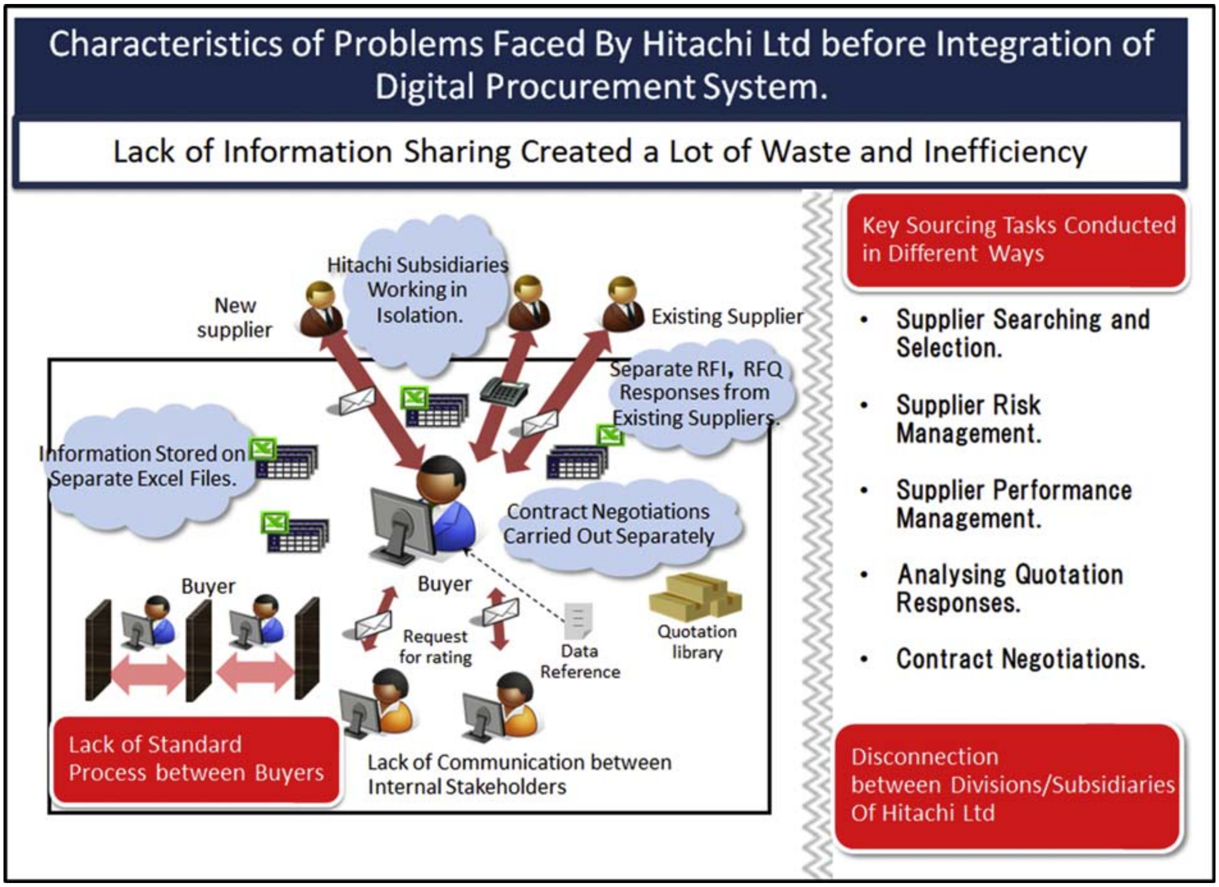


FIGURE 11.3 Procurement system problem statement. *Reform of S2C and supplier management. COE, Value-chain Integration Division Hitachi Ltd.*[1]

helping buyers to conduct RFP/RFQ activities. The repository also provides key supplier and category information needed to facilitate procurement automation (Jaggaer, 2017). In November 2017, Bravo Solution was acquired by Jaggaer. Jaggaer are an independent spend management technology company formed in 1995 in North Carolina, originally called SciQuest. They were rebranded as Jaggaer in 2017 (Jaggaer, 2021). A press release from Jaggaer explained "Bravo Solution aligns with Jaggaer's existing 'source to pay' technology suite other vertical strategy, offering a complete solution that has been adopted by businesses across the globe" (Jaggaer, 2017).

4.2 Hitachi Rail Group: implementing Jaggaer

In 2018 a Hitachi Ltd group level agreement was signed with Jaggaer to develop and deliver a configurable digital procurement system with the intent of giving all Hitachi group companies the opportunity to implement a platform capable of delivering spend management, S2P, P2P, and performance management processes and offering system integration between group companies, which had hitherto been limited. Fig. 11.4 is a schematic of the Jaggaer digital procurement system configuration architecture being deployed at Hitachi Ltd. The platform, named YUI, combines spend analysis and contract management with the S2P and P2P processes of the type described in Section 2.3. All processes use a supplier database maintained through a data lake supporting procurement across the corporation.

The first Hitachi Ltd group company outside of Japan to adopt the new Jaggaer system was the Hitachi Rail Group based in Europe, which is part of the mobility business unit. The company was originally formed in 1999 under the name, Hitachi Rail Europe. The structure of Hitachi Rail Ltd today began in 2015 when an Italian corporation called Ansaldo STS was acquired by Hitachi Ltd and rebranded Hitachi Rail Italy. Hitachi Rail Ltd and Hitachi Rail Italy were then merged to create the Hitachi Rail Group, which currently has its headquarters in London. A large percentage of the rolling stock that is built and operated by the Hitachi Rail Group is procured from a very large and complex global supply chain that includes Hitachi Ltd assembly facilities in Japan and various other sites in Europe, the United Kingdom, and North America. To improve spend management, S2P, P2P, and performance management, while simultaneously adhering to Hitachi Ltd.'s core values, Hitachi Rail Group have developed a category management structure (managing 28 separate categories) spanning four continents.

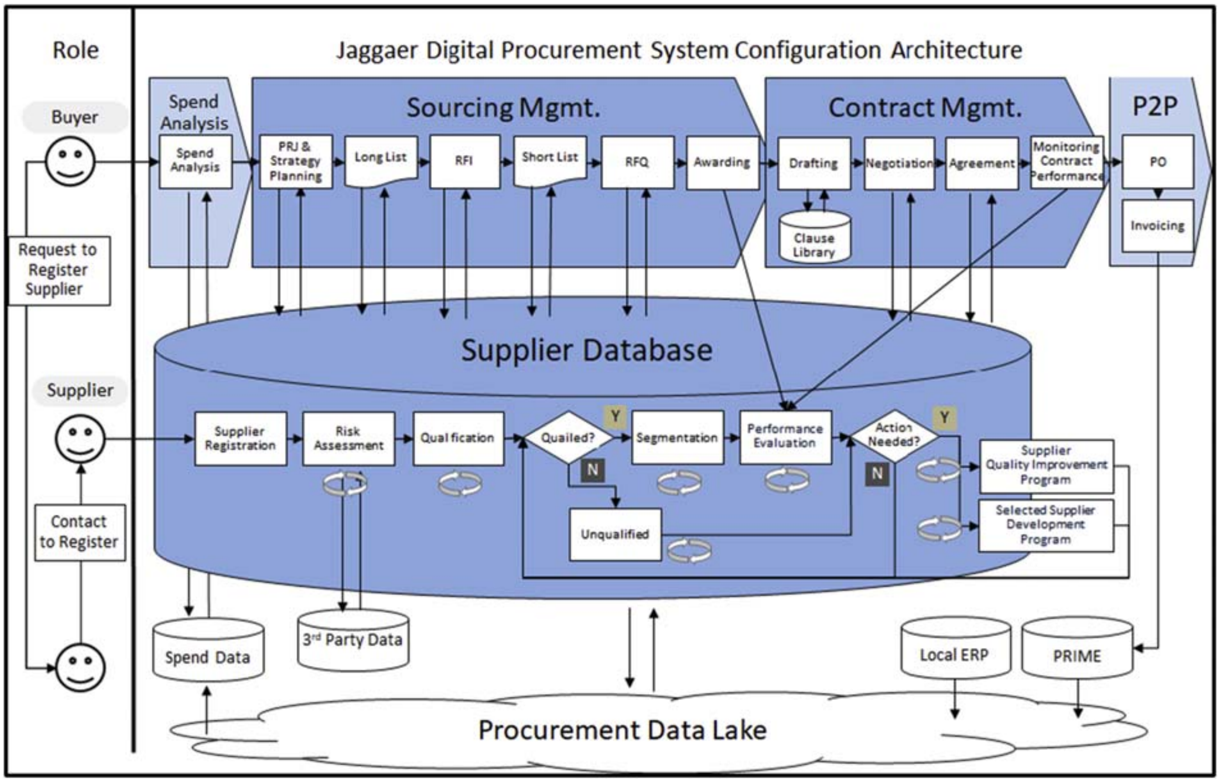


FIGURE 11.4 YUI system configuration architecture. *Reform of S2C and supplier management. COE, Value-chain Integration Division Hitachi Ltd*[1].

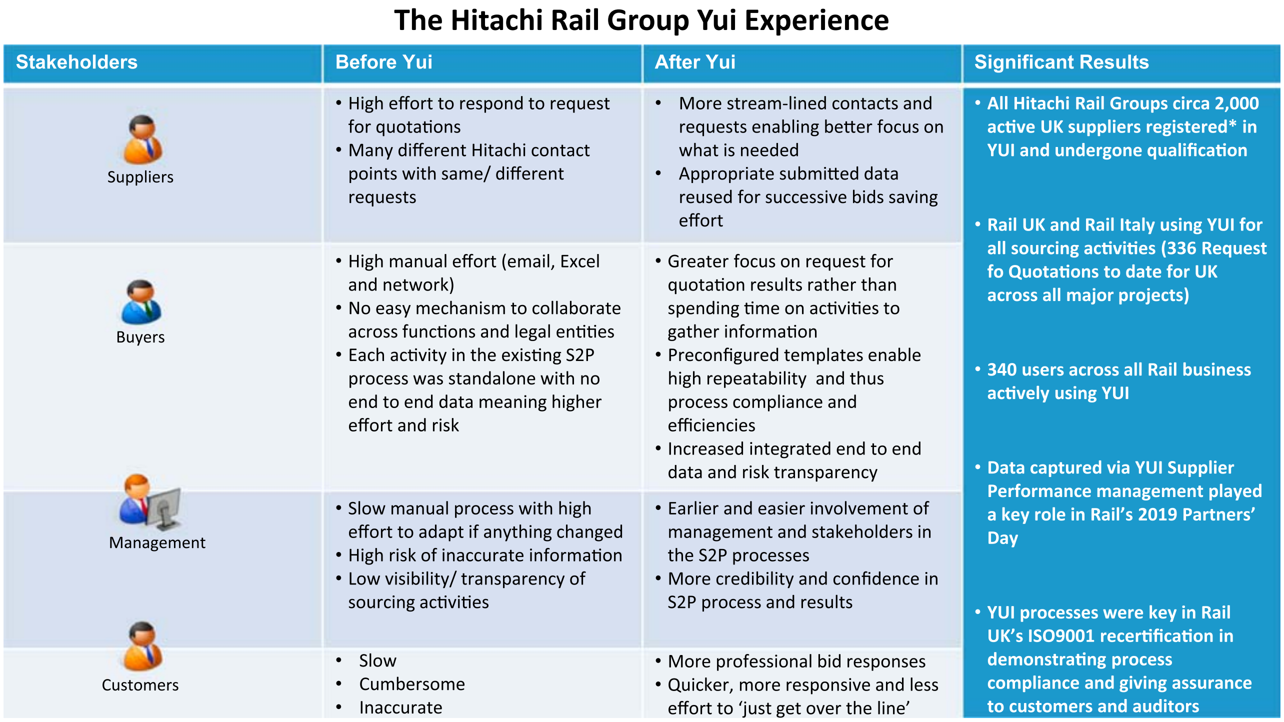
The digital procurement system was adopted by the Hitachi Rail Group in 2018 and renamed YUI which is a popular Japanese name. Hitachi Rail has progressively deployed various modules ranging from RFx to Performance Management and Contract Management. Fig. 11.5 summarizes the improvements that Hitachi Rail have made since the implementation of the system in 2018. Significant implementation progress has been made with improvements noted in processes with respect to suppliers, buyers, and Hitachi Rail's customers.

The most notable before and after improvements show that the implementation of YUI has reduced the number of manual procurement process activities right across Hitachi Rail, which has increased both the pace and the accuracy of sourcing activities. The platform has enabled procurement staff to focus on the process of organizing a sourcing strategy rather than labor-intensive jobs such as sending out and receiving commercial and technical information from suppliers. Adoption and implementation of YUI has yielded significant headline results in a relatively short space of time. Project risk management has improved because all active rail suppliers have undergone qualification and registration for YUI. The YUI platform provides complete transparency of all quality assurance activities in the supply chain. These include supplier selection activities and supplier information and past performance. The Hitachi Rail Group can demonstrate and assure compliance to government department public procurement procedures such as the UK's Department for Transport (DfT) who are familiar with Jaggaer systems as an existing customer. Furthermore, the supplier data lake functionality records and consolidates supplier pricing information attached to contracts with suppliers from all over the Hitachi Ltd group, thus helping category managers establish a "should" cost of products before and during price negotiations. The resulting information has contributed to helping the Hitachi Rail Group submit competitive bids for high profile rolling stock tenders.

4.3 Pilot study: supporting tenders on high-speed bid projects

High-speed intercity rail routes in the United Kingdom represent the largest rail infrastructure projects being undertaken in Europe today (HS2.Org, 2021). The main objective of high-speed intercity projects is to provide high-speed rail links between London and the rest of the United Kingdom (BBC, 2020). The data now being generated are helping Hitachi Rail procurement staff during contract negotiations and has significantly improved compliance and assurance, delivering competitive advantage throughout each bid process. Fig. 11.6 summarizes how the implementation of YUI has improved Hitachi Rail's ability to deliver a competitive bid for a high-speed intercity project.

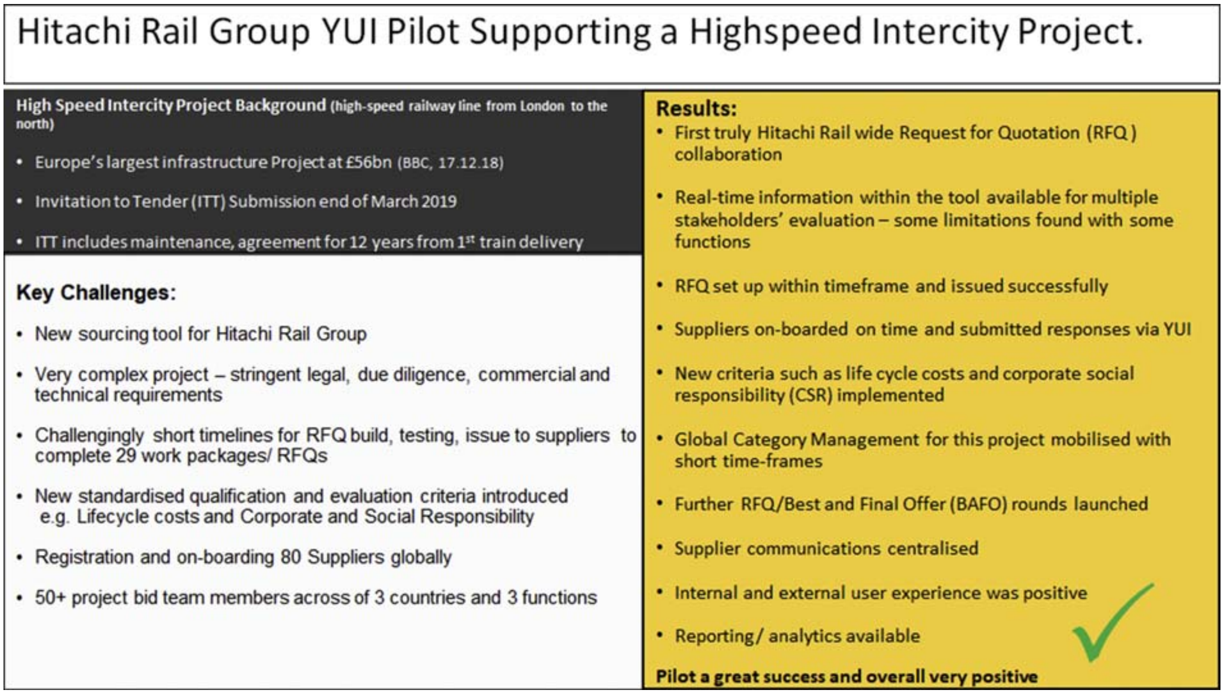
Hitachi Rail Ltd officially entered the competitive process to supply multiple train sets for one of the UK Government's high-speed rail link projects from London to the North by submitting an invitation to tender to the DfT at the end of March



The Hitachi Rail Group Yui Experience

Stakeholders	Before Yui	After Yui	Significant Results
Suppliers	• High effort to respond to request for quotations • Many different Hitachi contact points with same/ different requests	• More stream-lined contacts and requests enabling better focus on what is needed • Appropriate submitted data reused for successive bids saving effort	• All Hitachi Rail Groups circa 2,000 active UK suppliers registered* in YUI and undergone qualification • Rail UK and Rail Italy using YUI for all sourcing activities (336 Request fo Quotations to date for UK across all major projects) • 340 users across all Rail business actively using YUI • Data captured via YUI Supplier Performance management played a key role in Rail's 2019 Partners' Day • YUI processes were key in Rail UK's ISO9001 recertification in demonstrating process compliance and giving assurance to customers and auditors
Buyers	• High manual effort (email, Excel and network) • No easy mechanism to collaborate across functions and legal entities • Each activity in the existing S2P process was standalone with no end to end data meaning higher effort and risk	• Greater focus on request for quotation results rather than spending time on activities to gather information • Preconfigured templates enable high repeatability and thus process compliance and efficiencies • Increased integrated end to end data and risk transparency	
Management	• Slow manual process with high effort to adapt if anything changed • High risk of inaccurate information • Low visibility/ transparency of sourcing activities	• Earlier and easier involvement of management and stakeholders in the S2P processes • More credibility and confidence in S2P process and results	
Customers	• Slow • Cumbersome • Inaccurate	• More professional bid responses • Quicker, more responsive and less effort to 'just get over the line'	

FIGURE 11.5 Captured benefits of YUI implementation[2].



Hitachi Rail Group YUI Pilot Supporting a Highspeed Intercity Project.

High Speed Intercity Project Background (high-speed railway line from London to the north)

- Europe's largest infrastructure Project at £56bn (BBC, 17.12.18)
- Invitation to Tender (ITT) Submission end of March 2019
- ITT includes maintenance, agreement for 12 years from 1st train delivery

Key Challenges:

- New sourcing tool for Hitachi Rail Group
- Very complex project – stringent legal, due diligence, commercial and technical requirements
- Challengingly short timelines for RFQ build, testing, issue to suppliers to complete 29 work packages/ RFQs
- New standardised qualification and evaluation criteria introduced e.g. Lifecycle costs and Corporate and Social Responsibility
- Registration and on-boarding 80 Suppliers globally
- 50+ project bid team members across of 3 countries and 3 functions

Results:

- First truly Hitachi Rail wide Request for Quotation (RFQ) collaboration
- Real-time information within the tool available for multiple stakeholders' evaluation – some limitations found with some functions
- RFQ set up within timeframe and issued successfully
- Suppliers on-boarded on time and submitted responses via YUI
- New criteria such as life cycle costs and corporate social responsibility (CSR) implemented
- Global Category Management for this project mobilised with short time-frames
- Further RFQ/Best and Final Offer (BAFO) rounds launched
- Supplier communications centralised
- Internal and external user experience was positive
- Reporting/ analytics available

Pilot a great success and overall very positive

FIGURE 11.6 Supporting a high-speed intercity bid process. *Rail yui experience. Hitachi Ltd*[2].

2019. Hitachi Rail Group used the sourcing project as a pilot for the implementation of YUI. The hope was that YUI would help Hitachi Rail overcome key challenges to support the submission of a competitive tender on-time and to a high standard. As with all tenders for government-led sourcing activities, the project was highly complex from technical, commercial, legal, and compliance perspectives, exacerbated by short timelines for multiple packages of work. Fig. 11.6 shows how YUI enabled procurement staff to conduct a Hitachi Ltd group wide request for quotation that was successfully issued on time to all participating suppliers. Correspondingly, the selected suppliers were all on-boarded within the required timeframe and were able to submit their responses directly into YUI. If the tender is won, Hitachi Rail can begin the manufacture of the first train in 2022, putting it into service in 2025. The tender includes a 12-year maintenance agreement from first train delivery. The breadth of newly acquired capabilities derived from YUI provides a clear demonstration of how a digital procurement system can significantly add value on the largest scale procurement projects in a European context.

5. Looking ahead: the future of digital procurement systems

Advancements in digital procurement systems have meant that order placement can now be automated using pre-programmed bots that autonomously carry out tasks digitally in place of operational buyers who were previously doing the job manually. Tasks include the processing of purchase requisitions and raising purchase orders with suppliers (Schnellbächer et al., 2018). Digital bots remove the need for buyer intervention as the system can routinely act using predictive data analytics algorithms. The technology for automating transactional P2P processes has significantly improved on platforms such as Oracle EBS, Jaggaer, Ariba etc., as have the introduction of templates for managing S2P processes, albeit still requiring large amounts of manual intervention. Advancements in spend analysis/visibility tools, transactional P2P, and supplier performance management software have attracted more interest in the market, while the more judgment-based activities required in S2P category strategy formulation and contract negotiation appear less amenable to automation. However, Sommers et al. (2020) predict that by 2025, "all leading sourcing vendors will have the ability to generate prescriptive sourcing recommendations using machine learning." The timing may be optimistic but given the potential of digital procurement systems and their rapidly developing capabilities, significant developments can be expected.

5.1 Further automation of digital procurement systems

Improvements in digital procurement systems may motivate leading companies to move their supply chain operations to the next generation, which will see procurement processes, especially P2P, become completely automated (Nicoletti, 2018). System functionality will ensure that all automated purchases comply with procurement processes and procedures and will only require intervention from a procurement team should a problem arise. The technology could enable the democratization of the procurement process for routine purchases (Thomas, 2021). Automating the P2P process will enable procurement personnel to concentrate on solving more complex sourcing requirements.

Further automation does create further challenges. Adherence to export control law is an especially critical consideration for digital procurement system functionality. If technical information is shared with suppliers across international borders, then the data exchange must be controlled. Export control is a sensitive subject for high-tech industries and any type of data or information transfer of controlled technology (even verbally) is vigorously policed by governments including those in the US, UK, and in many EU countries. Hence, globally integrated digital procurement systems will need to have the capability to map out supply chains and indicate to the user when an export control license is required. Ignorance is not a defense. Blockchain technology may play a role to ensure all records can be traced as part of the end user declaration upon shipment, significantly speeding up the process at borders. Hvolby et al. (2021) highlight how the technology is being applied to supply chain management processes by Maersk/IBM with the Trade lens solution that uses blockchain to record and manage shipping documentation. Day to day procurement activities may be augmented by machine learning using blockchain technology to enable a permanent record of transactions from which a system can learn and adapt (Nicoletti, 2018).

Transactional P2P processes are configured to mirror agreed contract terms on performance expectations so that the system can instantly recognize when a service level agreement has not been met, triggering liquidated damage provisions automatically in real time. At present, supply chain software has the capability for payments made for incorrect or nonconforming deliveries to be instantly reversed out of a supplier's accounts including the cost of nonconformance provisions to encourage 100% delivery, quality, and cost performance. The functionality is available in existing ERP systems such as SAP S/4HANA and Oracle's JD Edwards system. Enforcement initially proved difficult to administer because e-procurement software was only capable of highlighting breaches in agreed performance metrics, not actioning them in most cases. To penalize nonconformances, De Giovanni (2020) predicts that future digital P2P processes will combine with smart contracts that utilize blockchain technology. Smart contracts are self-executing and capable of identifying contractual breaches from multiple deliveries, deducting all preagreed penalties instantly without the need for human intervention or investigation. Penalties incurred may therefore be nonnegotiable. The pressure to improve is then on the supplier.

5.2 The future of S2P digital procurement technology

Data Analytics software will play a key role in the realisation of S2P technology that enables procurement leaders to quickly extract and tailor the type of information they need from Internet sources in a way that is intuitive to the user (Thomas, 2021). Abdollahnejadbarough et al. (2020) report the application of such Advanced Analytics by Verizon to rationalize its very extensive supplier base.

There are opportunities to automate and implement "Kraljic-type" supplier categorization processes (Kraljic, 1983; Padhi et al., 2012) using appropriate data and Analytics. Digital S2P and contract management systems will have the ability to identify the best and most relevant information sources for the organization based on specific metadata. Digital procurement systems will need to be robust and flexible enough to identify and correct erroneous data, otherwise such systems will be at constant risk of failure. Handfield et al. (2019) suggest that it is not necessarily data cybernetics and access to real-time data that is going to drive the evolution of digital procurement systems throughout the Industry 4.0 period; it is an organization's ability to use the data accurately and seamlessly without data integrity issues limiting the usefulness of the outputs.

Unlike contemporary applications of digital procurement systems, (Handfield et al., 2019) note that future procurement technology will develop through Advanced Data Analytics and Cognitive Analytics. With Cognitive Analytics a computer can simulate human like intelligence traits within digital systems, i.e., to make sound judgments and decisions that were previously only trusted to human employees. The capability will be enhanced by connectivity to the information highway through cloud-based servers enabling digital procurement systems with the ability to integrate with other advanced technical solutions. Two further areas that are outside the scope of this chapter because of space constraints are platforms that seek to find suppliers and provide vetting services (e.g., Findsourcing.com and (SupplyOn, 2021) and digital support for negotiation, bidding, risk management, and auction process (e.g., Ivalua, Compass, and Exostar).

Companies will also utilize advanced communication technologies by sharing operational procurement processes in a virtual world with both suppliers and customers by remote viewing using 5G technology, live streaming and Virtual Reality (Wongkitrungrueng & Assarut, 2020). For example, having the capability to walk around the factory of a potential supplier on the opposite side of the world without physically being there saves costs on travel and helps companies achieve sustainability targets by reducing contributions to CO_2 emissions. Supplier approval audits may be conducted remotely. Performance management and problem solving can be done virtually and collaboratively rather than at arm's length.

5.3 Data integrity and cyber security in future digital procurement

Key drivers for change revolve around systems having significant machine intelligence to identify and control sensitive information and manage nonconformities. Bienhaus and Haddud (2018) note that this involves "all supply chain parties to determine weak links and define preventative measures to ensure operation of a highly connected supply chain ecosystem." Although part of the more general problem of interoperability, convergence of data formats is key to enabling digital procurement systems to interpret data streams from a globally dispersed supply chain without the risk of failure or nonconformances (Attaran, 2020). A crucial innovation will be when the technology is able to resolve data issues autonomously without human intervention and rectify failures to create continuous digital supply chain alignment. Digital procurement systems will have built in supply chain track and trace capability utilizing Big Data Analytics and IoT technology (Aryal et al., 2018). Details of each shipment may be stored on a QR code using a label on a pallet/stillage, giving customs officers all the information, they need to quickly scan documents and prevent delays at border crossings. Tracking capabilities will enable the buying organization to view exactly where the component or batch is in transit to ensure that lead-times are met. However, as earlier findings by Stephens and Valverde (2013) on e-procurement suggested, cyber security capabilities are needed to maintain sources of competitive advantage, as highly sensitive and commercially valuable data are vulnerable to cyber theft. Future digital procurement systems will require robust security protocols to not only prevent theft or sabotage of goods but also provide security for commercially sensitive data. All systems will need to be capable of continuously encrypting data to stay ahead of cyber threats.

6. Conclusions

As digital innovations are gradually adopted and as the technology progresses, the vision is that digital procurement systems will integrate with other supply chain functions and processes so that capabilities continuously evolve and facilitate the frictionless procurement paradigm (Waithaka & Kimani, 2021). As noted above, the automation of operational procurement processes is well advanced in current P2P technology. However, category management and sourcing strategy processes have proved more difficult to support using digital systems in a meaningful way, resulting in the continued use of manually supported procurement systems. The trend is unlikely to change until S2P systems prove their value to organizations. Only then will many organizations see the need to invest and catch up with the pace of change to stay competitive.

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Chapter 12

Measuring and managing digital supply chain performance

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Abstract

Measuring and managing performance to ensure the efficiency and effectiveness of business processes is a fundamental business activity. Supply chains are no exception. Various supply chain performance management frameworks and metrics have been developed by academics and practitioners and the topic is discussed widely in the research literature. However, many of the established frameworks do not appreciate the changing nature of performance measurement in a digital supply chain. In this chapter, we examine the relationships between supply chain performance metric categories and we present a data-driven framework for measuring and managing performance in a digital supply chain. The framework uses an Information Processing perspective to allow managers to visualize the flow of information and to organize the different metrics required for effective performance management of their supply chains. We use the framework to analyze three reported cases that illustrate a diversity of approaches to performance management in the digital age. We also take a step into the future and consider the impact of various emerging technologies, including supply chain performance dashboards, in the context of the framework. This chapter is aimed at managers and academic researchers interested in understanding how digital supply chains can benefit from a data-driven approach to performance management.

Keywords: Dashboard; Data-driven management; Emerging technologies; Performance management; Supply chain.

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1. Introduction

Measuring and managing supply chains to enhance efficiency and reduce costs has been a major concern at the core of operations management for decades (Balfaqih et al., 2016). Over the years, supply chain managers have used multiple techniques to enhance the performance of their supply chains. These include systems like just-in-time (JIT) (Cheng & Podolsky, 1996), total quality management (Evans, 2002), balanced score card (Kaplan & Norton, 1996), and Enterprise Resource Planning systems (Gunasekaran et al., 2004). The rise of omnichannel retailing coupled with major strides in the domain of digitalization have made supply chains of today different from the supply chains of the 20th century (Kamble, Gunasekaran, & Gawankar, 2020). Supply chain managers need to balance their overall performance management initiatives (Wu & Pagell, 2011) with the increasing need for sustainability in their supply chain operations (Kamble, Gunasekaran, & Gawankar, 2020). This sets the stage for a more evolved perspective on performance management in contemporary supply chains driven by digitalization (Cai & Choi, 2020).

The demand for digitalization in supply chains has led to development and adoption of technological capabilities to support the supply chain ecosystem. Allied Market Research estimates that the supply chain analytics market will rise to US$ 16.82 billion by 2027.[1] This includes technology firms providing services for dashboards, visualization, data crunching, as well as end-to-end performance management (Gartner, 2021). Digital supply chains have many more touchpoints and thus many more avenues to collect data and monitor supply chain performance (Nasiri et al., 2020).

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[1] https://www.alliedmarketresearch.com/supply-chain-analytics-market.

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Proper management and utilization of the capabilities provided by digitalization can provide opportunities to managers to improve the overall performance of the supply chain. However, digitalization initiatives across various aspects of business have also shown that inefficient management of data and technology may lead to chaos (Carillo, 2017; Jha et al., 2020). For instance, GE's transition to Internet of Things (IoT)-based product platforms resulted in significant loss of market value due to inefficient management of the digitalization initiative.[2]

Data are at the forefront of the digital revolution in supply chain. In this chapter, we present a data-centric view of performance management. This is driven by the existing digitalization initiatives as well as forthcoming technological innovations. Our proposed framework takes inspiration from an information processing framework (Ballou & Pazer, 1985; Sullivan, 1976; Zachman, 1987) and maps the different supply chain metrics to this data-based view. This framework enables managers to visualize the flow of information and to organize different metrics required for efficient management of supply chains. We present three case studies as representative examples to show how a data-centric approach to supply chain performance management can be designed and implemented in firms. In the last section, we present the impact of emerging technologies like blockchain and supply chain networks on the data-driven approach to performance management.

2. A framework for performance management in digital supply chains

2.1 Traditional view of performance management in supply chains

Neely et al. (1995) defined supply chain performance measurement systems as "a set of metrics used to quantify the efficiency and effectiveness of actions." Traditional supply chain performance management efforts have focused on resources, output, and flexibility (Beamon, 1999). Supply chain measurement studies have argued for the measurements to be verifiable to enable assessment of current status as well as assessment of its relationship with a target or goal metric (Melnyk et al., 2004). The measurement metrics could be used to monitor and control processes within the firm (also called as internal supply chain performance management) or outside firm boundaries (external supply chain performance management) (Kamble, Gunasekaran, Ghadge, & Raut, 2020; Maestrini et al., 2017).

Beamon (1999) stated that "the important challenge in creating any performance management system is deciding on what to measure." Supply chains are complex systems that have multiple subsystems, different actors, individuals, and processes intertwined with each other (Cheng et al., 2014). In this section, we summarize some of the major schools of thought on performance management in supply chains to highlight the major factors that need to be managed and measured to ensure high performance in supply chains.[3]

Balanced scorecard has been one of the foundational techniques for measurement of supply chain performance. Proposed by Kaplan and Norton (1996), it has been adapted in SCM by incorporating dimensions such as SCM goals and improvement. Another well known approach was proposed by the Supply Chain Council as far back as 1996, called the Supply Chain Operations Reference (SCOR) model. It was developed around the measures of cycle time, cost, service quality, and assets, and has had wide application in the retail and FMCG (Fast Moving Consumer Goods) sectors (Anand & Grover, 2015). The Resource Output Flexibility (ROF) model (Beamon, 1999; Chae, 2009) considers dimensions including resources, output, and flexibility and has been widely used to categorize the ever-growing number of metrics that firms may wish to analyze in a supply chain. Chae (2009) proposed a framework by adopting SCOR's meta level processes and combined them with Beamon's ROF classification. There have been other models proposed that aim to align the SC performance with firm's strategic goals. Bourne's (2000) framework is one such system that aligns the performance measurement system with firm strategy. Van Hoek (1998) proposed a framework to enable measuring performance that allows for supply chain competitiveness and directs management attention to those areas for supply chain optimization.

Literature on supply chain performance management has discussed three distinct measures to study the performance. These include measuring the resource performance (resource utilization), the flexibility performance, and the performance of output management (Arzu Akyuz & Erman Erkan, 2010; Beamon, 1999). Another area of performance management that has gained significant attention in recent years is reverse supply chain performance (Maestrini et al., 2017) to monitor return streams and more recently the circular economy.

An important aspect of managing any successful supply chain is the management of resources that are fed into the production systems (Elrod et al., 2013). While a host of resource level measurement metrics have been suggested in the

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[2] https://www.forbes.com/sites/blakemorgan/2019/09/30/companies-that-failed-at-digital-transformation-and-what-we-can-learn-from-them/?sh=2f406f78603c.

[3] For a detailed review of performance management systems, please see Maestrini et al. (2017), Arzu Akyuz et al. (2010) and Kamble, Gunasekaran, Ghadge, and Raut (2020).

literature, they can be grouped and studied together in three major subcategories—inventory, supplier, and production management. Inventory management metrics correspond to measuring and managing the levels of inventory that a firm holds (Elrod et al., 2013; Kamble, Gunasekaran, & Gawankar, 2020). These can be further subdivided into measures for finished goods inventory (FGI) or work in progress inventory (WIP). The second part of resource utilization is supplier management. Supplier management metrics can include metrics like raw material inventory (RMI) and supplier cost management (Elrod et al., 2013; Kamble, Gunasekaran, & Gawankar, 2020). The third part of resource management corresponds to the process of manufacturing itself. The prominent metrics employed in measuring this aspect of supply chain performance are manufacturing cost, return on investment, and wastage (Hendricks & Singhal, 2005).

This leads us to the second group of measures essential to understanding the performance of any supply chain—output-related measures. The first among the constituent measures are quality measures. Quality metrics analyze the failure rate of products being manufactured and sold through a firms' processes (Beamon, 1999). The second-related metrics correspond to customer service metrics that measure how quickly any potential problem is resolved and the loop closed (Kamble, Gunasekaran, & Gawankar, 2020). The third set of metrics relate to distribution management that is central in ensuring that the products produced by firms reach their end customers (Elrod et al., 2013). These are measured in terms of the cost efficiency of distribution channels as well as time efficiency of the channels. Performance dashboards are an important component of this element. Real-time dashboard-based monitoring and benchmarking against set targets provides managers the ability to ensure firms are able to deliver cost and time-efficient output. Without time-efficient channel monitoring, it is challenging to ensure JIT inventory management practices.

The third major category of supply chain metrics relate to flexibility (Stevenson & Spring, 2007). Managers require data on the flexibility aspects of the supply chain to ensure their firms are sufficiently flexible. Flexibility metrics can also be classified into three major groups. The first of them is modularity measurement, which measures the modularity of products and the production process (Lau et al., 2010). Studies in the domain of modularity of products have indicated that modular product architectures allow firms to be able to react faster and respond to changing consumer demands quickly (Lau et al., 2010). The second metric corresponds to the adaptability of the supply chain (Wamba et al., 2020). Adaptability metrics seek to measure how a firm and its supply chain can adapt to changing consumer demands, and poor supplier or distributor performance. The third component is diversity comprising metrics on the diversity of suppliers and distribution channels that may help to minimize risk and provide more flexible crisis management opportunities to a firm (Babich et al., 2007).

The increased focus on sustainability and wastage reduction has also prompted firms to pay more attention to reverse logistics and hence measure and monitor firms' performance in this aspect (Kocabasoglu et al., 2007). Maestrini et al. (2017) in their review of supply chain performance management studies have identified the growing role of reverse SCM metrics. An important point to note is that reverse SC metrics are not impacted solely by a firm's resource management. They are also affected by output management practices such as outgoing to incoming product ratio and the effectiveness of the reverse SC (Pochampally et al., 2009). Along with reverse logistics—related measures, another set of performance metrics relate to capacity utilization measures, which are dependent on primary constructs of resources, output, and flexibility (Maestrini et al., 2017). Capacity utilization metrics measure a firm's performance in utilizing its available manufacturing capacity. Capacity utilization targets vary substantially by sector.

Fig. 12.1 illustrates the different groups of supply chain measures and their corresponding role in different parts of supply chain management. The bidirectional arrows show the interdependency between different groups of measures. The relationship to the second-order metrics of capacity utilization and reverse logistics are shown with dotted lines.

2.2 Importance of data in digital supply chains

There are two major things that distinguish digital supply chains from the traditional ones. These are (a) an enhanced system wide integration and (b) use of digital technologies to monitor and collect data about each and every stage of product movement in supply chains (Büyüközkan & Göçer, 2018; Nasiri et al., 2020). Performance management systems designed for the digital age have to account for these characteristics and, most importantly, the availability and collection of large amounts of data for supply chain operations.

Research studies have identified the need for accurate data to assess the performance of supply chains at operational levels. As far back as 2004, Gunasekaran et al. (2004) stated that "Operational level measurements and metrics require accurate data and assess the results of decisions" (p. 335). With the rise of performance management philosophies like JIT, coupled with the growth of globalized supply chains, the need to ensure accurate data for effective and precise management in supply chains has only increased (Li et al., 2018; Singh et al., 2018).

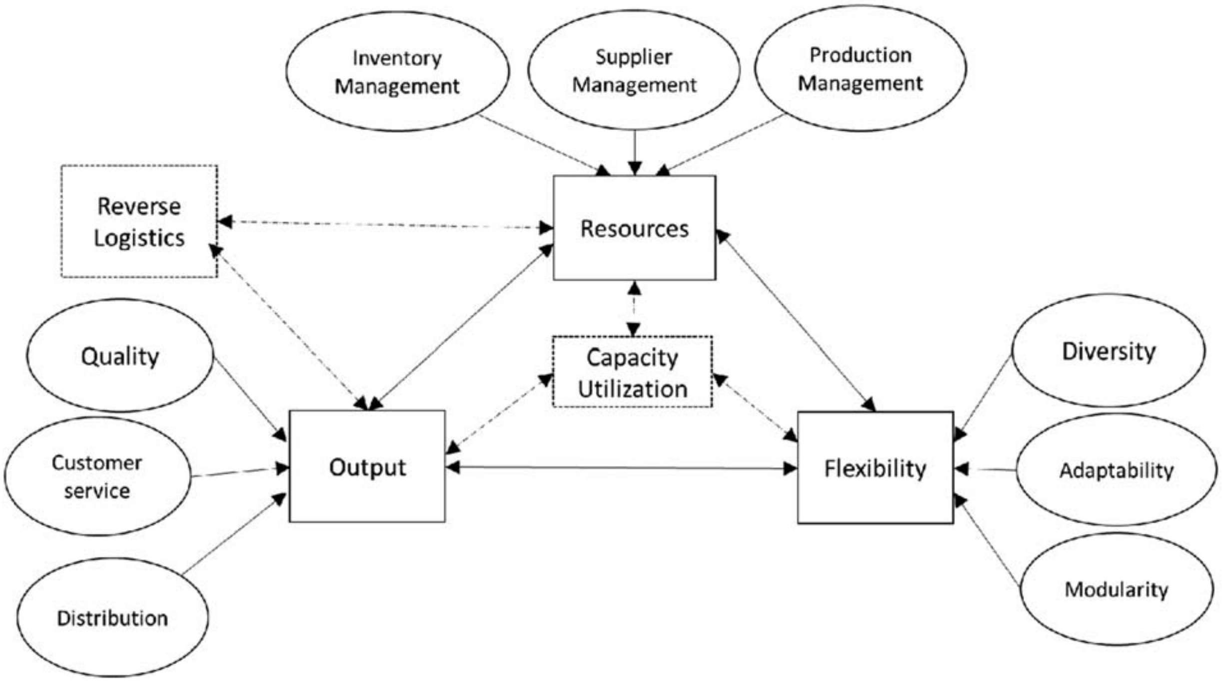

FIGURE 12.1 The relationship between the major supply chain performance metric categories.

The digital supply chains of the current age require faster response and, as a consequence, need fast analysis of performance metrics. Arzu Akyuz and Erman Erkan (2010) pointed out that supply chains would do well to resolve issues around the high number of metrics made available and the link between overall strategy and measurement. The availability of data from the different stages of the supply chain can enable managers to make better and more informed decisions. This has also increased the need to incorporate Big Data and Analytics in supply chains (Jha et al., 2020). The integration of data-driven processes in supply chains necessitates a data-centric view for performance management. A data-centric view of a supply chain is consistent with data-centric views being widely advocated in industry, areas such as IoT (Qin et al., 2014), information security (Umer et al., 2017), and innovation (Werder et al., 2020), among others.

2.3 A data-driven framework for performance management

A digital supply chain is heavily reliant on technological advances in Big Data Analytics, automation, and digitalization, to optimize the performance. The management and measurement of performance in such a system is reliant on high quality data collection and on following the data trail (Nasiri et al., 2020). The data trail refers to the way data are generated and transformed in a systemic process with multiple subprocesses (Broughall, 2015). We propose here a data-driven performance management framework for digital supply chains.

The fundamental building block of the proposed framework is the input—process—output (IPO) framework that broadly classifies a digital system into its three major subsystems (Ballou & Pazer, 1985; Sullivan, 1976). The IPO model has been used widely in the extant literature to understand topics such as group behavior (Ilgen et al., 2005), information systems development (Seidel et al., 2013), and new product development analysis (Stock, 2014). A digital supply chain relies on accurate and timely dissemination of data along with the physical materials to ensure its efficient performance (Nasiri et al., 2020). Hence, capturing and analyzing data at differing stages of such a transformation ensures that managers have insight into every step of the process. Our framework proposes an additional stage of "outcome" that translates the outputs of a data-based performance management system into actionable insights.

The framework, shown in Fig. 12.2, is a decision enabling framework that supports managers to answer the question of "what data can be used", in "what fashion", leading to "what kind of decisions."

The input data for the processing stage are sourced from relevant parts of the supply chain. The input data will vary from supply chain to supply chain and will depend on the type and complexity of production. Typically, for retail or FMCG it is likely to consist of

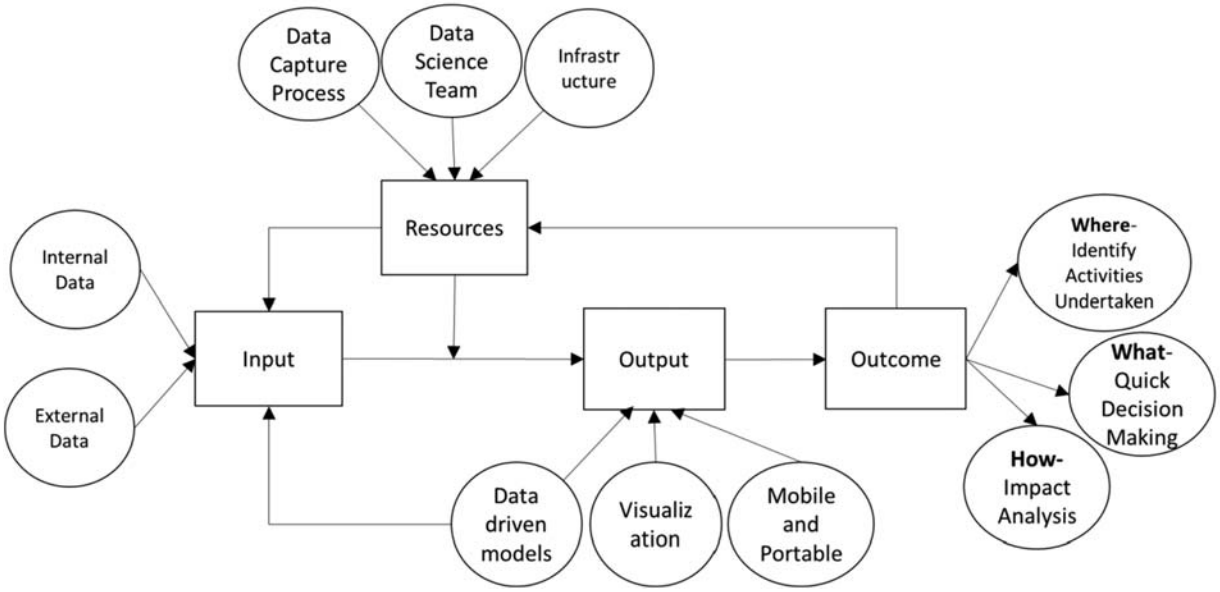

FIGURE 12.2 A framework to denote the relationship between data driven inputs and supply chain performance outcomes.

- Inventory data—RMI, FGI, WIP
- Distribution data—lead times, inventory turn over
- Costs data—raw material costs, manufacturing costs, distribution costs
- Sales and marketing data—revenue, advertisement, marketing
- Quality management data—fault rate, waste management
- Customer data—customer service level

These sources of data are not an exhaustive list but rather indicative and are likely to vary for different industries. Extant research has classified the data into external and internal sources (Bourne et al., 2000) to separately capture and identify data generated within the firm and outside. The next step in managing and measuring the performance of supply chains is processing the input data into useable outputs. Digital supply chains require specialized processing and output mechanisms to be useable by managers in day-to-day operations (Jha et al., 2020; Nguyen et al., 2018). The processing of input to output in a data-driven digital system is dependent on three major types of data processing resources. These are the process—data capture process, the people—data science team, and the technology—data storage infrastructure (Sun et al., 2018). Efficient performance measurement and management systems need to optimize the use of the three data processing resources.

- Data capture process—No amount of processing can convert wrongly captured data into useful insights. The requirement is to have verifiable and accurate data collection from all stages of procurement, manufacturing, and distribution (Côrte-Real et al., 2020).
- Data science team—Large amounts of data require highly specialized skills to be able to extract insights from them (Sun et al., 2018). A strong team should not only have excellent data skills but a nuanced understanding of business processes and supply chain to be able to comment authoritatively on the required metrics.
- Data storage infrastructure—Research in the domain of big data for supply chain has repeatedly called for high quality technical infrastructure for supply chain divisions to ensure the reliability of the insights generated from datasets (Liu, 2013; Zhong et al., 2016).

Output from the processing of supply chain data needs to fulfill two basic criteria to be useful for most managers. First, the output should be bite-sized (Hardoon & Shmueli, 2013). This implies that the output should be easy to understand and consume for managers. Secondly, the output should be portable and easy to view on multiple devices (Hardoon & Shmueli, 2013). Growing usage of mobile and handheld devices in firms (Stephens, 2020) mandate that the outputs be easy to view in these small devices to be of use in real-time. Hence, the output from the data processing systems should have the capabilities of being adaptable to the screen being used, have high visualization content, and use appropriate models to make correct projections. This also increases the importance of visualization through dashboards in the performance measurement and management domain. High quality visualization in the form of dashboards can enable quick absorption of the insight as research has shown the presence of the goldfish effect or "short attention span" for modern managers (Galloway, 2017) (see Section 4.1).

While it is essential that the outputs of a data processing systems are presented in an easy to read manner and are portable, business requirements necessitate the translation of these outputs into actionable points. An effective performance management system in the digital age should be able to utilize the information from an organization's data processing systems to help make effective decisions (Akhtar et al., 2019). There are three kinds of decisions that should be supported by the system:

- Where—The system should be able to identify where business intervention is required. A digital supply chain may collect data from innumerable points in the whole supply chain. The need for quick processing and action is high in a world of increased competition (Sauter, 2014). Hence, the need for the systems to identify the critical action points.
- What—Research in decision support systems has repeatedly highlighted the effectiveness of systems that propose not one but multiple possible human interventions in a system supported decision-making setup (Metcalf et al., 2019). The system should provide a choice of interventions that businesses could employ to resolve the issue in the current supply chain.
- How—The system should have predictive capabilities (Raffoni et al., 2018). With such capabilities, the system would be able to predict the impact of the suggested changes or interventions. This would enable businesses to have higher confidence in the decision being taken with the assistance of the system.

This is an indicative structure for performance management systems to support businesses in their use of digital supply chain data. A point to note here is that not all performance management systems in all supply chains will have all the components identified in our framework. Also, the components of the framework may not be linked in a linear fashion. There may be complex interconnections in the feedback loops in Fig. 12.2.

3. Case studies

We discuss three industry case studies that have used data and analytics-based performance management systems to enhance decision-making in their supply chains—Cisco Systems, Ramco Cements Limited, and Tetra Pak. These are primarily manufacturing companies belonging to different industry verticals—information technology, cement, and packaging, respectively. The cases represent three different geographies with Cisco Systems from the United States, Ramco Cements from Asia (India), and Tetra Pak from Europe (Sweden). Although the three case studies are similar in the way in which they make use of analytics for performance management, they also depict how the use of analytics for performance management has advanced over time. Cisco Systems is the earliest of the case studies (around 2010) and shows how analytics allowed the company to move from an operations focus to a customer focus. Ramco Cements belongs to a later time period (around 2012) and shows the use of visualization and dashboards for performance tracking of employees and dealers. The Tetra Pak case study is the most recent one (around 2017) and showcases a number of advanced features for performance tracking and visibility over the entire supply chain that helped in fulfilling the objectives of the company.

3.1 Cisco Systems

In order to understand the role of data science in a company's performance management, Johnson (2012) studied the role of data-led descriptive, predictive, and prescriptive analytics in the Customer Value Chain Division of Cisco. The division, which was part of Cisco's Operations group, was responsible for integrating its globally dispersed supply chain that involved nine functional teams in 32 countries. These teams managed more than 50,000 purchased parts used in building 8,000 products. The products were mostly configured to order and so understanding customers' preferences and delivering the products while satisfying those preferences was a major challenge. About 86% of products were delivered by channel partners and this made order management and delivery a daunting task. The teams worked with 1,000 suppliers, 4 contract manufacturers, and 5 original equipment manufacturers. The division was given the responsibility to come up with a unified strategic plan that could connect the widely dispersed teams located all across the globe. The leadership team at Cisco wanted to know which levers in the supply chain affected customer experience.

To go about this data-centric exercise, customer metrics were preferred over the previously dominant operational metrics. These customer metrics included the number of product launches that fulfilled customer needs, the number of customer orders that were delivered on time, without errors and with complete documentation, and the customer satisfaction that was recorded at the time of delivery of the product. Most of the data were obtained from the CRM system in use at Cisco (Bhaskar & Zhang, 2005). The data were stored on a platform that automated performance reporting and helped to identify the various key cause—effect relationships between the different customer metrics. The data science team comprised subject matter experts, analytics leaders, six-sigma black belts, among others.

The company used a Balanced Scorecard as well as its component, the Strategy Map, that provides a visual depiction of the strategic goals pursued by the organization (Hu et al., 2017). These tools were used to shift the emphasis from operational efficiency to customer satisfaction for manufactured products. Each of the scorecard metrics identified by the company was mapped to the customer "moment-of-truth" to highlight the most impactful metrics using strategic analytics. Regression models, structured equation modeling, longitudinal studies, and behavioral modeling were commonly used. Although the analysis started first with descriptive analytics, it soon moved to predictive and prescriptive analytics to deliver more impactful results. The exercise aimed to move the company from a product centric to a customer-centric view (Lee & Day, 2019).

A series of workshops were conducted by the data science team. These were mandatory and brought together various stakeholders of the company under the same roof. These included the key influencers who could motivate others to join the initiative; the skeptics who did not support the initiative and who had to be convinced of its benefits; and the data scientists who could provide and analyze the data to satisfy the skeptics. In order to add external validity to the work carried out, a survey was conducted by an external firm. The survey showed what dimensions of quality affected customer satisfaction and operational effectiveness, similar to a Six-Sigma approach.

The initiative resulted in several achievements. The focus of the division shifted to efficient order management and delivery to customers. The division realized that the performance quality depended on the quality of the product components. Contrary to popular belief, returns of products did not strongly impact the customers' satisfaction with the delivery of the product. However, the impact of lead time on customer satisfaction was high and so it was imperative to control the metrics that influenced the lead time of an order. The number of deliveries of perfect orders of products to customers increased significantly. This led to a tremendous improvement in the reported customer experience. At the same time, the initiative resulted in the company adopting intelligent ways of looking into customer metrics through environmental scanning, strategy review, functional scorecard development, and strategic initiative storyboarding. The initiative led to improvements in a number of key metrics such as customer satisfaction, perfect orders of products achieving Six-Sigma quality, and employee feedback that showcased their familiarity with the strategy of the division.

3.2 Ramco Cements Limited

Dutta and Bose (2015) studied the application of big data analytics in one of the projects of a cement manufacturing company, *Ramco Cements Limited*. Ramco Cements manufactures and sells "Portland cement" all over India. Cement is a very competitive industry in India and Ramco was in the process of increasing its footprint in the country. However, Ramco was not able to monitor the performance of its own employees in an efficient manner due to the presence of manual processes and data collected in the form of spreadsheets. Moreover, the key performance indicators (KPIs) used for performance evaluation suffered from various inconsistencies (e.g., multiple names for the same KPI) and could be manipulated to obtain higher financial rewards. The top management of Ramco wanted to bring transparency to the performance evaluation process. They used a technology-centric business intelligence system called PerfMon to overcome these difficulties (Vallurupalli & Bose, 2018).

Ramco captured the data that were needed for PerfMon from the in-house ERP system. No manual entry of data was allowed. The project team went through a rigorous process of identifying suitable KPIs as well as the weights of these KPIs to be used for evaluation of performance of Ramco's employees. The historical values of these KPIs for all employees were obtained for ease of comparison of performance with the past. The project team consisted of the members of the IT team who were responsible for the technical design and for interfacing with the various users and discovering their requirements and concerns.

The PerfMon consisted of three main components—analytics engine, dashboard, and a Google Maps—based interface. The analytics engine helped to obtain trends from the performance data. It also computed summaries and allowed comparisons within various peer groups so that incentives could be provided to the employees. Visualization played a major role in making the business intelligence system user friendly and intuitive. The managers could visualize the performance of employees at different locations and compare their performance with others with respect to the KPIs that they could select from the interactive interface. The system was accessible from mobile devices.

The PerfMon system was also used for tracking the performance of Ramco's dealer network that was responsible for selling cement to end customers. The Google Maps–based dashboard showed the geographical locations of each distributor on a map of India. It was a color-coded heat map that showed how the distributor was performing in terms of various KPIs (e.g., sales volume, payments outstanding, sales growth, etc.). The PerfMon dashboard for the distributors provided visibility to the leadership team about which distributors were performing well and which were below par and needed intervention. It also helped the managers to identify weak markets where the competition was strong and the growth was low (Dutta & Bose, 2015).

The leadership team at Ramco realized that large-scale adoption was a necessity in order to make this system successful. They took several actions to make it happen. The employees were stopped from using any spreadsheets at the meeting. They were only allowed to use PerfMon for discussion of performance. Also, several workshops were conducted by the IT team to train users on the use of the system and to respond to any of their concerns. A utilization report was published from time to time and users whose utilization fell below the expected level were sent alerts about their low usage. The result of these actions was high usage of the system, little to no resistance to change, and higher transparency of performance evaluation throughout the organization. The managers could use the system to generate different insights from the review meetings, which became shorter as well as more productive. The employees reported that due to the time savings at the review meetings they could dedicate more time to solving customers' problems. The performance evaluation system implemented at Ramco largely achieved its objectives with a small financial investment. It was able to stop manipulation of KPIs and was able to facilitate data-centric performance-related decision-making.

3.3 Tetra Pak

Maroff and Seifert (2020) studied the performance shift in Tetra Pak's supply chain owing to the digital transformation initiatives undertaken by the company. Tetra Pak was best known for the manufacturing of four-sided containers to store liquids. The company had annual sales of 11.5 billion euros and had a presence in 160 countries. The company deployed 12 different types of packaging systems for containers to be used for different types of liquids. Tetra Pak's goal was to have 40% of its packaging recycled by the year 2020. Tetra Pak was a strong user of technology and made various technical advances to reduce logistics cost and ensure high efficiency in its operations. The company had three priorities—a connected workforce, advanced analytics, and connected customer solutions with digital capabilities. It wanted to use latest technologies to serve these priorities.

A 2016 study of Tetra Pak showed that it lacked mobility and analytics solutions. In order to overcome these shortcomings, the company built a Data Science Centre of Excellence. A global analytics team was responsible for spearheading innovative initiatives. One goal of this team was to track the performance of equipment used in the factories using sensor data. Almost one billion data points from numerous sensors from more than 20,000 pieces of equipment were stored in the Microsoft Azure cloud-based system. Along with that, materials movement data from RFID devices and automated guidance vehicles in factories were also stored. The company also used remote sensors to track the critical parameters of complex equipment that were operating in its customers' premise. The data were used primarily for the purpose of predictive maintenance. Machine learning and pattern recognition algorithms were used extensively to identify equipment that needed immediate service.

Tetra Pak devised a new platform called Xamarin for building mobile apps that could be beneficial to the employees of the organization to accomplish their operational and maintenance activities. The company organized 2-day Xamarin hackathons where the attendees brainstormed about various mobile applications that could be built. After the hackathon design sprints were organized, external experts, functional experts, and the data scientists worked together to devise the best digital solutions for the problems on hand. One such development was the use of Microsoft's HoloLens[4]-based Augmented Reality solution that could identify maintenance-related requests and carry out repairs much faster. The device was connected through the mobile app to expert teams at the headquarters in Lund to solve various technical issues. Another important innovation was the connected package[5] where the use of QR code on packaging allowed the user to log on to Tetra Pak's database and get the latest information about the ingredients and nutritional information about the products. Tetra Pak also created an end-to-end supply chain control tower that provided managers with real-time data about the availability of raw materials so that production decisions could be automated as well as shipments could be scheduled to minimize lead time. The use of digital twins that created digital simulations of the factory environment helped to support the functioning of the control tower. Another important initiative was a blockchain-based partnership with Maersk and

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[4] http://www.micorosft.com/en-IN/hololens.

[5] https://www.tetrapak.com/en-in/insights/cases-articles/increased-sales-connected-package.

Nestle called Food Trust that tracked the lifecycle of food ingredients and provided information about the origins of the ingredients of food inside the Tetra Pak containers (Piller, 2020).

The data-centric performance management of activities at Tetra Pak created a strong impact for the company (Sayeda, 2019). It could deploy technicians faster, resolve problems quicker, and serve the customers better. The close monitoring of the equipment through the sensors helped to reduce the number of quality incidents and product recalls, predict machine failures and bring in efficiency in the operation of the equipment at its own factories as well at customer locations. Through the use of digital tools, Tetra Pak was able to successfully advance from connected supply chains to predictive analytics and automation.

Table 12.1 compares the three cases with respect to the framework presented in Fig. 12.2.

The similarities and differences between the case studies become clear with regard to the four different aspects of the framework—data, resources, output, and outcome.

Data: We observe that quantitative data dominated the area of performance management across the three case studies. There was a significant emphasis on internal data such as customer order–related data as seen in the case of Cisco, or customer equipment–related data as seen in the case of Tetra Pak. Specific external data items related to the case were becoming more prevalent such as geo-locations as in the case of Ramco Cements, and data from sensors as in the case of Tetra Pak. The data were becoming more voluminous, but the velocity of the data remained low to medium. Tetra Pak was the only company that included high volume data obtained from sensors in equipment and RFID devices and AGVs. The companies mostly focused on internally generated data to support management decisions and did not use any third-party data or publicly available data. There was a strong emphasis on using high quality external data from customer premises to support decision-making.

Data Processing Resources: Data science is a resource (for data processing) intensive field and requires the support of computing power and analytical abilities of the people involved in the task. In all three case studies the companies made sure the data originated from reliable internal resources (such as ERP or CRM) or customer managed resources. All companies involved a team of experts to carry out data science–related tasks. The teams often included business heads along with technologists. None of the companies used external consultants or vendors in managing the projects. There was no significant investment in infrastructure for accomplishing the projects. Tetra Pak was the only company that used cloud-based storage for their project to retain the flexibility of scaling up or down the scope of the project as needed, although such use is likely to become much more common in today's business environment.

Output: In all three case studies mathematical models played an important role in generating these outputs. These models ranged from structured equation modeling in the case of Cisco to pattern recognition algorithms in the case of Tetra Pak. Ramco Cements was the only company that did not adopt mathematical models as the analysis was primarily descriptive rather than predictive. The presentation format of the output was very important. In the case of Ramco Cements, this was evident through their innovative use of a Google Maps–based dashboard. Tetra Pak went a step further by incorporating an interactive tool like HoloLens in the decision-making process. While Cisco did not focus on the availability of results on mobile devices, this focus was there for Ramco Cements and Tetra Pak. The creation of the Xamarin platform for mobile apps by Tetra Pak showed the importance the company attached to the availability of analysis on mobile devices.

Outcome: A data-driven project can be successful only when it leads to actionable insights. This effort was seen in all three case studies. Cisco went to the extent of involving skeptics in their initiative to win them over and influence others. The projects impacted various stakeholders and provided them with previously unknown insights, better grasp of drivers of customer satisfaction, and full visibility of various processes. Although none of the case studies reported how much cost savings they achieved through the projects, it was clear that they resulted in numerous tangible and intangible benefits and enabled the companies to take more effective decisions and improve relationships with customers.

The framework provides a general-purpose template for understanding the execution of performance management projects. In summary, the analysis of the three case studies indicates the factors influencing the success of a data-driven approach for performance management.

TABLE 12.1 A comparison of the three case studies using the proposed framework.

	Cisco	Ramco Cements	Tetra Pak
Data			
Internal data	Critical data about product launches, product orders, and product deliveries were analyzed	KPIs and the weights for KPIs derived through due diligence	Operations data from equipment at own premises Images of finished goods Data about inbound and outbound shipments RFID and AGV data for loading of goods to trucks
External data	Surveys were conducted and customer satisfaction with deliveries were captured	Geo-locations of employees and dealers were used	Operations data of equipment at customer premises Scans of QR codes on packages Data on goods in transit from vendors or to customers
Data processing resources			
Data capture process	CRM system captured customer and products data	KPIs obtained from the ERP system	Sensor-based data from equipment Remote sensors for customers' equipment
Data science team	Analytics leader, subject-matter experts, six-sigma black belt under the leadership of a senior vice president	A cross-functional team made up of technology and domain experts with the IT team leading	Data scientists and functional experts made up the global analytics team
Data storage infrastructure	No additional infrastructure was needed	No additional infrastructure was needed	Microsoft Azure cloud-based data storage was used
Output			
Data-driven models	Balanced scorecard, strategy map, regression and structured equation modeling, behavioral modeling, longitudinal studies	Analytics engine for descriptive analytics	Predictive algorithms and pattern recognition for complex problem solving
Visualization	Platform used for generating performance reports Strategy map helped to visualize the strategic goals of the organization	Google Maps—based interactive dashboard	HoloLens-based augmented reality gear was used for handling quality incidents
Mobile and portable	Mobile devices not used in performance management	Available on different mobile operating systems and employees encouraged to use the system on mobile devices	Xamarin platform was used for building innovative mobile apps
Outcome			
Activities undertaken	Series of mandatory workshops conducted to bring together data geeks, influencers, and skeptics Survey conducted by external firm on customer satisfaction	Training programs conducted to enhance change management Utilization reports of hits regularly monitored	Two-day hackathons for brainstorming and developing innovative mobile apps

Decision-making	Understanding of levers in supply chain management influencing customer experience Strategic plan for order delivery Prioritization of dimensions of the quality improvement effort	Easy accessibility to performance KPIs Discovery of unknown insights	Effective prediction of machine failures Faster deployment of technicians Real-time information about inbound and outbound shipments
Impact analysis	Improvement in customer satisfaction Increase in the number of timely orders Integration of globally dispersed supply chains	Increased productivity of review meetings More time for customer problem solving	Reduction in the number of quality incidents Improvement in the efficiency of operating equipment Easier access to information about content of containers for customers

4. Impact of emerging technologies on performance measurement and management

Future supply chains are likely to be impacted in three broad areas, viz., information collection, information processing, and automation (Hippold, 2020; Stackpole, 2020). With the advent of technology and the availability of Internet connectivity, it is now more feasible than ever before to capture information and data right across the supply chain, enabled by existing and emerging technologies. We use the framework in Section 1 to explain how the emerging technologies can be used for measuring, managing, and more importantly creating new sources of data collection to enhance supply chain management and supply chain performance.

4.1 Supply chain dashboards

As far back as 2004, Davenport and Brooks (2004) discussed the utility of dashboards in providing current and up-to-date information to senior management. With supply chain data from new technologies being plentiful and available at hand, organizing and presenting the data becomes an important element for efficient and effective decision-making. Supply chain performance dashboards are very helpful in achieving the same. Some of the key characteristics of a good dashboard include flexibility (the ability to provide customized data queries and deep dive views), secure views (depending on the user authority in the organization), and multi-party access (different departments within the organization or different entities of the supply chain). A contemporary dashboard collects data from multiple sources in real time and performs preliminary analysis to present supply chain KPIs in an integrated display. This typically includes information on targets and past performance to enable goal tracking and benchmarking (Hofman, 2016). In Gartner's market analysis of supply chain dashboards, they highlighted their important role as a mechanism to connect supply chain performance to corporate goals (Hofman, 2016). Moreover, the need for customized dashboards is emerging in recent times, such as sustainability specific dashboards that help firms in sustainability management and reporting (Shields & Shelleman, 2020).

In terms of technology providers, Tableau[6] has recently gained prominence in the market for dashboard solutions. However, the market is very competitive with almost all major enterprise solution providers, like IBM, SAP, and supply chain technology providers like JDA and Logility, providing supply chain dashboard solutions.[7] A number of supply chain collaboration platforms are emerging that digitally connect various trading partners of a supply chain to enhance performance in planning and executing interparty supply chain transactions. They also feature dashboards. Active multi-party collaboration dashboards in such systems help to plan better and make the monitoring process more effective and responsive (the SAP Ariba supply chain collaboration is one such example).

4.2 Other emerging technologies

Blockchain in its simplest form is a universal digital ledger of transactions that may be distributed over the entire network under consideration. The impact of blockchain technology in the space of supply chain management is mostly in the output and outcome modules of our framework. As far as the output is concerned, blockchain potentially provides information to multiple entities of the supply chain on a real-time basis. The output can be in the form of easy to access mobile applications that relevant parties can use. With the availability of data on a real-time basis, blockchain may enable quick decision-making (outcome module). Blockchain technology may support (a) ordinary operations decision and (b) extraordinary decisions. With the help of smart contracts embedded in blockchain technology, rule based day-to-day decisions (ordinary decisions) can be executed with minimal human intervention (BCCS, 2020). For instance, implementation of blockchain in unit load devices in the airlines industry[8] has led to smooth cargo tracking. However, a misplaced or damaged cargo reported on a blockchain network requires human intervention for the appropriate rerouting of the item.

IoT enables smooth communication between various devices, which in turn improves the performance of a supply chain domain consisting of interdependent processes. IoT could impact the input, output, and the outcome stages of our framework. The usefulness of IoT is most visible in the "input" part. Different types of sensors in IoT devices capture various forms of information including location, temperature, humidity, light, movement, pressure, and other

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[6] https://www.marketwatch.com/press-release/tableau-services-market-size-review-future-growth-share-company-profiles-2021-comprehensive-analysis-trends-and-forecast-2027-by-regions-2021-06-17.

[7] https://www.predictiveanalyticstoday.com/top-supply-chain-analytics-software/.

[8] https://www.sita.aero/pressroom/news-releases/tracking-of-ulds-through-blockchain-to-save-industry-$400m/.

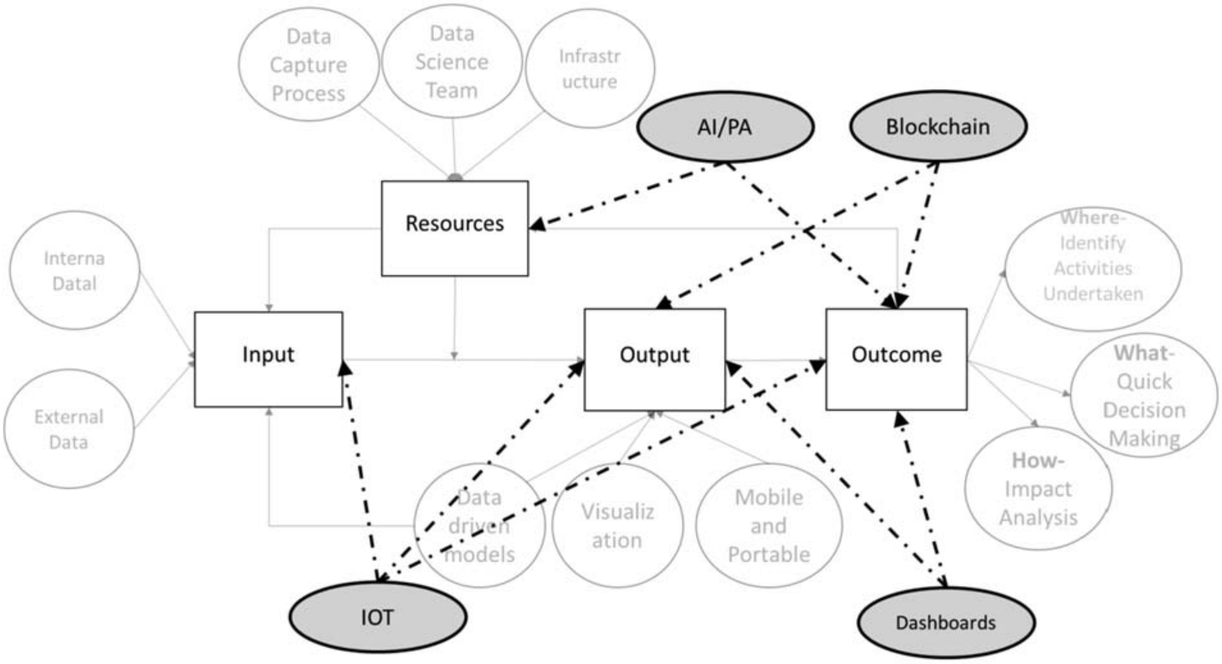

FIGURE 12.3 Impact of emerging technologies on supply chain performance management framework.

environmental factors. The basic structure in terms of the platform used in IoT is Internet-based, which makes the output from such a technology very easy to locate and comprehend for supply chain managers. The availability of IoT protocols such as MQTT (https://mqtt.org/) helps data to be shared among various devices making output availability easier and faster. Two important components of IoT technology may help firms in their decision-making—data storage capacity and compatibility with data analytics tools. The availability of huge data storage capacity complements the machine learning modules of IoT technology, which in turn can also help firms in predictive decision-making. Moreover, since devices may talk to each other on a real-time basis, supply chain managers can set rules to be executed almost on a real-time basis, thereby enabling independent and fast decision-making.

With the enhanced availability of finer data using the emerging technologies (IoT, Blockchain, and Telematics), supply chain performance can be further improved by intelligent processing of the data using tools from Artificial Intelligence and predictive analytics, which could support the Resources stage in the framework. In turn, the analytics performed by these tools can be presented directly in the output module with the help of creative data visualization techniques embedded in the tools. Applications include anticipating demand and supply changes (Jacobs, 2020), and discovering patterns in disjointed datasets to better understand price dependency on parameters such as competition, product proliferation, product life cycle, and manufacturing cost. Fig. 12.3 illustrates the impact of emerging technologies on various modules of the proposed framework.

5. Conclusions

In this chapter, we have focused on the performance management aspects of digital supply chains, presenting a data-driven framework for managing and measuring performance in digital supply chains. Supply chain strategy is one part of an overall business strategy. Performance management metrics, and how performance is managed, should be consistent with overall business goals. The case studies show that not all supply chain implementations have all the elements delineated in our framework. Firms need to choose, based on their needs and resources, the areas to focus on to support their goals.

The business strategy and, therefore, supply chain performance management strategy should take both the existing as well as upcoming technological developments into account. Firms should be cognizant of emerging technologies, as they may have deep implications on the way data are collected, processed, and managed in supply chains. The digital age combined with emerging technologies may overwhelm businesses with data from every minute activity in a supply chain.

The framework provides a top-level view of how firms should look at the flow of data to decide what resources for performance management should be deployed given the needs of the firm.

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Chapter 13

The art of cyber security in the age of the digital supply chain: detecting and defending against vulnerabilities in your supply chain

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Abstract

As the digitalization of supply chains accelerates and the importance of cyber risk management across the supply chain is recognized, both academics and practitioners are paying much more attention to the topic. However, there is a lack of theoretical foundations and practical solutions to underpin and sustain the effective management of supply chain cyber security. This chapter provides a holistic definition for supply chain cyber security and conducts a thorough review of both nonacademic industry sources and the academic literature. Through analysis of industry sources, 18 common best practice principles are identified. These are classified hierarchically—strategic (e.g., supply chain cyber vulnerability and threat identification), tactical (e.g., cyber security education of employees), and operational (e.g., real-time cyber security monitoring). The review of the academic literature complements existing reviews by including the most recent studies, identifying the most significant, and classifying the research. The most common research topics are noted, the main quantitative methodologies deployed are identified, and technology-specific supply chain security research is highlighted. Lastly, 19 key questions for supply chain cyber security research are posed under four categories—modeling and theoretical foundations, implementation of security strategies, interactions between theory and practice, and the analysis of real-world cases.

Keywords: Cyber-attacks; Cyber security; Digital supply chain; Disruptive technologies; Supply chain cyber risk management; Supply chain cyber security; Supply chain disruption.

1. Introduction

In 2013, Target, the US retail giant was struck by a supply chain cyber-attack. Hackers had infiltrated Target's system, exploiting the credentials of one of Target's third-party contractors. Malware was injected into the system and, as a result, credit card data related to 1797 stores in the United States were stolen. Target was unable to take responsive actions in an agile manner and faced more than 90 lawsuits filed by its customers and banks. The company had to pay $18.5 million as a legal settlement and experienced a 46% decrease in its holiday season profits (Hong, 2017; Manworren et al., 2016). The total cost was reported to be much higher (Reuters, 2017).

In 2017, Maersk, the global shipping and logistics provider with more than 574 offices in 130 countries, was hit by the malware, NotPetya. Maersk had to carry out infrastructure reinstallation of 4000 new servers, 45,000 new PCs, and 2500 applications. Shipment delays had a major impact on supply chains and Maersk's losses were significant (Allen, 2018; Greenberg, 2018; Prabhughate, 2020). SolarWinds is a firm that mainly provides systems management software for IT professionals. In 2020, malware was injected through an update from SolarWinds' servers. Among the customers of SolarWinds, are national organizations and global companies including the US Department of Defense and many firms from the US Fortune 500. Due to the malware, over half of SolarWinds' 33,000 customers became vulnerable to

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TABLE 13.1 **Some major cyber-attacks in the 21st century.**

Year	Incident
2013	Target was hit by a supply chain cyber-attack and the financial information of 40 million customers were stolen
2014	Custom-built malware infiltrated through Home Depot's payment system, using a third-party vendor's ID and password. 56 million payment cards were exposed in a data breach
2017	Maersk was attacked by the NotPetya malware and lost 310 million dollars
2020	Mediterranean shipping company and CMA CGM were hit by malware and ransomware cyber-attacks and suffered data breaches
2020	IT infrastructure company SolarWind were infiltrated and its clients were exposed to risks

Sources: Based on Hong, N. (2017). Target to pay $18.5 million to settle massive 2013 data breach. Wall Street Journal. Available at: https://www.wsj.com/articles/target-to-pay-18-5-million-to-settle-massive-2013-data-breach-1495561952?page=1. (Accessed 30 July 2021), Manworren, N., Letwat, J., & Daily, O. (2016). Why you should care about the Target data breach. *Business Horizons*, *59*(3), 257−266, Roman, J. (2014). Home Depot: 53 million E-mails stolen; Breach resulted from third-party Vendor Compromise. 53 bank Info security. Available at: https://www.bankinfosecurity.com/home-depot-53-million-emails-stolen-a-7537. (Accessed 30 July 2021), Allen Sr, C. H. (2018). Developing and implementing a maritime cyber security risk assessment model. *USF Mar. LJ*, *31*, *77*, Greenberg, A. (2018) The untold story of NotPetya, the most devastating cyberattack in history. *Wired*. Available at: https://www.wired.com/story/notpetya-cyberattack-ukraine-russia-code-crashed-the-world/. (Accessed 30 July 2021), Knowler, G. (2020). CMA CGM says online services restored after cyber attack: JOC. Available at: https://www.joc.com/maritime-news/cma-cgm-says-online-services-restored-after-cyber-attack_20201012.html. (Accessed 30 July 2021), and Williams, J. (2020) What you need to know about the SolarWinds supply chain attack: SANS. Available at: https://www.sans.org/blog/what-you-need-to-know-about-the-solarwinds-supply-chain-attack/. (Accessed 30 July 2021).

cyber-attacks (Williams, 2020). Some of the major cyber-attacks occurring in the 21st century are listed in Table 13.1. Each of these events provides a wake-up call for both supply chain professionals and cyber security experts.

There are many reasons for the growing interest in and importance of supply chain cyber security, including the supply chain disruptions caused by the pandemic. As the COVID-19 pandemic struck, the entire planet and many production plants were shut down. Many firms needed to find alternative suppliers and new logistics routes that transformed their supply chain (Kilpatrick & Barter, 2020). In this unprecedented supply chain transformation, the IT network of firms and entire supply chains were exposed to more vulnerabilities as new and different participants meant more potential points of cyber risk exposure and more potential points of penetration by cyber-attackers (Olson et al., 2020). Digitalization itself has played an important role in the heightening of supply chain cyber security concerns. With social distancing and remote working, the cyber network of a firm had to be extended, becoming more vulnerable (Boehm et al., 2020; Scroxton, 2021). Furthermore, new technologies such as drones, AGVs, IoT devices, and AI techniques that play a key role in supply chain digitalization may increase efficiency and effectiveness but at the same time heighten the possibility of supply chain cyber-attacks and the magnitude of their consequences (Dalmarco & Barros, 2018). Lastly, the supply chain of high-value products such as COVID-19 vaccines pose risks of cyber-attacks from hackers around the world (Corera, 2020). The number of cyber-attacks occurring across various industry sectors continues to increase (Langlois et al., 2020).

Various definitions of supply chain cyber security and related terms have been given in a range of literature (see Table 13.2). Two streams of definition concerning supply chain and cyber security are evident. One is concerned with the cyber security of cyber-based ICT products such as software, which is a product-centered perspective (Australian Government, 2019; Boyson, 2014; CISA 2021). The other is mainly concerned with cyber risks generated by the use of Information Technology in, or along the supply chain of any type of product or service, which is a process-centered perspective (Ghadget et al., 2020; Khan & Estay, 2015). Thus, cyber supply chain risk management (or ICT supply chain risk management) and supply chain cyber risk management exist. This is consistent with the findings of Gomes Filho et al. (2021).

In this chapter, the concept of cyber supply chain risk management and supply chain cyber risk management are combined. Cyber risk in supply chains can stem both from the product/service itself and/or the process within the supply chain. As the core objective of many firms is to mitigate every possible cyber risk present in their supply chain, taking such a holistic and inclusive approach toward supply chain cyber security is important. Thus, the definition of supply chain cyber security used in this chapter is as follows: *Supply chain cyber security is the act of maintaining the operations of a supply chain in the face of any type of cyber risk*. It incorporates both ICT and non-ICT products and service supply chains. This definition aligns with that of supply chain cyber resilience defined in Gomes Filho et al. (2021).

The remainder of this chapter provides a summary of the state of the art of practice concerning supply chain cyber security based on an analysis of authoritative sources from government, industry, consultancies, and other bodies.

TABLE 13.2 Existing definitions of supply chain cyber security.

No.	Source	Term	Definition
1	Australian Government (2019)	Cyber supply chain risk	All kinds of vulnerabilities and threats that attribute to every activity that concerns the entire lifecycle of an IT product or service in a cyber environment of an organization
2	Boyson (2014)	Cyber supply chain risk management	Strategy and program of an organization to assess and mitigate risk across the end to end processes of IT network, hardware, software systems supply chains
3	CISA (2021)	Cyber supply chain risk management	Risk identification, evaluation, prevention, and mitigation throughout the lifecycle of ICT products and services in their supply chain
4	Ghadge et al. (2020)	Supply chain cyber risk	Information technology—related events that occur either accidently or intentionally and cause supply chain disruptions by undermining the supply chain infrastructure integrity
5	Khan and Estay (2015)	Supply chain cyber resilience	The ability of a supply chain to maintain its operational performance while facing cyber risk

A detailed analysis of the research literature from the last 2 decades is then performed. This review augments existing academic reviews by taking a highly structured approach to the analysis of the most significant papers published on the topic. Cyber security issues are highlighted related to new and emerging technologies being deployed in supply chains. This chapter concludes with a set of key questions for future research on supply chain cyber security derived from both the current state of practice and the existing research literature.

2. Governments, consultancies, and industry approaches

In the last 2 decades, numerous government guidelines, consultancy papers, and industry reports concerning or related to supply chain cyber security have been published. Many governments have become concerned about the cyber risk affecting the security of supply chains (NCSC, 2021; UK Government, 2021). Here we identify and summarize 30 different government, industry, and consultancy literature sources published between 2011 and 2020. Table 13.3 categorizes these sources.

This literature may be viewed as the state of the art of practice in supply chain cyber security. Most of the sources are concerned with three issues: (1) the importance of supply chain cyber security and the increasing number and scale of cyber-attacks on, or affecting supply chains; (2) the types of supply chain cyber risks; and the (3) best practices for supply chain cyber security management to mitigate or seek to eliminate cyber security risks in the supply chain. The types of

TABLE 13.3 Types of industry literature on supply chain cyber security.

No.	Categories	Sources
1	Government and Nonprofit Organization Guidelines and Reports (16)	Australian Government (2019), CISA (2021), CRS (Jaikaran, 2020), Healthcare & Public Health Sector Coordinating Councils (Dunkle et al., 2019), MITRE (Miller, 2013), NCSL (Mance, 2016), NDIA (Melnyk et al., 2018), NERC (2019), NIST (Boyens & Bartol, 2020), NIST (Conway et al., 2016), NIST (Martin & Shepard, 2015), NIST (Paulsen et al., 2020), NPS (Maule, 2021), Office of the Deputy Assistant Secretary of Defense for Systems Engineering (Reed et al., 2014), UK NCSC (2018), RUSI (Taylor & Lucas, 2020)
2	Corporate reports and whitepapers (7)	Aspen (Brew et al., 2020), Dell (2020), ESG (Oltsik, 2015), Huawei (Scott, 2019), Microsoft (Charney & Werner, 2011), Netherlands Cyber Security Council (Voster et al., 2015), SANS (Shackleford, 2015)
3	Consultancy reports and whitepapers (7)	Accenture (Olson et al., 2020), Burns & Mcdonell (Farquharson et al., 2017), Deloitte (Mossburg et al., 2020), Infosys (Prabhugahate 2020), LMI (Wilkerson, 2014), Mckinsey & Company (Boer et al., 2020), PwC (McConkey & Campbell, 2019)

risks and mitigation strategies identified vary by literature source. Most of the guidelines, reports, and whitepapers focus on the cyber supply chains concerned with digital products based on IT such as software. Most of the industry practices aim at preventing a supply chain cyber-attack that can exploit certain vulnerable components or points across the entire supply chain.

Fig. 13.1 illustrates different types of supply chain cyber security threats in the supply chain. The diagram presented is motivated by and synthesized from some diagrams and illustrations in the existing literature (Davis, 2015; Ghadge et al., 2020; Pandey et al., 2020; Shackleford, 2015; Urciuoli et al., 2013).

In Fig. 13.1, different supply chain cyber security threats are categorized into five groups, depending on the root cause of the subject of disruption resulting from each supply chain cyber security threat. Furthermore, each supply chain cyber security threat is present in multiple phases of the supply chain, making the supply chain even more vulnerable to cyber-attacks. As a result, various mitigation strategies are needed to protect supply chains from cyber threats.

The common principles set out by most industry reports and government guidelines are summarized in Table 13.4. The table provides a comprehensive list of 18 principles that are considered as current best practices in supply chain cyber security from industry, consultancy, or government perspectives.

Out of 18 common principles identified, the most frequently noted ones were "supplier selection on thorough auditing and certification," "adoption of cyber security frameworks and standards," "cyber vulnerability and threat identification and list creation." One tendency is that companies often neglect the principles based on traditional information security such as "encryption mechanism," "penetration testing," "IT network segmentation, and layer-based cyber security." These principles could be considered the basics of corporate cyber security even without considering the entire supply chain's cyber security. Therefore, companies need to focus on the basic principles of traditional information security, while being vigilant on the cyber security of their supply chains.

We have further analyzed this set of 18 principles in terms of whether they are (1) strategic, (2) tactical, or (3) operational, in relation to the management of supply chain cyber security. This hierarchical perspective is typical in the supply chain management decision-making process. Guerra and Estay (2018) have made a similar attempt through a structured review of academic literature. They identified 12 key themes in supply chain cyber risk management and classified them into strategic and tactical categories. We take a similar approach toward the "practice literature" to analyze the current status of supply chain cyber security best practices. Furthermore, we add an important layer of decision-making, which is the "operational level." We also provide a richer set of principles. Table 13.5 classifies the 18 common supply chain cyber security principles in this way.

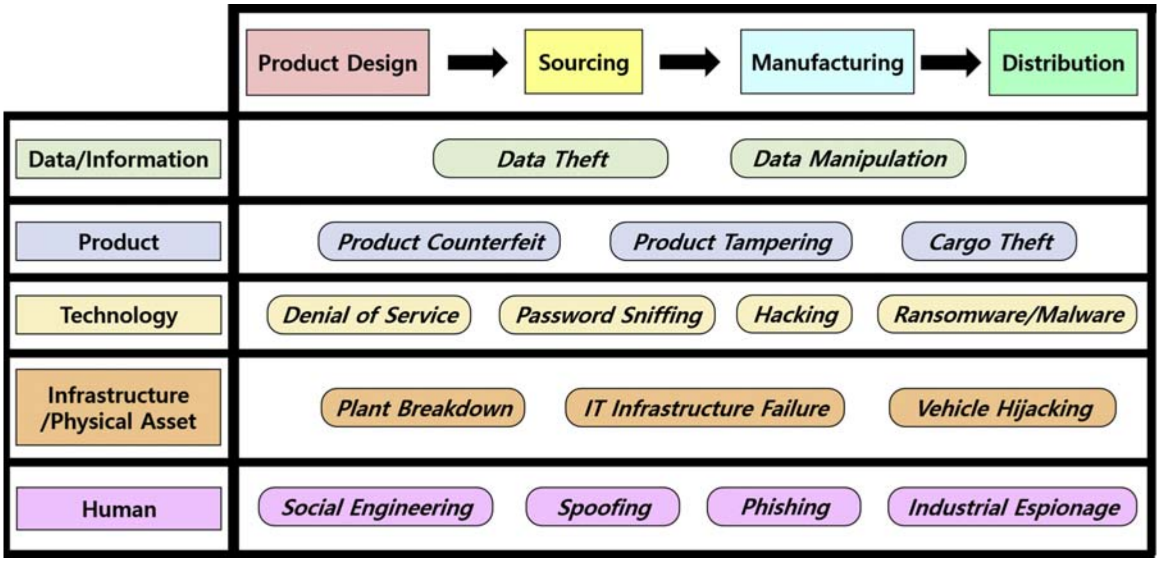

FIGURE 13.1 Illustration of different types of supply chain cyber security threats. *Credit: Based on Urciuoli, L., Männistö, T., Hintsa, J., & Khan, T. (2013). Supply chain cyber security—potential threats.* Information & Security*: An International Journal,* 29*(1), Davis, A. (2015). Building cyber-resilience into supply chains.* Technology Innovation Management Review, 5*(4), Shackleford, D. (September 2015). Combatting cyber risks in the supply chain. SANS institute. Available at: https://www.raytheon.com/sites/default/files/capabilities/rtnwcm/groups/cyber/documents/content/rtn_273005.pdf. (Accessed 30 July 2021), Ghadge, A., Weiß, M., Caldwell, N. D., & Wilding, R. (2019). Managing cyber risk in supply chains: a review and research agenda.* Supply Chain Management*: An International Journal, and Pandey, S., Singh, R. K., Gunasekaran, A., & Kaushik, A. (2020). Cyber security risks in globalized supply chains: conceptual framework.* Journal of Global Operations and Strategic Sourcing.

TABLE 13.4 Common principles of supply chain cyber security best practice.

No.	Principle	Source
1	Create a list of potential cyber vulnerabilities and threats in technological, operational components and participants across the supply chain (21)	Australian Government (2019), Boer et al. (2020), Brew et al. (2020), Charney and Werner (2011), CISA (2021), Dunkle et al. (2019), Farquharson et al. (2017), McConkey and Campbell (2019), Melnyk et al. (2018), Miller (2013), Mossburg et al. (2020), NERC (2019), Olson et al. (2020), Paulsen et al. (2020), Prabhughate (2020), Reed et al. (2014), Scott (2019), Taylor and Lucas (2020), UK National Cyber Security Center (2018), Voster et al. (2015), Wilkerson (2014)
2	Undertake cyber security education of employees (7)	Australian Government (2019), Boer et al. (2020), CISA (2021), Farquharson et al. (2017), NERC (2019), Prabhughate (2020), UK National Cyber Security Center (2018)
3	Create a Supply Chain Cyber Security Task Force (8)	Australian Government (2019), Boer et al. (2020), Boyens and Bartol (2020), Farquharson et al. (2017), Mossburg et al. (2020), Oltsik (2015), Olson et al. (2020), Reed et al. (2014)
4	Perform supply chain mapping (identification of participants in the entire supply chain network) (13)	Boyens and Bartol (2020), Conway et al. (2016), CISA (2021), Dell (2020), Dunkle et al. (2019), Farquharson et al. (2017), Martin and Shepard (2015), McConkey and Campbell (2019), Olson et al. (2020), Reed et al. (2014), UK National Cyber Security Center (2018), Voster et al. (2015), Wilkerson (2014)
5	Perform regular or real-time cyber security monitoring (13)	Australian Government (2019), Boer et al. (2020), Boyens and Bartol (2020), CISA (2021), Conway et al. (2016), Dell (2020), Mance (2016), Martin and Shepard (2015), Maule (2021), McConkey and Campbell (2019), Olson et al. (2020), Prabhughate (2020), Shackleford (2015)
6	Maintain close collaboration and communication with other parties in the supply chain (10)	Boer et al. (2020), Boyens and Bartol (2020), Brew et al. (2020), CISA (2021), Farquharson et al. (2017), Mance (2016), McConkey and Campbell (2019), Melnyk et al. (2018), Shackleford (2015), UK National Cyber Security Center (2018)
7	Adopt cyber security standards and frameworks (21)	Australian Government (2019), Boer et al. (2020), Boyens and Bartol (2020), Charney and Werner (2011), CISA (2021), Conway et al. (2016), Dell (2020), Dunkle et al. (2019), Farquharson et al. (2017), Jaikaran (2020), Mance (2016), Martin and Shepard (2015), McConkey and Campbell (2019), Melnyk et al. (2018), NERC (2019), Olson et al. (2020), Paulsen et al. (2020), Prabhughate (2020), Scott (2019), Taylor and Lucas (2020), Wilkerson (2014)
8	Audit, certify, and select other supply chain partners (especially suppliers) with respect to cyber security (25)	Australian Government (2019), Boer et al. (2020), Boyens and Bartol (2020), Brew et al. (2020), Charney and Werner (2011), CISA (2021), Conway et al. (2016), Dell (2020), Dunkle et al. (2019), Farquharson et al. (2017), Mance (2016), Martin and Shepard (2015), Maule (2021), McConkey and Campbell (2019), Melnyk et al. (2018), Mossburg et al. (2020), NERC (2019), Olson et al. (2020), Paulsen et al. (2020), Reed et al. (2014), Scott (2019), Shackleford (2015), Taylor and Lucas (2020), UK National Cyber Security Center (2018), Wilkerson (2014)

Continued

TABLE 13.4 Common principles of supply chain cyber security best practice.—cont'd

No.	Principle	Source
9	Contractual agreement on the cyber risk information sharing and cyber security collaboration across the supply chain (8)	Australian Government (2019), Brew et al. (2020), CISA (2021), Dunkle et al. (2019), Farquharson et al. (2017), Olson et al. (2020), Shackleford (2015), UK National Cyber Security Center (2018)
10	Utilize financial insurance program to mitigate the risk of cyber-related disruptions (6)	Boer et al. (2020), Boyens and Bartol (2020), Brew et al. (2020), CISA (2021), Dunkle et al. (2019), McConkey and Campbell (2019)
11	Control sensitive data and asset access management (10)	Boer et al. (2020), Brew et al. (2020), Charney and Werner (2011), CISA (2021), Conway et al. (2016), Dell (2020), NERC (2019), Olson et al. (2020), Paulsen et al. (2020), Shackleford (2015)
12	Create a cyber threat scenario list and respective response and recovery plan (12)	Boer et al. (2020), Boyens and Bartol (2020), CISA (2021), Conway et al. (2016), Martin and Shepard (2015), McConkey and Campbell (2019), Miller (2013), Mossburg et al. (2020), NERC (2019), Oltsik (2015), Reed et al. (2014), Voster et al. (2015)
13	Take cyber security into account in product design, product specification, and product lifecycle management (11)	Australian Government (2019), Boyens and Bartol (2020), CISA (2021), Conway et al. (2016), Dell (2020), Farquharson et al. (2017), Martin and Shepard (2015), Maule (2021), Oltsik (2015), Reed et al. (2014), Wilkerson (2014)
14	Develop cyber threat intelligence based on cyber threat data analysis (8)	Boer et al. (2020), Brew et al. (2020), CISA (2021), Maule (2021), McConkey and Campbell (2019), Olson et al. (2020), Prabhughate (2020), Shackleford (2015)
15	Adopt IT Network segmentation and layer-based cyber security (2)	Prabhughate (2020), Shackleford (2015)
16	Perform supply chain penetration testing (simulation of a cyber-attack as a mock test) (3)	Dell (2020), McConkey and Campbell (2019), Reed et al. (2014)
17	Use encryption mechanisms and other cyber security measures such as virus detection and firewalls (3)	CISA (2021), Dell (2020), Reed et al. (2014)
18	Undertake continuous cyber security improvement and infrastructure updates (11)	Australian Government (2019), Boer et al. (2020), CISA (2021), Dell (2020), Jaikaran (2020), Melnyk et al. (2018), NERC (2019), Olson et al. (2020), Prabhughate (2020), Reed et al. (2014), UK National Cyber Security Center (2018)

TABLE 13.5 Supply chain cyber security principles at different levels of decision-making.

Level	Decision
Strategic (7)	Supply chain cyber vulnerability and threat identification, Supply Chain Cyber Security Task Force, Cyber insurance program, Adoption of cyber security standards and frameworks, Supply chain mapping, Creation of a cyber threat scenario list and respective response and recovery plan, Sensitive data and asset access management.
Tactical (8)	Infrastructure update, Cyber security education of employees, Audit, certify, and select other supply chain partners (especially suppliers) in terms of cyber security, Contractual agreement on the cyber risk information sharing and cyber security collaboration across the supply chain, Cyber security requirement incorporated product lifecycle management, Supply chain penetration testing, IT Network segmentation and layer-based cyber security, Encryption mechanisms and other cyber security measures such as virus detection and firewalls.
Operational (3)	Real-time cyber security monitoring, Close collaboration and communication with other parties in the supply chain, Cyber threat intelligence based on cyber threat data analysis.

This multilevel perspective is useful in considering the practices that might be adopted strategically at a high level, over a long time horizon (e.g., supply chain mapping or a cyber insurance program). Tactically, practices are undertaken at an intermediate level over a medium-term horizon (e.g., supply chain penetration testing or IT network segmentation). Operationally, practices are embedded at the appropriate levels and points in an organization and would be expected to be undertaken routinely, consistently, and proactively over time (e.g., real-time monitoring and responding to cyber threat intelligence).

3. Research on supply chain cyber security

Supply chain cyber security has emerged as a hot topic for academic research in the last few years. Nine review papers have been published on supply chain cyber security and related topics since 2015. Table 13.6 lists these papers, the period each review covers, the number of papers reviewed, and summarizes breifly the principal contribution of each review.

In Section 2, this chapter has presented an overview of the current state of supply chain cyber security thinking and concepts from the perspective of current practice, evidenced by publications from industry, governments, and consultancies. In order to identify key questions for future research, the current state of practice has been combined with a further review of the research literature. The difference between this review and previous review papers is threefold. First, the review includes the most recent articles published up to early 2021. Second, the most significant 103 articles are selected and analyzed. Third, a structured analysis is performed based on common topics in supply chain cyber security research,

TABLE 13.6 Overview of review papers in cyber security and supply chain.

No.	Author and date	No. of papers reviewed (publication year)	Contribution
1	Khan and Estay (2015)	213 (1998–2015)	Definition for supply chain cyber resilience and several future directions for both academia and industry.
2	Guerra and Estay (2018)	123 (2000–2018)	Identification of supply chain cyber risk mitigation strategies. Design of a supply chain cyber risk management framework.
3	Ghadge et al. (2020)	41 (1990–2017)	Identification of the types of cyber risks, cyber risk propagation, cyber security challenges, mitigation strategies, a conceptual model, and future research directions through descriptive and thematic analysis.
4	Radanliev et al. (2020)	173 (1996–2020)	Identification of the relationship between IoT, machine learning, AI, and cyber risk through a taxonomic review and case-study research. Provides an analytical framework, design principles, and a roadmap for Industry 4.0 supply chains.
5	Enayaty-Ahangar et al. (2020)	68 (2003–2019)	Classification of cyber infrastructure security literature based on application, mission, and optimization model.
6	Sobb et al. (2020)	119 (1991–2020)	Analysis of cyber risk and mitigation strategies in military supply chain 4.0. Analysis of the impact of each disruptive technology in a military context.
7	Cheung et al. (2021)	103 (2010–2020)	Classification of supply chain and logistics cyber security literature based on the cyber security measure. Provides seven key insights on future research.
8	Gomes Filho et al. (2021)	33 (2000–2020)	Identification of various cyber risks in the supply chain and their relationship to different flows (information, material, financial) in the supply chain. Provides a comparison between two distinct concepts, cyber supply chain risk management and supply chain cyber risk management.
9	Latif et al. (2021)	41 (2010–2020)	Identification of four research areas of supply chain cyber security, which are IoT, information security, network security, and web application security.

the research methodologies deployed, and the cyber risks associated with new technology issues that are identified. The results of the review are summarized in a number of tables to facilitate readability, easy reference, and because of the limit on word count.

The review period covers research articles published or accepted between January 2000 and March 2021. The types of articles examined include journal papers, conference proceedings, and book chapters. The Scopus database has been utilized for the collection of articles. The query used is similar to that used but Cheung et al. (2021) but "cyber risk" is added as one of the search keywords. The query used for the search in the Scopus database is as follows.

TITLE-ABS-KEY (("supply chain") OR ("supply" AND "chain")) AND TITLE-ABS-KEY (("cyber" AND "security") OR "cybersecurity" OR "cyber-security" OR "cyber resilience" OR "cyber-resilience" OR "cyber-resilient" OR ("cyber" AND "resilient") OR "cyber risk" OR ("cyber" AND "risk")) AND (LIMIT-TO (LANGUAGE, "English"))

A total of 460 documents were identified. Through manual screening, 101 articles about supply chain cyber security published from 2000 to 2021 were identified and critically reviewed. Two additional articles were identified during the literature review process. Thus, a total of 103 articles related to supply chain cyber security were identified.

Common research topics were identified from 103 papers published between 2000 and 2021. Table 13.7 lists and describes the most common research topics considered in supply chain cyber security in these articles.

The summary information shown in Table 13.7 shows five dominant areas of focus for the body of research on supply chain cyber security. The majority of papers surveyed belong to one of three areas; supply chain cyber security investment optimization, supply chain cyber security methodology and framework development, and supply chain cyber security case study. Supply chain cyber security investment optimization is both theoretically and practically important. However, due to

TABLE 13.7 Common research topics in supply chain cyber security.

No.	Topic	About	Examples
1	Supply chain cyber security investment optimization (16)	Optimization of the investment in cyber security measures and infrastructure against a cyber-attack. Models the interaction between supply chain participants (defenders) and attackers as well.	Bandyopadhyay (2011), Cheung and Bell (2021), Colajanni et al. (2018), Colajanni et al. (2020), Gupta et al. (2021), Li and Xu (2021), Nagurney and Nagurney (2015), Nagurney et al. (2017), Njilla (2020), Paul and Zhang (2021), Rodger and George (2017), Sawik (2020), Schmidt et al. (2021), Simon and Omar (2020), Wang (2017), Zheng and Albert (2019)
2	Supply chain cyber security conceptualization and education (8)	Overview of supply chain cyber security and supply chain cyber security education.	Bartol (2014), Boyson (2014), Cohen et al. (2018), Davis (2015), Pal and Alam (2017), Urciuoli (2015), Warren and Hutchinson (2000), Wilding and Wheatley (2015)
3	Supply chain cyber security frameworks and methodology development (45)	Development of a concrete framework for supply chain cyber risk assessment and risk mitigation strategies.	Akinrolabu et al. (2017), Barron et al. (2016), Boiko et al. (2019), Boyes (2015), Cayetano et al. (2018), Collier et al. (2014), Debnath et al. (2020), Duzha et al. (2017), Dynes et al. (2007), Eggers (2021), Feltus et al. (2014), Gaudenzi and Siciliano (2018), Guerra and Estay (2018), Gunes et al. (2021), Hampton et al. (2021), Heath et al. (2017), Henson and Sutcliffe (2013), Hou et al. (2019), Hutchins et al. (2015), Isbell et al. (2019), Jensen (2015), Kalogeraki, Apostolou et al. (2018), Kalogeraki, Papastergiou et al. (2018), Keegan (2014), Khalid et al. (2018), Kuypers et al. (2014), Lamba et al. (2017), Lewis et al. (2014), Masvosvere and Venter (2015), McFadden and Arnold (2010), Mileski et al. (2018),

TABLE 13.7 Common research topics in supply chain cyber security.—cont'd

No.	Topic	About	Examples
			Nasir et al. (2015), Norman et al. (2020), Omitola and Wills (2018), Pandey et al. (2020), Polatidis, Pavlidis, and Mouratidis (2018), Reuben and Ware (2019), Schauer et al. (2019), Siciliano and Gaudenzi (2018), Sobb and Turnbull (2020), Torres-Barrán et al. (2021), Vanajakumari et al. (2020), Windelberg (2016), Wolden et al. (2015), Yeboah-Ofori and Islam (2019)
4	Supply chain cyber security case studies (30)	Case studies of the cyber security of region, industry, organization, product, technology, specific supply chain.	Ahokas et al. (2017), Carmody et al. (2021), Colicchia et al. (2019), Couce-Vieira and Houmb (2016), de Haan (2020), de la Peña Zarzuelo (2021), Fraile et al. (2018), Gupta et al. (2020), Hannan (2018), Johnson (2016), Kennedy et al. (2019), Kim and Im (2014), Kshetri (2017), Lambert et al. (2013), Lees et al. (2018), Linton et al. (2014), Lu et al. (2013), Mylrea and Gourisetti (2018a), Mylrea and Gourisetti (2018b), Rongping and Yonggang (2014), Sakib et al. (2021), Sokolov et al. (2014), Tsoutsos and Karri (2020), Tuptuk and Hailes (2018), Turnbull (2018), Urciuoli et al. (2013), Venter (2014), Wells et al. (2014), Williams (2014), Xu et al. (2018)
5	Supply chain cyber security Data Analytics and cyber threat intelligence development (4)	Real-time detection and response to cyber risks based on data analytics.	Polatidis, Pimenidis et al. (2018), Yeboah-Ofori and Boachie (2019), Yeboah-Ofori, Islam, and Brimicombe (2019), Yeboah-Ofori, Islam, and Yeboah-Boateng (2019)

the complexity and abstractness of mathematical modeling, it has not been developed enough. Supply chain cyber security conceptualization and education, supply chain cyber security Data Analytics, and cyber threat intelligence development have received less attention compared to other topics. Recent rising awareness of companies and governments toward supply chain cyber security and technological advances such as machine learning and reinforcement learning could positively impact their development. The automation and self-learning aspect of supply chain cyber security could complement human cyber security experts and enhance both the efficiency and the effectiveness of supply chain cyber security.

Previous review papers fail to summarize comprehensively the main quantitative research methodologies used in supply chain cyber security research. Table 13.8 summarizes the main quantitative methodologies deployed in supply chain cyber security research and indicates which modeling studies are empirically based. Although Enayaty-Ahangar et al. (2020) and Cheung et al. (2021) identify some recent quantitative methodologies in cyber security research, articles that were published more recently and that include methodologies such as variational inequality, mixed integer linear programming, robust optimization, and simulation were not highlighted.

As can be seen in Table 13.8, game theory is the most frequent quantitative approach taken to supply chain cyber security research. None of the game theory papers show a clear empirical basis and thus their usefulness in practice may be more limited (and similarly with studies using calculus of variations). Other common quantitative methodologies stem

TABLE 13.8 Quantitative methodologies used in supply chain cyber security research.

No.	Methodology	About	Example	Empirically based papers
1	Game theory (10)	Models the behavior of rational attackers and defenders	Bandyopadhyay (2011), Cheung and Bell (2019), Colajanni et al. (2018), Colajanni et al. (2020), Gupta et al. (2021), Li and Xu (2021), Nagurney and Nagurney (2015), Nagurney et al. (2017), Njilla (2020), Simon and Omar (2020)	None
2	Simulation (45)	Numerical analysis of specific cyber risk scenarios, policies, or frameworks	Fraile et al. (2018), Khalid et al. (2018), Polatidis, Pavlidis, and Mouratidis (2018), Polatidis, Pimenidis et al. (2018), Sakib et al. (2021)	Khalid et al. (2018), Polatidis, Pavlidis, and Mouratidis (2018), Polatidis, Pimenidis et al. (2018), Sakib et al. (2021)
3	Robust optimization (1)	Optimal cyber security investment in consideration of worst case scenario	Zheng and Albert (2019)	Zheng and Albert (2019)
4	Linear/integer/mixed integer linear programming (3)	Optimal allocation of resources in cyber security	Rodger and George (2017), Sawik (2020), Schmidt et al. (2021)	Rodger and George (2017), Sawik (2020), Schmidt et al. (2021)
5	Stochastic programming (3)	Models uncertainty in supply chain attacks	Heath et al. (2017), Paul and Zhang (2021), Schmidt et al. (2021)	Heath et al. (2017), Paul and Zhang (2021), Schmidt et al. (2021)
6	Variational inequality (4)	Optimal attack-defense policies with mathematical rigor	Colajanni et al. (2018), Colajanni et al. (2020), Nagurney and Nagurney (2015), Nagurney et al. (2017)	None
7	Machine learning (1)	Learning about attack patterns over time	Yeboah-Ofori and Boachie (2019)	Yeboah-Ofori and Boachie (2019)
8	Bayesian networks (2)	Uses Bayesian statistics to update belief on a cyber-attack	Sakib et al. (2021), Yeboah-Ofori, Islam, and Brimicombe (2019)	Sakib et al. (2021), Yeboah-Ofori, Islam, and Brimicombe (2019)

from different branches of optimization techniques. As they are mathematically abstract, their capacity to model the details and complexity of real-world supply chain cyber security is limited. More frequent adoption of other novel methodologies such as simulation, machine learning, and Bayesian networks can effectively deal with such complexity and add another layer of variety to quantitative supply chain cyber security research.

New and emerging technologies used in supply chain applications may pose new or additional cyber security threats. Most of the academic literature about supply chain cyber security does not take a technology-specific approach. Table 13.9 identifies common themes, risks, and challenges in supply chain cyber security brought by specific disruptive technologies.

Table 13.9 shows that the majority of the literature investigates a particular technology or a set of technologies that impact supply chain cyber security. The most common technologies or systems investigated are cyber-physical systems, the Internet of Things, and Cloud computing. When analyzing the impact of disruptive technologies on supply chain cyber security, both supply chain and information security perspectives should be considered. From a supply chain perspective, each disruptive technology belongs to a specific supply chain activity or multiple activities and can disrupt that specific part of the supply chain when it is under cyber-attack. From an information security perspective, each disruptive technology has its unique cyber vulnerability pertaining to the information security structure specific to the technology. Thus, supply chain and information security thinking are both needed to holistically capture and analyze the cyber risks and their supply chain implications of disruptive technologies.

TABLE 13.9 Common themes, risks, and challenges in supply chain cyber security brought by disruptive technologies.

Technologies	Common themes	Risks and challenges	Source
Drones (4)	GPS-related cyber-attack, access control, network security	Transportation side disruption due to drone hijacking or destruction, theft of high-value product during the delivery process	Boudway (2021), Ossamah (2020), Shane and Sanger (2011), Vattapparamban et al. (2016)
Autonomous vehicles (1)	Development of cyber security guidelines and regulations by governments	Transportation side disruption due to vehicle hacking, data breach, global navigation satellite system manipulation	Taeihagh and Lim (2019)
Robotics (4)	Various layers of cyber-attack (hardware, firmware, application) and their respective countermeasures	Manufacturing, warehousing, transportation operation disruption due to robot hacking	Clark et al. (2017), Duong et al. (2020), Khalid et al. (2018), Poudel (2013)
Additive manufacturing (4)	Design protection, protection of intellectual property, reverse engineering	Hacking of additive manufacturing facility, leading to supply-side disruption	Barron et al. (2016), Gupta et al. (2020), Tsoutsos and Karri (2020), Tuptuk and Hailes (2018)
Internet of Things (8)	Real-time monitoring, regular security update of IoT devices, standardization	Detection of cyber threat through supply chain visibility, manipulation of IoT sensors, an attack against IIoT devices in logistics and manufacturing, vulnerability of IoT embedded products	Boiko et al. (2019), Fraile et al. (2018), Isbell et al. (2019), Kshetri (2017), Lamba et al. (2017), Omitola and Wills (2018), Tuptuk and Hailes (2018), Vanajakumari et al. (2020)
Blockchain (4)	A potential solution to various supply chain cyber security issues, a tool for coordination in supply chain cyber security	Supply chain cyber resilience due to preservation of transaction data, enhanced supply chain visibility, smart contract	Kshetri (2017), Mylrea and Gourisetti (2018a), Mylrea and Gourisetti (2018b), Xu et al. (2018)
Artificial Intelligence (3)	Data Analytics for supply chain cyber security decision-making	Real-time detection of supply chain cyber security risk, large-scale data analysis, quantitative risk analysis, real-time mitigation strategy through supply chain cyber security intelligence	FireEye (2014), Shackleford (2015), Mavroeidis and Bromander (2017)
Cyber-physical systems (11)	Cyber security architecture design	Real-time simulation of the supply chain through digital twin, real-time quantitative analysis of the risk during cyber disruption	Cohen et al. (2018), Gunes et al. (2021), Hou et al. (2019), Kalogeraki, Apostolou et al. (2018), Kalogeraki, Papastergiou et al. (2018), Khalid et al. (2018), Pandey et al. (2020), Tsoutsos and Karri (2020), Tuptuk and Hailes (2018), Wells et al. (2014), Yeboah-Ofori and Islam (2019), Yeboah-Ofori et al. (2019)
Cloud computing (7)	Security control of network infrastructure, end-device—related cyber risk	Various cyber risks such as account hijacking, data breach, and denial of service	Akinrolabu et al. (2017), Boiko et al. (2019), Boyes (2015), Kshetri (2017), Lamba et al. (2017), Tsoutsos and Karri (2020), Tuptuk and Hailes (2018)

4. Research frontiers

This chapter has examined both industry practice in supply chain cyber security and the current state of academic research in this area. By synthesizing the knowledge, insights, and issues gained from both streams of literature, we have identified a comprehensive set of key questions in supply chain cyber security that need to be addressed, which we present in Table 13.10.

Table 13.10 shows four major categories that can be informed by research studies to provide more knowledge and a better understanding of supply chain cyber security. The theoretical foundations of the subject need further investigation and analysis to understand the nature of cyber-related threats and to provide quantitative models that show their impact in

TABLE 13.10 Key questions in supply chain cyber security.

Category	Research questions
1. Modeling and theoretical foundations of Supply ChainCyber Security	• What are the key supply chain cyber risks and threats? • What are the available mitigation strategies corresponding to each supply chain cyber risk? • How can we quantitatively analyze the impact of each supply chain cyber risk? • How can we analyze the dynamic interaction between supply chain cyber-attacker and defender?
2. Implementation of Supply Chain Cyber Security strategies	• How can supply chain cyber security regulators (e.g., governments) and industry firms and practitioners coordinate with one another? • How can we accomplish supply chain cyber security investment optimization and coordination along the entire supply chain? • How can we conduct a cost—benefit analysis of each supply chain cyber security measure from the perspective of an individual firm? • How can we develop new supply chain cyber security frameworks and best practices? • Which of the existing supply chain cyber security guidelines and frameworks are easy to implement? How effective are they, and why? • How can we create a concrete list of cyber threat scenarios and a supply chain cyber risk management playbook? • How can we develop supply chain cyber security Data Analytics and supply chain cyber threat intelligence?
3. Interactions between theory and practice in Supply Chain and Cyber Security	• How can we develop new supply chain cyber security measures from a traditional information security point of view (e.g., encryption mechanisms and technologies)? • How can we bridge the gap between industry and academia in supply chain cyber security? • What are the main differences between IT security implications of supply chain and supply chain implications of cyber risks? • How can we analyze the cyber security of each component of the supply chain, ranging from sourcing, manufacturing, logistics, product design, storage, pricing, financial transaction to information exchange?
4. Real-world case studies of Supply Chain Cyber Security	• What lessons can we learn from real-world supply chain cyber-attacks and the best practices of specific firms? • How does the supply chain cyber security landscape differ region by region considering the cyber infrastructure, the regulatory environment, and the nature of the dominant industries? • How should each industry or product approach supply chain cyber security? • How will each existing disruptive technology and new emerging technologies impact supply chain cyber security?

complex supply chain environments. The deployment of supply chain cyber security strategies is the second category requiring research efforts. There are many issues around regulatory environments, effective implementation frameworks for monitoring and intelligence gathering, and the developemnt of cyber risk management playbooks. All these issues have an impact on the strategic, tactical, operational cyber security decision-making of a firm. How the theory base can inform future thinking and approaches to supply chain cyber risk management is captured in the third category, which highlights research issues such as risks in different supply chain functions and different components of the supply chain. Evidence and analysis of real cases is the focus of the fourth category. Research is needed on differences in cyber risks in different industrial sector supply chains, and evidence on the types of risks emerging in new technologies. A supply chain cyber security research question might fall into multiple categories. Nevertheless, this framework will help researchers conducting supply chain cyber security research discover new research avenues and identify the research landscape surrounding research questions as well.

5. Conclusions

As the transformation to digitally enabled supply chains proceeds at a fast pace, and as the frequency of cyber-attacks against supply chains across industries increases, the theoretical foundations and systematic solutions available for effective supply chain cyber security have become critically important. Supply chain cyber security is now a major issue for supply chain professionals and practitioners and is an important research topic in the digital supply chain. Emerging challenges for supply chain cyber security include the continuing digitalization and globalization of supply chains, the adoption of disruptive technologies, and the growing volume of cyber-related regulations. With the development of new disruptive technologies such as Additive manufacturing, drones, IoT, and blockchain, supply chain cyber security will continue to pose significant challenges for all stakeholders in contemporary and future supply chains.

Governments, industry, consultancies, and other policy organizations have published a range of supply chain cyber security guidelines and frameworks. Based on an analysis of 30 different sources, this chapter has identified and presented 18 common principles that capture the current state of supply chain cyber security best practices. Furthermore, the principles have been categorized in terms of their primary focus—strategic, tactical, or operational. From the analysis of practice and a structured review of the research literature, 19 key questions in supply chain cyber security have been posed under four categories—modeling and theoretical foundations, implementation of supply chain cyber security strategies, interactions between theory and practice, and real-world case studies. The questions identified can inform future research and practice in supply chain cyber security.

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Part IV

Digital Supply Chain – sectoral cases

Chapter 14

Digital retail—key trends and developments

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Abstract

Digital technologies are reconfiguring and reshaping the retail value chain fundamentally, affecting the modes of customer engagement with retailers, the fulfillment and delivery options offered, as well as back-end operations and manufacturing. These developments have accelerated strongly with the COVID-19 pandemic and the shift from traditional to online retail channels worldwide. The retail sector continues to undergo a major digital transformation. We examine the current state of digital retail and highlight the key trends and capabilities shaping today's retail business models. We discuss the evolution of delivery and fulfillment formats over three decades from traditional e-commerce to today's Quick commerce, which offers multiple modes of engagement and interaction for customers who are increasingly channel-agnostic and seek convenience and a personalized retail experience. Our narrative is illustrated through two brief case examples from innovative pioneers in platform-based retailing in Western and Asian markets — Alibaba and Amazon. We describe how these platforms are powerful mediators in ever more complex retailing ecosystems that combine digital and physical assets. We discuss the implications of digital disruption for retail strategy, front-end retailing operations, and back-end logistics and manufacturing. The discussion helps scholars and practitioners to understand the changing digital retail landscape that is emerging worldwide.

Keywords: Alibaba; Amazon; Data analytics; Digital transformation; Omni-channel retail; Personalized marketing; Supply chain.

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1. Introduction

The retail economy has undergone seismic changes in the last decade. Digital transformation has been at the heart of these changes. Digital transformation is real and widely pervasive, and its implications are strongly visible in the retail industry, which has traditionally been known for intense competition and narrow profit margins (McKinsey & Company, 2020). The industry has seen the demise of many traditional bricks-and-mortar retailers, including prominent and well-known global brands such as Toys R Us (Bomey, 2018) and national brands such as Debenhams in the United Kingdom after two centuries of trading (Butler, 2020). The global wave of store closures by traditional retailers mirrors the digital revolution and the growth in online shopping, bringing increased competition and uncertainty (Butler, 2018; Lisicky, 2021). New technology-enabled business models have introduced more rivalry and intensified competition in many industries. For example, the fashion retail industry now faces competition from the clothing rental sector with the advent of online rental platforms such as Rent the Runway (Brydges et al., 2021). Digital technologies have empowered sportswear brands such as Nike to scale up the direct-to-consumer (D2C) model and develop new interactive concept stores (e.g., Nike Rise, Nike Live, Nike Unite) to directly engage with consumers, reducing the need to mobilize retailers as intermediaries (Nike, 2020).

However, digital transformation also presents many new opportunities for retailers, both for conventional bricks-and-mortar retailers and newer platform-based retailers. Novel channels such as mobile apps, social media, and Artificial Intelligence (AI)-enabled voice assistants allow retailers to expand their reach in interacting with customers and achieve sales through more channels. Extended customer interfaces generate more customer data that can be analyzed to attain

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granular details on individual customers and their preferences, which facilitates micro-segmentation and enables more personalized product/service offerings (Strycharz et al., 2019). Technology advancements enable retailers to offer new payment options (e.g., mobile payments), expedite the check-out process (e.g., self-service checkouts), and provide customer services cost-efficiently (e.g., chatbots). By reconsidering and adjusting their business strategies, deploying resources for new digital initiatives, redesigning the organization and culture, retailers may achieve sustained competitive advantages through personalized service offerings to customers at the front-end of the business while achieving enhanced efficiencies in back-end operations (hbr.org., 2017).

This chapter provides an overview of the transformative journeys that retailers have embarked on through digitalization and highlights the fresh thinking and practices across fundamental areas of the retail value chain, including store operations, supply chain (particularly logistics and manufacturing), marketing, and information technology (IT). We first outline the breadth of changes and challenges throughout the contemporary retail industry compared to the traditional retail landscape of decades ago. We then provide a succinct analysis of two cases (Alibaba and Amazon) to showcase the digital initiatives displayed by Internet giants in both Western and Asian markets. Based on the analysis, we discuss and highlight initiatives that retailers have typically taken to digitalize their operations to appeal to modern consumers.

2. The reshaping of the retail value chain

Digital has had a fundamental impact on the structure of the retail value chain in recent years (Hänninen, Kwan et al., 2021). For example, from a marketing perspective, both Data Analytics and digital marketing tools and technologies enable retailers to now target individual consumers in contrast to mass marketing and foster more innovations (Strycharz et al., 2019), while from an operations perspective, retailers are now able to fulfill orders and deliver them to customers faster and more flexibly (Marchet et al., 2018). In this section, we describe how digital has transformed the manufacturing, retail, and supply chain activities in the retail value chain and identify the critical drivers for these changes.

2.1 Manufacturing in the retail value chain

Manufacturing activities were traditionally tightly coordinated by retailers (Mitronen & Möller, 2003). The growth of chain-based self-service retail formats after World War II (WWII), however, led to the decentralization of many manufacturing activities as retail chains concentrated on the act of retailing and outsourced many of their existing manufacturing activities to others (e.g., Jefferys, 2011). The retail value chain became populated with many prominent manufacturers, particularly in the fast-moving consumer goods (FMCGs) context (Corstjens et al., 1995). In the late 1990s, the emergence of large retail chains (e.g., Walmart in the United States), prompted many large manufacturers to develop closer relationships with retailers (Hänninen, Luoma et al., 2021). This enabled many prominent FMCG players (e.g., P&G, Nestle, Unilever) to thrive and become increasingly integrated with retail activities. For example, by sharing demand and supply-side data, both retailers and manufacturers could develop win-win value propositions and maximize their business efficiencies (Croson & Donohue, 2003).

At the heart of the digital transformation of manufacturing are data and IT (Hänninen, Kwan et al., 2021). The first barcode standards, introduced in the late 1970s, enabled more sophisticated identification of products, which later provided the foundations for automatic replenishment and more efficient inventory management practices (Hänninen, Luoma et al., 2021). This culminated in the development of ECR (efficient consumer response) and other strategies in the 1990s to further develop the interdependencies between retailers and manufacturers. Tesco, for example, started selling customer data (i.e., Clubcard data) to preferred suppliers in the late 1990s to help all parties to better coordinate supply chain activities (Humby et al., 2004). While activities like ECR helped improve both retailers' and manufacturers' business performance, these were very much aimed at the most prominent and powerful suppliers. Many smaller suppliers had limited power, capabilities, or resources to attain or analyze customer data (Bloom & Perry, 2001).

However, digital channels like social media, fueled with digital marketing, make it easier for smaller manufacturers to now reach consumers and target a global consumer base (Alicke et al., 2017). Also, novel, convenient, and flexible delivery and fulfillment services make it possible for smaller manufacturers to bypass traditional intermediaries in the retail value chain and reach consumers directly. This has fueled the creation of D2C businesses, where manufacturers serve consumers directly through their own retail channels (Pasirayi & Fennell, 2021). At the same time, the role of private or own-brand labels continues to be significant (Wu et al., 2021). Online retailers like Amazon are now also heavily developing their own private labels that may directly threaten the competitive position of many large manufacturers.

Digital is significantly changing the power structure between manufacturers and retailers (Hänninen, Luoma et al., 2021). On the one hand, retailers may play a reduced role as manufacturers take more control over the customer relationship through D2C businesses. On the other, manufacturers also face increasing competition from retailers' private or own labels. Looking into the future, 3D printing and the implications of Industry 4.0 in many aspects of production may be of concern for manufacturers, particularly regarding the protection of copyright and intellectual property (Rindfleisch et al., 2019). The circular economy is also a growing trend. Manufacturers face mounting pressure to develop durable and recyclable products driven by the global sustainability crisis (Gusmerotti et al., 2019). This opens the door to new business models (e.g., rental marketplaces), which again has significant implications for the structure of the retail value chain for many products (Brydges et al., 2021).

2.2 Retailing—the emergence of the platform model

The retailer has historically maintained tight control over the retail value chain. Many retailers, particularly in food retail, owned the warehousing, distribution, and storefronts in the past and they coordinated most, if not all, associated retail activities. Some grocery retailers are also wholesalers, meaning that besides operating stores, they also take care of merchandise procurement and distribution within their distributed grocery store networks. Today, retailers have gradually moved away from vertical integration as many activities like warehousing, logistics, and distribution can now be procured from the market instead of keeping these activities on the balance sheet (Hänninen et al., 2019).

The postwar period saw a retail transformation from small and local store units to large national chains with integrated networks (Foster et al., 2016). For example, Walmart, founded in 1962, quickly established a vast network of stores across the United States and grew into the retail powerhouse it is today by the late 1900s. At the same time, shopping malls and retail parks moved retailing from urban centers like the high street to the outskirts of cities (Korthals Altes, 2016). This meant that many large retail chains dominated the industry (e.g., Walmart, Sears, Kmart) with "self-service" type businesses, which proved popular. Technology, in the form of inventory management and supply chain coordination software, also played a major role in this period. It solidified the position of the major retailers as they had more data and visibility of the flow of goods. This made the entry barriers to retail relatively high (Hänninen, Luoma et al., 2021). While many retail chains attempted internationalization in the late 1900s, there were notable failures (e.g., Walmart in Germany, Tesco in the United States), often due to the difficulty in adapting to local customs, culture and competition (Hunt et al., 2018). Those chains that succeeded in internationalization, such as H&M and Ikea, also took a relatively long time to do so.

Digital, however, has considerably changed the nature of retailing, particularly from a business and earnings model perspective (Reinartz et al., 2019). The mid-1990s marked the beginning of e-commerce, with the first pure-play retailers launching retail businesses centered on the home delivery of goods and services. While many initial e-commerce businesses failed (e.g., Webvan), others ultimately became highly successful (Hänninen et al., 2019). Both Amazon and eBay, for example, continue to be digital giants, with Amazon particularly spearheading digital trade today. While some firms such as Webvan sought to build an entire infrastructure for e-commerce themselves, both eBay and Amazon developed essentially as intermediaries. They primarily intermediate products between consumers and sellers, thereby reducing the costs of retail space and inventory. This helps explain their success and differentiation from other earlier e-commerce formats (Gans, 2020). While eBay continues to serve particular small- and medium-sized enterprises (SMEs) and consumer-to-consumer transactions, Amazon is now a digital powerhouse, with a marketplace connecting sellers to consumers worldwide. It has become the archetype of the platform retailing model.

Today's dominant retail business model is the platform model (van Alstyne et al., 2016). Rather than having tight vertical control over the retail value chain, today's most prominent retailers simply act as intermediaries for the transactions between buyers and sellers (Hänninen et al., 2019; Libert et al., 2014). These business models are fueled by data and the possibility to match supply and demand algorithmically. Contemporary digitally based retail business models have evolved further to become ecosystems centered on a host of digital services. Media and entertainment, finance, public services, travel, on-demand delivery, and social interactions have all become integrated in retailers' platform business models. Through mega apps such as WeChat in China or Lime in Japan, they form a unified ecosystem business model (Reinartz et al., 2019). Retailing now encompasses ever more complex ecosystems made up of a multitude of different actors from various fields of business.

2.3 Delivery and fulfillment

Delivery and fulfillment have become a critical part of the retail value chain as retailers take the responsibilities for the challenging last mile to ship products/services to the destinations stipulated by their online customers (Hänninen et al., 2019). This marks a considerable change from traditional bricks-and-mortar retail operations, which were geared at delivering pallets or large units of products to stores (or warehouses). In contrast, the online platform model must focus on picking, packing, and delivering individual items to online consumers (Vakulenko et al., 2019). The rapid influx of on-demand delivery platforms also enables the delivery of individual items from small local stores or warehouses within minutes (Villa & Monzón, 2021). Table 14.1 summarizes the evolution of delivery and fulfillment formats over three decades from tradional e-commerce to today's Quick commerce.

Conventional retailers historically operated their own warehouses and also often had their own delivery operations, moving products from manufacturers to warehouses and finally to stores (Mitronen & Möller, 2003). Gradually, these have been outsourced to other logistics partners. Information sharing empowered by IT innovations now allows for collaborative planning, forecasting, and replenishment, yielding benefits for all members along the supply chain such as mitigating the bullwhip effect and facilitating strategic supplier relationship management (Lee et al., 2004). This means that an increasing amount of data can now be seamlessly shared across actors in the retail value chain to ensure that products are distributed to the right place and at the right time, enabled by technology such as Radio Frequency Identification (RFID) tags.

E-commerce has created demands for new delivery solutions such as home delivery and click-and-collect. Click-and-collect options have become increasingly popular, particularly during the COVID-19 pandemic, with customer spend shifting from offline to online channels. In the United States alone, online sales grew by over 30% (Digital Commerce 360, 2021). Online orders (both for home delivery and click-and-collect) can be fulfilled from integrated warehouses, conventional retail stores, dedicated e-fulfilment centers, or the so-called dark-stores, and even directly from suppliers (know as drop-shipping) (Marchet et al., 2018).

The requirements for delivery solutions has injected momentum for the courier, express, and parcel (CEP) market with rising demand to bridge the last mile in online delivery cost-efficiently. National post offices, traditional logistics integrators like FedEx, and emerging click-and-collect service providers such as Collect + have all been innovating and investing in faster and cheaper delivery and collection options to seize a share of this increasingly important market in many regions (Ranieri et al., 2018). Furthermore, delivery services have been leveraged as a marketing tool by providing subscription models to increase customer lock-in (Cohen, 2018). The significant innovation in this space was driven by Amazon's free 2-day delivery in the early 2000s, which raised customer expectations for free and fast delivery of goods. In the late 2010s, free next-day or even same-day delivery became very much the norm worldwide (Ecker et al., 2020).

Today, the rise of on-demand delivery platforms, such as Uber Eats or Deliveroo, enables the delivery of anything from restaurants to grocery stores within 1 hour in major cities worldwide (Woodcock, 2020). Thus, in addition to traditional logistics players, many new actors have participated in the delivery industry, enabling faster, novel, convenient, and flexible delivery and fulfillment services. Similarly, many Internet giants such as Amazon or Alibaba are innovating new ways to do deliveries and also increasingly investing in their own delivery infrastructure. At the same time, fulfillment services have become a business of their own. Fulfilment by Amazon (FBA), for example, is a business in which Amazon sells fulfillment capabilities to firms (Zhu & Liu, 2018). Specifically, many sellers in Amazon's marketplace pay Amazon to store, pack, and ship products regardless of whether the sale was made through the Amazon platform. The combined effects of reduced logistics costs and the increasing availability of fulfillment service providers help explain why it has never been easier to set up an online retail business and reach a global consumer base (Hänninen et al., 2019).

3. Platform-based retail ecosystems—the cases of Alibaba and Amazon

Here we present the cases of the two leading global platform businesses—Alibaba and Amazon − that have been innovative pioneers in platform commerce and the digital transformation of retail. We outline the digital initiatives they have taken and the innovations they have made to maintain their competitive positions and prosper in the digital economy.

3.1 Alibaba Group

Since its inception in 1999, Alibaba has experienced exponential growth on its e-commerce platform and become a household name with the world's biggest IPO ($25 billions) in 2014 (Xu, 2020). As a dominant player in the world's fastest growing Chinese e-commerce market, Alibaba has overtaken Walmart in global sales, and has higher transactions on its websites than that of eBay and Amazon combined (Loeb, 2013; Zeng, 2018). Their declared vision is to help build an open, coordinated, and prosperous e-commerce ecosystem (Alibaba, 2021), The company has a wide and still growing scope of platform-based businesses including marketplace, finance, logistics, technology, and media and entertainment (see Fig. 14.1). Empowered by network coordination and data technology, the ecosystem stewarded by Alibaba provides a resourceful platform for an ecosystem that includes vendors, customers, marketers, logistics companies, and other service providers enabling them to collaborate and interact smoothly and efficiently (Zeng, 2018).

TABLE 14.1 Overview of the evolution of delivery formats.

	Traditional E-commerce (1990s)	Multichannel E-commerce (2000s)	Omni-channel E-commerce (2010s)	Quick commerce (2020s)
Focus	Selection	Value	Value	Speed
Selection (SKUs)*	Large (20k + SKUs)	Medium (10k + SKUs)	Small (3–10k SKUs)	Micro (<3k SKUs)
Expected delivery speed	4–5 days	2–3 days	1–2 days	<1 h
Delivery outlet	Large warehouse	Large warehouse; store	Large/small warehouse; store	Small warehouse; store
Delivery vehicle	Truck	Truck; van	Van; car	Car; bicycle
Delivery to	Home, store, postoffice	Home, store, postoffice	Home, store, postoffice, locker	Home
Logistics provider	Retailer	Retailer, logistics partner	Retailer, logistics partner	Delivery platform
Customer experience score for last mile delivery	Low	Low	Medium	Medium
Pioneering players	Amazon, eBay	Tesco, Walmart	Alibaba, Amazon	Gopuff, Uber Eats

*Note: SKU is an acronym for Stock Keeping Unit.

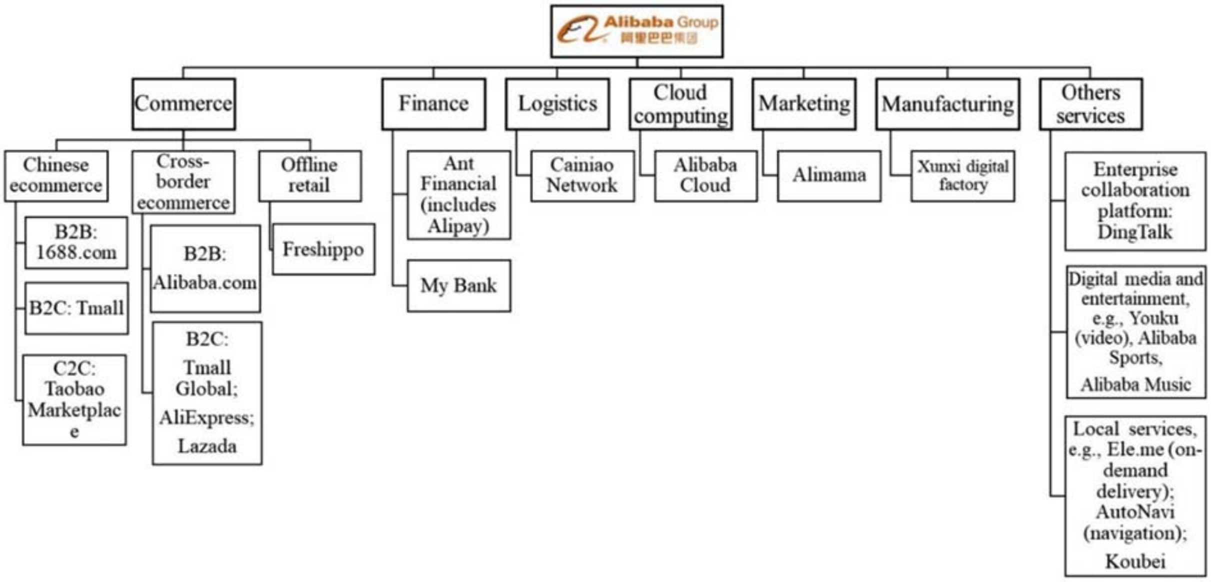

FIGURE 14.1 Major business units in Alibaba Group. *Data source from Alibaba. (2021). Alibaba group: Our businesses. https://www.alibabagroup.com/en/about/businesses and Zeng, M. (2018). Alibaba and the future of business.* Harvard Business Review, *96, 88–96.*

In enabling these players to do business, Alibaba has taken control of the three primary flows in supply chain: product flow (via Cainiao Network), information flow (via Alibaba Clouding), and financial flow (via Ant Financial). In this way, the concepts of "Smart logistics network" (2013), "New retail" (2016), and "New Manufacturing" (2016) have been introduced[1] and implemented to reshape China's retail sector. We describe the three concepts here.

14.1.1 Smart logistics network

The skyrocketing growth of its e-commerce and the increasing pressure on the logistics systems made it a necessity for Alibaba to revamp its logistics capabilities and gain full control of product flow in its ecosystem. To this end, Cainiao Network Technology Co., Ltd. (CN) was established by Alibaba in 2013 with a consortium of leading logistics service providers such as Yintai Group (specialists in Warehouse management), Fosun Group (for real estate and warehouse construction), Forchn (for line haul), SF express (for shipment and delivery), and major domestic CEP service providers including ZTO, YTO, STO, and Yunda (Falcone et al., 2019). The paramount objective of CN is to connect and coordinate big players in the logistics service industry and leverage their infrastructure and expertise to build a pervasive, fast, transparent, and convenient network to achieve domestic delivery (in China) within 24h and international delivery within 72h (Lin, 2019). The strategy adopted to realize this vision is to develop the "sky net," "ground net," and "people net" to link and coordinate customers, clients, and logistics partners (see Fig. 14.2).

The sky net is a data-driven digitalized supply chain network; the ground net is the global and domestic logistics infrastructure such as warehouses, fulfilment centers (FCs), and delivery hubs; the people net bridges the last mile delivery with Pick-up/Drop-off stations in colleges and universities, and communities in urban and rural areas. For data technology, CN has invested in YiLiu Technology to apply its Internet-of-Things (IoT) technology to digitalize the CN's entire supply chain (Wei, 2018). Also, CN has standardized the "datafication" of logistics information such as invoices and package labels to enable Alibaba to use its massive cloud computing capabilities to record, store, retrieve, and analyze data more accurately and efficiently. The troves of logistics data, advanced analytics, and cloud computing power allow CN to optimize its operations such as dynamic delivery routing with the incorporation of real-time delivery requirements and traffic and weather information, providing customers with faster, traceable, more convenient, and accurate services (Falcone et al., 2019; Lin, 2019).

For logistics infrastructure, CN has spent in the region of 100 billion yuan ($15 billion) to build a smart logistics network in China in 5–8 years to support approximately 30-billion daily sales and 10 trillion annual sales from its retail

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[1] Jack Ma introduced Alibaba's "Five New" Strategy in 2016, including New Retail, New Manufacturing, New Finance, New Technology, and New Energy. We elaborate on the New Retail and New Manufacturing here in line with the theme of this chapter.

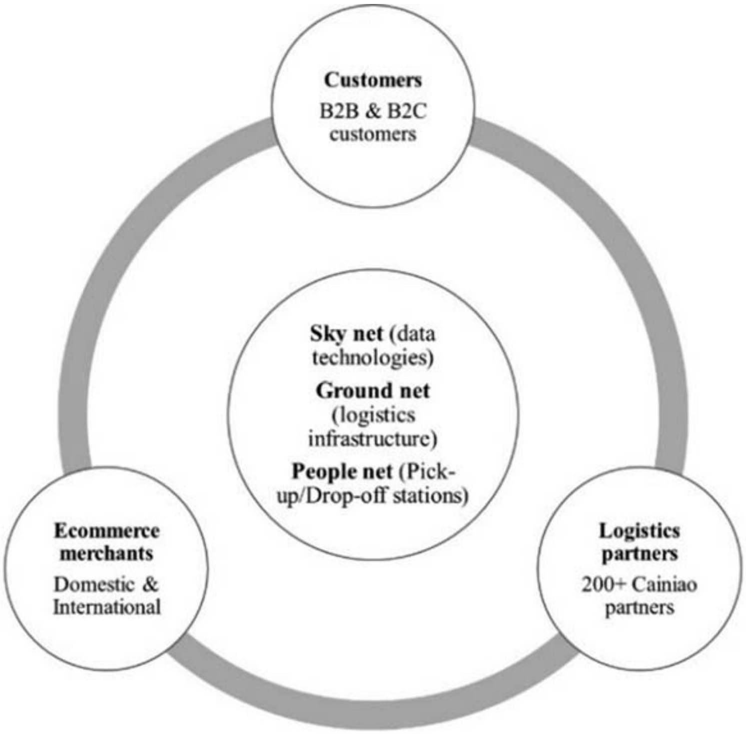


FIGURE 14.2 The strategic dimensions of Cainiao Network.

china marketplace (Sohu, 2016). It has also continually invested in a global fulfilment network including international shipping routes (Hu, 2020) and overseas warehouses in Russia, France, Malaysia, Australia, etc. (Lin, 2019), to exploit the increasingly important cross-border e-commerce. To provide better last mile delivery solutions, CN has developed a network of over 40,000 Pick-up/Drop-off stations in China (Lin, 2019). Such Pick-up/Drop-off stations provide alternative collection services for customers apart from home delivery options. Additionally, these stations handle online returns, enable customers to send out parcels, and offer community-based services such as laundry and group buying (Lin, 2019). The development of the three above mentioned nets in CN helps to underpin the digital upgrade and business prospects of logistics partners, support e-commerce merchants with smart logistics and supply chain solutions, and serve customers with merged online/offline experience and higher price/performance ratio in delivery services. CN provides the backbone for implementing the New Retail and New Manufacturing initiatives.

3.1.2 New retail

The “New Retail” concept encapsulates the core tenets of the Omni-channel retailing business strategy. The ultimate Omni-channel model seeks to integrate both the online and offline channels to ensure a seamless and channel-agnostic shopping experience for the customer (Verhoef et al., 2015). The “newness” of this concept can be best illustrated together with two further pillars: providing engaging and enriched shopping experience with a customer-centric mindset, and broadening the variety of application formats (see Fig. 14.3).

Alibaba’s propriety grocery retail chain, Freshippo (previously known as Hema, 207 self-operated stores as of December 31, 2020), clearly depicts the mastery provision of the data-driven hybrid online/offline experience and the creation of engaging social shopping experience (Alibaba, 2021). The roles of experience center, consumption center, and distribution center (DC) converge in each Freshippo store with advanced in-store mobile technology (Bird, 2018). For example, price tags are equipped with QR codes so that customers can use the Freshippo App on their mobile devices to check the origin (e.g., government certificate endorsing organic products) and the freshness of vegetables (e.g., information on when the product is delivered to the store), ratings and reviews from fellow shoppers, delivery options available, etc. (Falcone et al., 2019). Unsurprisingly, customers can make the payment using the app connected with their Alipay accounts or via biometric facial recognition (Falcone et al., 2019). The Freshippo robot restaurants that combine the physical and digital experience exemplify the application of digitalized retail in the restaurant industry. They also add another

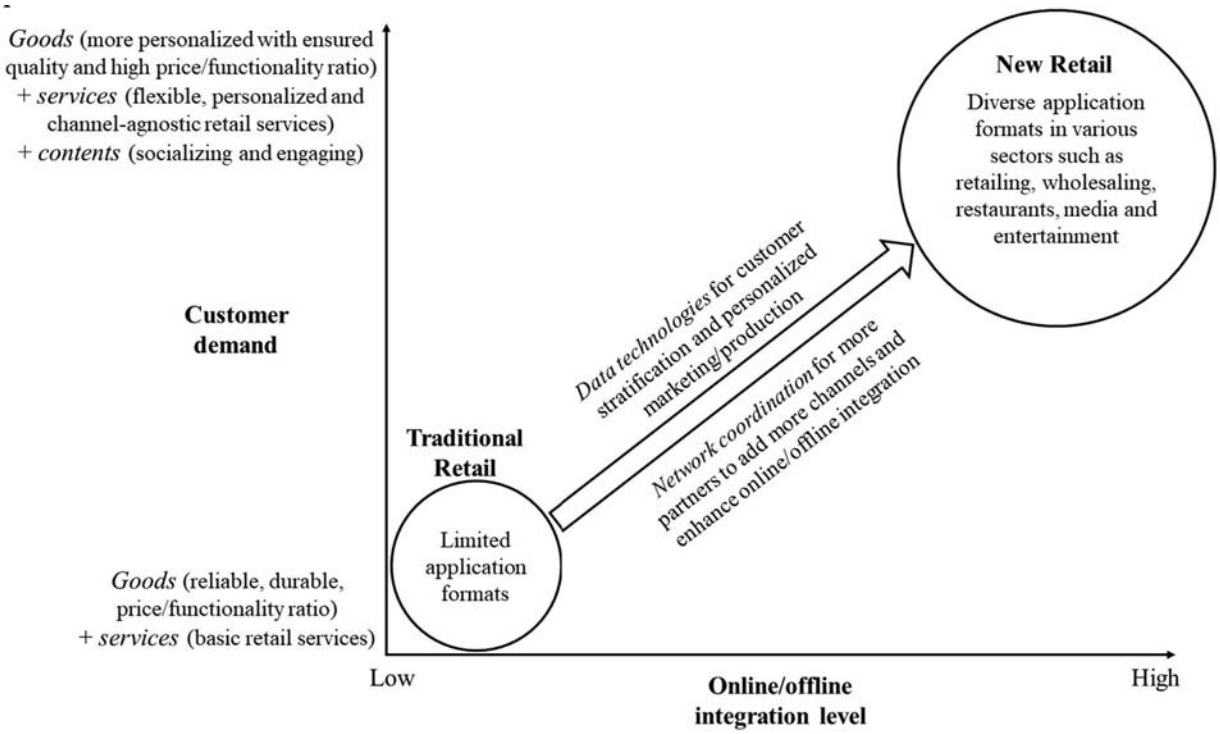


FIGURE 14.3 The illustration of Alibaba's New Retail concept.

layer—the socializing element—where the pleasure of shopping for fresh produces (e.g., seafood) personally and dining out with friends and families is satisfied. Further, each Freshippo store is facilitated with a conveyor belt (on the sidewall and ceiling) in which store associates place bags of packed online orders for delivery after being fulfilled using the store inventories. This enables a maximum 30-minute delivery for customers residing within 3-km radius of a Freshippo store (Alibaba, 2021), facilitating fast cross-channel fulfilment.

The New Retail revolution has been rolled out across China with Alibaba's proprietary e-commerce and offline presences in conjunction with its ecosystem partners. Alibaba launched "Lingshoutong (LST)" initiative ("retail integrated" in English) in 2014 with the aim to help millions of small and independent stores in China to transform in the digital era (Lin, 2018). The LST platform coordinates three parties—merchants, city partners, and brands/distributors—to yield corresponding benefits, while harnessing the opportunity to collect previously inaccessible customer data and enrich Alibaba's Omni-channel solutions (see Fig. 14.4). Participating merchants can optimize their merchandising decisions guided by the insights generated from customer analytics available in the LST app. They have access to logistics and digital inventory management systems supported by Alibaba for faster and cost-efficient delivery and lower stocks-out risks (Alizila, 2018). Sales data recorded in those participating stores can be shared with and leveraged by brands for product design and development, customization, and targeted marketing strategies. Two examples are the fruit-flavored coffee in Nestle (Alizila, 2018) and the individual-serving Oreo cookies in Mondelez (Koe, 2019). For Alibaba, it extends its service to small towns and villages to reach more customers and expands its offline store networks to facilitate Omni-channel solutions such as Buy-Online-Pickup-in-Store (BOPS) and Buy-Online-Return-in-Store (BORS). Besides, it now has access to such customer data, which can be utilized to further enhance its online and offline commerce capabilities.

3.1.3 New manufacturing

Alibaba unveiled its Xunxi Digital Factory (Xunxi in short) on September 16, 2020, signifying the first stride in its endeavor to launch a new cloud-based manufacturing model (Alibaba, 2020). By leveraging Alibaba's digital technologies such as cloud computing, AI, and IoT, Xunxi offers SMEs in the apparel sector a digitalized end-to-end manufacturing supply chain solution to allow for customer-centric and personalized production smartly and flexibly (Alibaba, 2020). Alibaba chose the apparel industry for the new manufacturing initiative because it has consistently been one of the biggest categories on Alibaba's retail marketplace in China, and because of its fast fashion nature with dynamic customer

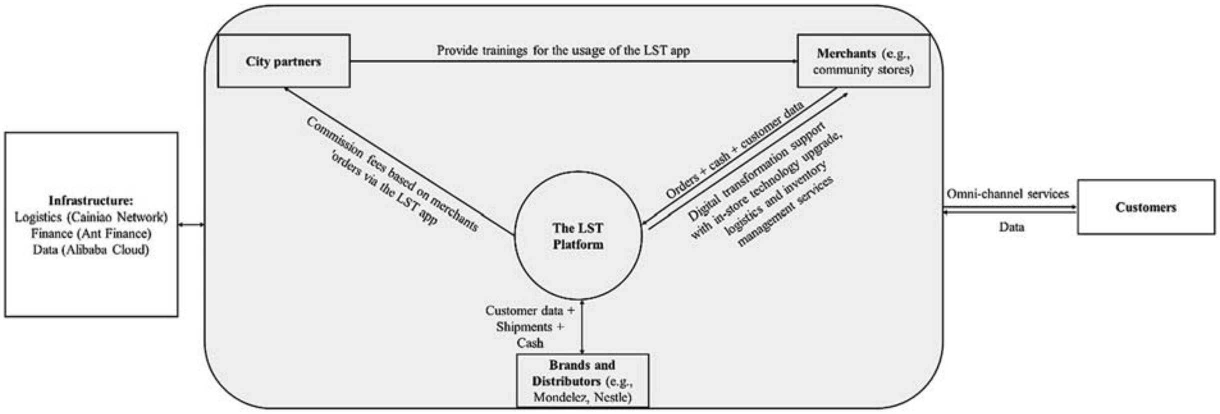


FIGURE 14.4 The illustration of the Lingshoutong (LST) platform. *Adapted from Lin, K. (2018).* LST-digital supply chain for small retailers *(*2018 investor day*).*

preferences and increasing demands for personalization (Alibaba, 2020). Amid an increasingly challenging era with labor shortages in domestic manufacturing, the wave of apparel production migration from China to Southeast Asian countries (e.g., Vietnam and Indonesia), and the Industry 4.0 revolution in developed countries (e.g., the United States), it is imperative for the Chinese manufacturing industry to modernize and upgrade with intelligent digital technologies (Global Times, 2020). Xunxi marks such attempts by accelerating the digital transformation in the Chinese apparel industry.

The core idea of the production approach in Xunxi is "made-in-cloud." Empowered by clear customer insights from data analytics and smart forecasting, Xunxi can respond to real-time market trends, thus achieving "made-to-sell" and reducing inventories. Cutting-edge technologies (e.g., AI-aided cutting machines, IoT-enabled sewing systems, AI-driven advanced planning system for scheduling and workflow adjustment, automated in-house logistics) have been harnessed to streamline production processes and also make manufacturing more agile, efficient, and sustainable. For example, a one-stop online system powered by AI algorithms schedules and arranges items from the same materials to be processed together even if designated for different orders to improve production efficiency and reduce fabric waste (Li, 2020). Such data intelligence and digital technologies enable Xunxi to produce small-batch orders more responsively at reasonable costs. As a result, the minimum order quantities can be reduced from the industry-average of 1000 to 100 pieces and the lead time can be shortened from the industry-average of 15—7 days, which outperforms the eminent fast fashion brand Zara (Sohu, 2020). This lowers the manufacturing barriers for SMEs and livestreams broadcasts in Alibaba's Taobao and Tmall platforms, who can then focus on marketing and design assured by the responsive and cost-efficient manufacturing capacity from Xunxi (Alibaba, 2020). In this way, it can retain and attract more brands to its marketplace platforms and better appeal to customers' changing needs. In doing so, it nurtures the network effects and cultivates its ever-expanding ecosystem.

3.2 Amazon.com, Inc.

Since its establishment by Jeff Bezos in 1994, Amazon has expanded quickly from an online marketplace originally for books to offer millions of products including toys and games, consumer electronics, homeware, fashion apparel, food, etc. It surpassed Walmart in market capitalization in 2015 and has charted a growth path, projected to have gained 50% of the US e-commerce retail market's gross merchandise volume (GMV) in 2021 (Krantz, 2015; Statista, 2021b). At the core of Amazon's business philosophy lie four guiding principles: customer centric, relentless invention and innovation, operational excellence, and long-term thinking (Amazon, 2020). To enhance online and offline channel integration for better customer service and higher operational efficiencies, Amazon has gradually built up a physical store network since 2015 with its first bricks-and-mortar store called Amazon books (Wahba, 2015). It accelerated the development of its physical presence by acquiring Whole Foods in 2017, gaining access to consumer data and private branded products from the acquisition (Petro, 2017). Driven by the passion to serve and delight customers, Amazon has continually developed new services such as Prime, Fulfilment by Amazon (FBA), Amazon Web Services (AWS), world-class entertainment, etc. (see Fig. 14.5). To enable a comparative analysis between Alibaba and Amazon and underline the similarities and differences of these two retail giants in the digital economy, here we focus on delivery and logistics, retail, and manufacturing operations in Amazon.

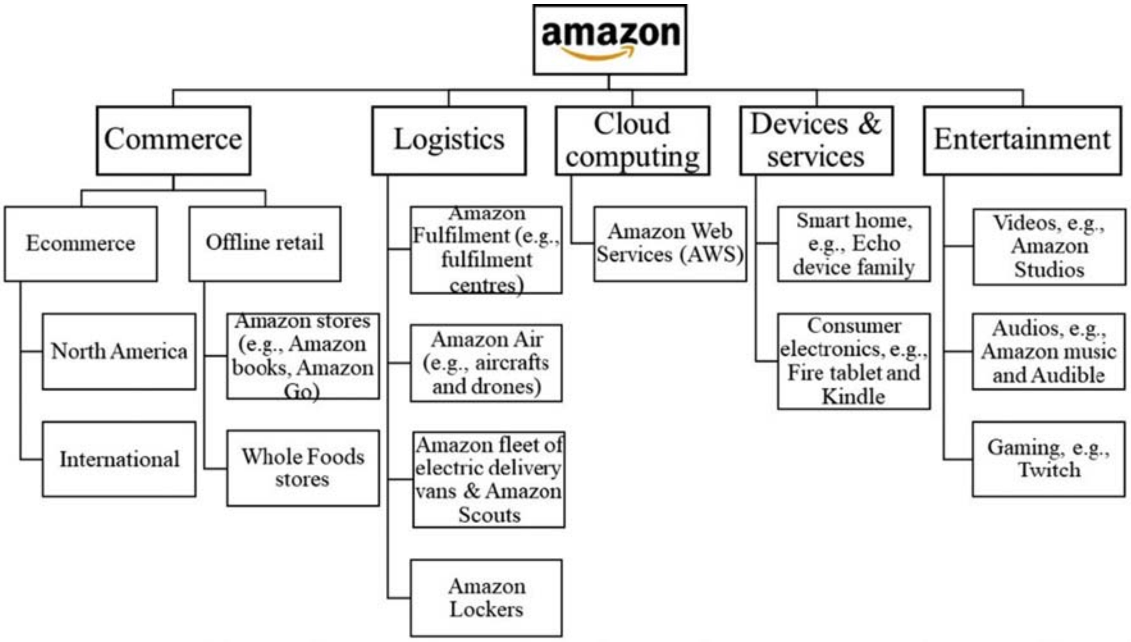


FIGURE 14.5 Major business units in Amazon. *Data source from Amazon. (2021c).* Amazon: What we do. *https://www.aboutamazon.com/what-we-do and Amazon. (2020).* Amazon annual report.

3.2.1 In-house fulfilment

Different from Alibaba, Amazon has been operating its own distribution network of facilities worldwide (see Fig. 14.6). Since logistics service qualities such as speed, convenience, and reliability are critical to maintain competitive advantage for businesses in the digital economy (Lee & Lin, 2005; Nguyen et al., 2018), Amazon has pushed relentlessly for faster deliveries (e.g., Amazon Prime Now for free 2-hour delivery) by developing and scaling up its distribution capabilities. It has invested nearly $1.5 billion to expedite its traditional 2-day delivery to 1-day as a default for its Prime members, which has resulted in rising revenues and historically high performance during holiday periods in 2019 (Rushe, 2020).

The Amazon distribution network combines the functional specialization of facilities and the deployment of state-of-the-art technologies. To cope with the characteristics of online orders with low volume, high variety, high frequency, and high levels of uncertainty, fulfillment centers (FCs) with various types, sizes, and automation technologies are utilized to

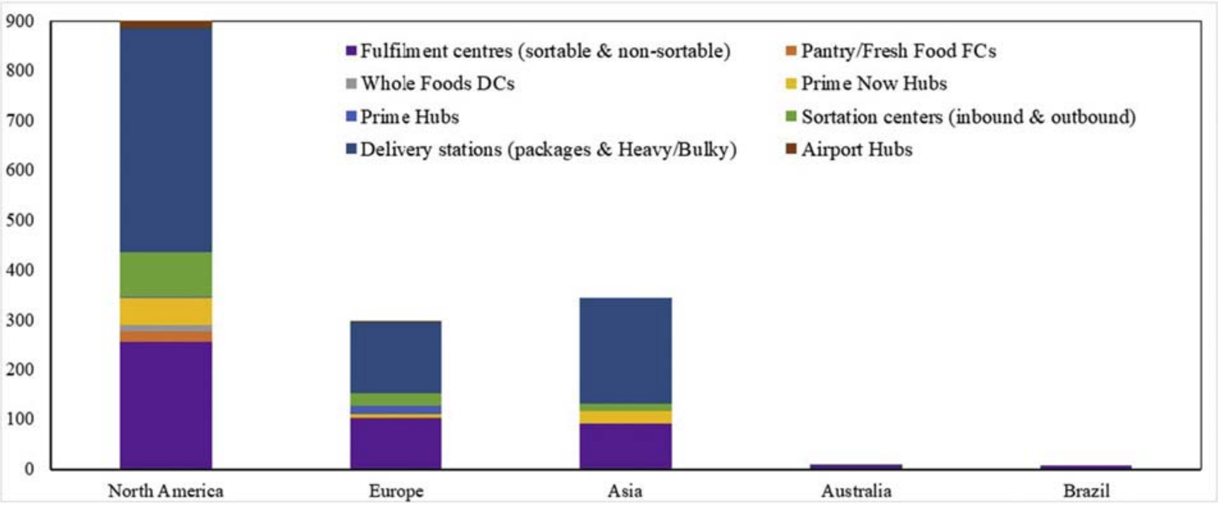
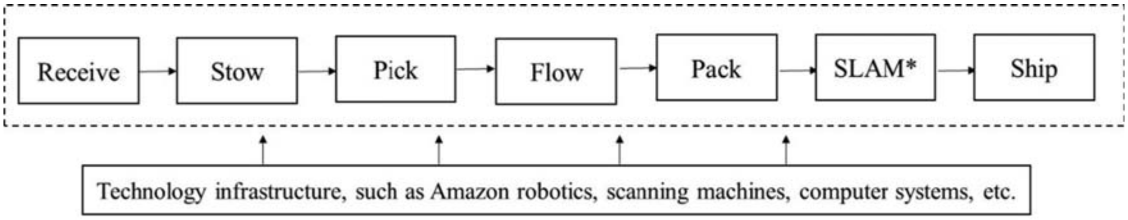


FIGURE 14.6 Amazon global distribution network as of May 2021. *Data source MWPVL. (2021).* Amazon distribution network strategy. *https://www.mwpvl.com/html/amazon_com.html.*



*: SLAM is an abbreviation of Scan, Label, Apply and Manifest

FIGURE 14.7 Operations process within a typical Amazon fulfilment center. *Data source Amazon. (2021a).* Amazon delivery & logistics. *https://www.aboutamazon.com/what-we-do/delivery-logistics*.

pick, pack, and ship orders quickly and efficiently (Amazon, 2021b). Fig. 14.7 illustrates the typical operations process within an Amazon FC. Amazon uses a random stow method to spread popular items across the FC rather than aggregate in one place (Amazon, 2021; Rodrigue, 2020). Via QR codes and a scanning system, sortable popular items are scattered randomly on automated racks with item locations recorded, which then arrive at the location of the warehouse operative to pick the requested items for specific orders, i.e., Amazon operates a Goods-to-Person (GTP) system (Bozer & Aldarondo, 2018). This method matches the online order characteristics with reduced retrieval time and increased storage space utilization compared to the conventional practice of storage by item category (Rodrigue, 2020). By using advanced IT, both digital and physical operations can be integrated within facilities, which improves inventory availability. Robotics have been widely used to enable safer and more efficient material handling operations, such as palletizers to move heavy totes around quickly and safely (Amazon, 2021a). The invention of Amazon drones and Scout further exhibit the wide application of modern technology within Amazon's distribution network. Such autonomous delivery services use proprietary computer-vision and AI algorithms to detect objects and people and ensure safe, reliable, and stable delivery at required speed[2] (Scott, 2019; Wilke, 2019).

Compared to Alibaba that leverages its own physical stores, as well as the stores in its LST program, Amazon complements its store network (Amazon stores and Whole Foods stores) with the widely rolled out Amazon lockers[3] in strategic locations such as shopping malls, convenient stores, apartment buildings, etc. (Holsenbeck, 2018). The wide geographical network of Amazon locker facilities helps alleviate the challenges for attended home delivery (e.g., low first attempt delivery success rate and tight delivery window) (Agatz et al., 2011). Its technology and logistics experience have supported the phenomenal growth in its retailing businesses with continually expanding ranges of products offered. These have also enabled the innovation of new business models with an extra revenue stream, i.e., the Fulfillment by Amazon (FBA) program, which has been available since 2006. By paying service fees, third-party sellers on the Amazon marketplace can store their products in Amazon's FCs and Amazon handles back-end operations such as pick, pack, ship, and provide customer service for these products (Zhu & Liu, 2018). Meanwhile, fast and free delivery options are offered to Amazon Prime members together with other exclusive benefits (e.g., Prime videos, e-books, etc.) to cultivate customer loyalty
(Wu & Gereffi, 2018).

3.2.2 Innovative retail

Amazon has been a trailblazer for innovation in retail. In 1999, it secured its one-click ordering patent for customers to shop 'hassle-free' without keying in billing, shipping, and payment information for each online transaction (Mellahi & Johnson, 2000). Its invention of AI-based voice assistant such as Amazon Alexa was also a game changing retail innovation. In addition to many other functions, customers can use Alexa's hands-free speaker for voice shopping, adding items to their Amazon carts from home (Simms, 2019). Linked to Amazon e-commerce offerings, customers can shop with Alexa, set price drop alerts, get deals and promotion notifications, and track their packages, which broadens the channel scope for Amazon to interact with customers, provides more convenient experiences to customers, and increases customer

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[2] Amazon drones can delivery packages weighing up to five pounds to customers in maximum 30 min; Amazon scouts with a walking pace can be used for same-day, 1-day, and 2-day shipping for Prime members.

[3] Amazon lockers have stringent requirements on the physical size and weight of parcels, though most items on Amazon.com can be delivered to a locker.

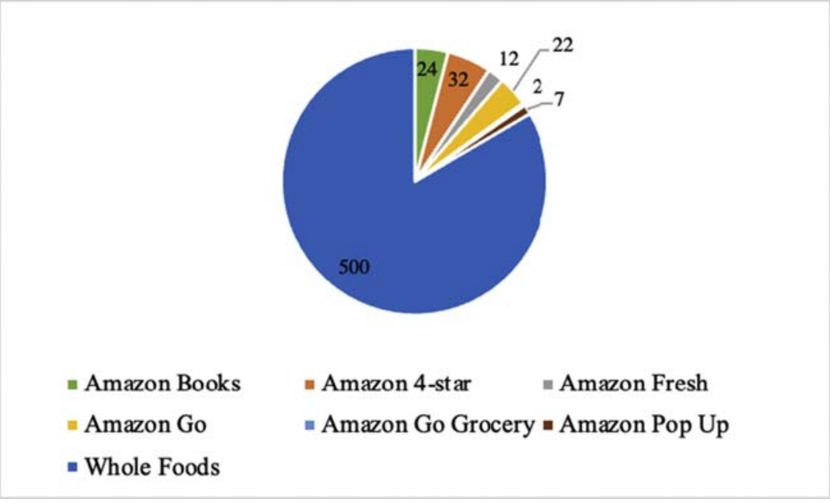

FIGURE 14.8 Types of physical retail stores owned by Amazon.[4] *Data source Amazon. (2021b).* Amazon facilities. *https://www.aboutamazon.com/workplace/facilities and Statista. (2021a).* Amazon physical retail stores 2020. *https://www.statista.com/statistics/1155873/amazon-store-openings-number/.*

"stickiness." To seek online and offline channel integration, Amazon has also developed physical presences with grocery stores, bookstores, pop up stores, and 4-star general merchandise stores, together with the store network of Whole Foods (see Fig. 14.8). All of these stores are deployed to offer cross-channel services such as pickup and returns options for online purchases. The Amazon 4-star stores are also embodiments of channel integration by carrying some of the most popular items on Amazon.com, ranging from electronics, toys, to books and games (Wilson, 2020).

The current pinnacle of innovative retail may be the checkout-free shopping experience offered in Amazon Go and Amazon Go Grocery stores. With an Amazon account and the free Amazon Go app on their mobile devices, customers can simply scan the QR code from the app when entering the store, put items in their baskets or bags (without the need to scan each item), and just walk out of the store, i.e., the so-called Just Walk Out technology (Tillman, 2021). Such technology consists of a combination of computer vision, sensor fusion, and a deep learning algorithms. The system of sensors, cameras, and RFID readers identify customers and the items they take from the shelves, updating their virtual carts automatically (Amazon, 2021d; Tillman, 2021). Customers' Amazon accounts are then debited, and receipts are sent to the app, avoiding waiting lines or checkout operations. By investing in a physical retail store network with new-generation technologies, Amazon can offer more cross-channel services and also innovate convenient shopping experience in stores, which is increasingly important for 'time-poor' customers.

3.2.3 AWS for smart factory

Compared to Alibaba, Amazon has a wider scope of its own branded products from AmazonBasics (private label for thousands of items such as batteries, apparel, housewares) to electronics such as Amazon Alexa, Kindles, Fire TV, and tablets. However, it has outsourced the production of its branded products to manufacturers globally (Leonard, 2019). For example, it has recently partnered with Foxconn's Cloud Network Technology to begin its first production line of Fire TV Stick in India (The Economic Times, 2021). Despite the absence of manufacturing infrastructure, Amazon has excelled at providing digital transformation to help businesses optimize their factory operations with the assistance of AWS cloud services. In fact, 65% of IndustryWeek's 50 Best Performing US Manufacturers and 80% of Forbes' listed Top 25 IoT Startups to Watch in 2019 use AWS services (AWS, 2021). State-of-the-art automation, AI, robotics, and data technologies (e.g., for data storage and analysis) are indispensable technologies for the Industry 4.0 revolution (Frank et al., 2019). Cloud computing services such as AWS are the backbone to support and enable the functioning of these technologies. Amazon focuses primarily on providing services and solutions to manufacturers to help them digitalize and optimize their factory operations through its AWS business, while Alibaba takes a step further to develop its digital factory and handle the manufacturing operations for its platform partners as well as offering of cloud services from its Alibaba Cloud business.

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[4] Current summary includes one Amazon 4-star coming soon in Washington and three temporarily closed Amazon Go stores (one in New York and two in Seattle) as of May 2021.

4. Discussion

In this section, we discuss the impacts of digital disruptions on retail business strategy, front-end retailing, and back-end logistics and manufacturing operations by synthesizing information from the above case studies and the extant academic and practitioner literatures.

4.1 Transition to a platform business model with ongoing investment in physical assets

With the advancement and proliferation of digital technologies, the platform business model has risen to prominence where the strategic emphasis of the focal business is to create a network of participants (e.g., customers, sellers, software developers) and orchestrate their resources to enable smooth interaction and value co-creation between platform participants (Libert et al., 2014; van Alstyne et al., 2016). Leading retailers such as Amazon and eBay in the United States and Alibaba and JD.com in China are typical network orchestrators based on the platform business model. As depicted in our cases, Internet giants have invested and leveraged their cutting-edge technologies so as to provide participants in their business ecosystems innovative and value-adding solutions, including merchandising, marketing, logistics, payment, and manufacturing. This cultivates an increasingly attractive platform where more value can be created and business performance can be enhanced. Consequently, more users with a variety of tangible and intangible resources participate, further reinforcing and strengthening the platform's network effects (Libert et al., 2014).

Alongside orchestrating resources from platform participants, both Alibaba and Amazon have consciously developed their own physical infrastructure and assets but with different strategic foci. For Alibaba, the primary objective of building up infrastructures such as Freshippo supermarkets, warehouses, pick-up stations, and Xunxi digital factory is to facilitate engagement with customers and better tap into external resources. For example, its network of warehouses and pick-up stations empowers its logistics partners (e.g., CEP companies) to plan and execute online fulfilment and delivery, cost-effectively. For Amazon, its enormous distribution facilities are used to store and distribute goods for its own retail business and also for its FBA partners. In other words, Amazon has invested in physical infrastructure to provide services to platform participants rather than primarily leveraging participants' competencies for value co-creation as Alibaba does. Besides, Alibaba is skillful in spreading its physical retail footprint by leveraging resources in its platform via the LST initiative, while Amazon inclines to develop its own infrastructure. As the network orchestrator in their platforms, both companies have underscored the importance of developing physical infrastructure and assets but with different standpoints in leveraging such assets for value creation.

4.2 Channel-agnostic, convenient, and personalized retail experience

Investments in physical retail stores in Alibaba and Amazon and the convergence of the offline retail businesses with their well-established online businesses have epitomized the Omni-channel paradigm, which exhibits a high degree of channel integration (Verhoef et al., 2015). The presence of physical stores enriches the number of channels through which businesses interact and engage with customers. Further, it facilitates cross-channel service offerings such as BOPS, BORS, and Ship-From-Stores (SFS) (Gao et al., 2021; MacCarthy et al., 2019). Such offerings imply that downstream customers can enjoy a high degree of flexibility in choosing where and how they shop, and that retailers can also exploit flexible back-end operations (e.g., order fulfilment, delivery, and returns) by integrating online and offline resources (e.g., inventories, personnel) for cost and speed efficiencies as well as responsiveness.

Technologies deployed in the physical retail stores in Alibaba and Amazon have also underlined the strategic roles of retail stores in the digital world. Beacons, RFID, robotics, sensors, and cameras give customers easy access to product information, store navigation, payment, and check-out (McKinsey & Company, 2020). For retailers, the control of the customer interface provides the opportunity to capture a plethora of customer data, which feeds back to their decision-makings via data analytics to improve customer experience and enhance business performance with personalized marketing, dynamic pricing, optimized merchandising, shelf management, workforce planning, etc. (Reinartz et al., 2019). Such feedback-driven business operations can attract more customers with associated data and consequently generate more insights from Analytics, in doing so further improved customer service with more optimized offerings, i.e., form a virtuous loop. Apart from digitally transformed physical retail stores, AI-enabled voice assistants (e.g., Amazon Alexa, Siri, Google Assistant, AliGenie) have emerged as an additional channel for retailers to engage and interact with customers. Some customers even regard these voice assistants as "best buddies" owing to their gratifying sociability (Purington et al., 2017). Such devices can also change the way customers shop with easy and frictionless tools to check product reviews, get recommendations, set alerts for discounts and promotions, and place orders. For retailers, it is imperative to integrate the voice technology into their business systems to capture more customer data, better understand customers' intentions and behaviors, convert leads to sales, and offer tailored marketing and services to customers (Simms, 2019). In summary, the digital transformation in retailing ensures more personalized and convenient shopping experience, and also enables retailers to better control the customer interfaces and capture associated data to exploit a virtuous loop with continuously improved business operations with the assistance of data and decision analytics.

4.3 Faster and flexible logistics capabilities

Retail digitalization is creating a new logistics landscape. The new landscape combines flexible infrastructure and resources for fulfilment and delivery with more specialization of logistical facilities (e.g., FCs) for purposely designed automation, and value-adding innovative customer service offerings. Customers yearn for faster, more flexible, and cheaper delivery options for their online shopping to compete with the instant gratification granted via offline store channels (Marchet et al., 2018). The increasingly prevalent on-demand delivery options such as Prime Now and Meituan[5] have altered customer expectations for fulfilment speed (Deloitte, 2017). The high returns rate from online channels further exacerbates the challenges posed on retail logistics (Robertson et al., 2020). For retailers with integrated online and offline businesses, they can take a single view on their inventories within the retail system and fulfill online orders flexibly from retail facilities such as physical stores. Stores can also be deployed as the entry points for product returns, i.e., the BORS offering, alongside the options to return via post to warehouses or returns centers (Gao et al., 2021).

The COVID-19 pandemic further accelerates the deployment of physical stores for online fulfilment/return purposes given dwindled store traffic (Quinn, 2021). Clearly, the role of physical retail stores has been redefined. It has been enriched to be more than just a customer interface to offer a range of appealing customer services and capture more customer data. Nowadays, physical stores have been deployed as "mini" DCs to facilitate forward order fulfilment and backward returns options for online businesses. As stores are located closer to customers compared to DCs, the store network therefore enables retailers to offer more flexible and faster delivery and collection options (MacCarthy et al., 2019). The novel role played by stores reinforces the strategic moves made by online players such as Alibaba and Amazon to invest and integrate online and offline resources to stay competitive in the Omni-channel retailing era.

Digital technologies have not only propelled retailers to leverage stores and DCs for order delivery and returns but also empowered retailers to attain smart logistics solutions to be leaner and more agile. Technologies such as RFID chips, automation, robotics, Augmented Reality (AR) or Virtual Reality (VR), IoT, and unmanned vehicles have increased the operational efficiency and accuracy greatly in warehousing operations, and also in vehicle routing and distribution management (McKinsey & Company, 2020). For example, with the help of mobile communication systems, geographic information system (GIS) and global positioning system (GPS), computing power, and decision support systems (DSS), logistics managers can update the vehicle routing in real-time, taking into account incoming customer orders, weather and traffic conditions (Rincon-Garcia et al., 2018). Data Analytics also allows retailers to make anticipatory shipping and therefore quick delivery by predicting customer shopping patterns and shipping the potentially requested items to the nearest DCs before order placement by customers (Lee, 2017). To control the product flow, major retailers such as Amazon in the United States and JD.com in China may resort to develop their own logistics arms. On the other hand, retailers such as Alibaba could exert their influence as network orchestrators to leverage the expertise and capabilities of their logistics partners in the platform. Comparatively, retailers with in-house logistics operations can bundle their logistics service offerings and other services in their business ecosystems (e.g., Amazon Prime for free next-day delivery and prime videos and music) as powerful marketing tools (Wu & Gereffi, 2018).

4.4 Manufacturing operations

Manufacturers have also revolutionized their operations with new strategic initiatives to remain competitive in the digital era. The first noticeable innovation is product design and development, seeking to create new values in the consumption ecosystem (Subramaniam et al., 2019). Product design and development should take into account the connectivity and interdependencies of different products when being consumed. For example, manufacturers of home improvement products (e.g., bulbs and curtains) need to ensure that their products are compatible with the connected smart home system together with a wide range of other products and services (Deloitte, 2017; Subramaniam et al., 2019). Integrated manufacturing-retail information and D2C interface enable manufacturers to provide customers with bespoke products/

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[5] Meituan is a leading Chinese e-commerce platform particularly famous for its on-demand food delivery service, together with other services such as bike-sharing, car-hailing, movie tickets, etc.

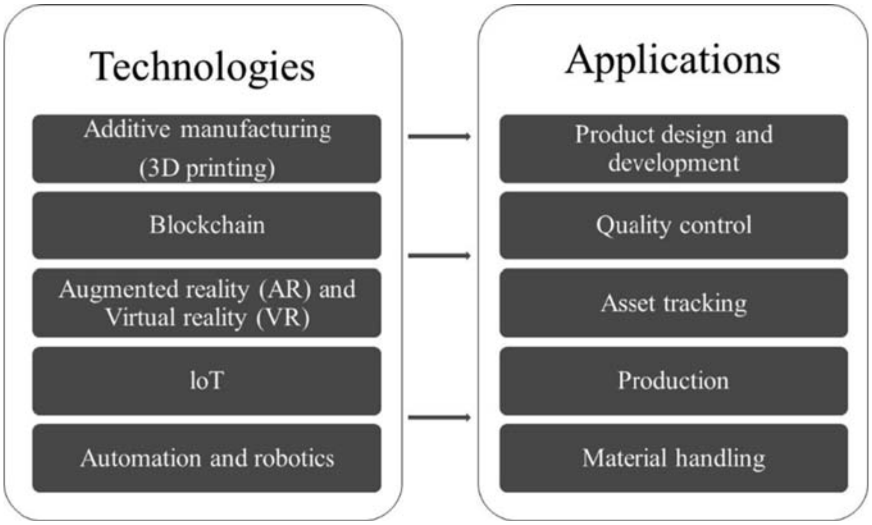

FIGURE 14.9 Typical Industry 4.0 technologies and their applications in manufacturing.

services (Holweg et al., 2019). Besides, the rise of the sharing economy enabled by the technologies encourages manufacturers to design and produce more durable products for sustainability purpose (Abhishek & Zhang, 2021).

Second, the power structure between platform owners and their suppliers has also altered as platform owners such as Amazon tap into the manufacturing space and compete with platform partners (Zhu & Liu, 2018). Since platform owners facilitate the interaction and engagement between suppliers and customers, they can build up their knowledge on different product sectors and customer preferences and behaviors. Therefore, some platform owners have chosen to enter the manufacturing market with their private label products and compete with their collaborating suppliers (Ritala et al., 2014; Zhu & Liu, 2018). This relationship raises questions for both the platform owners (e.g., when and which product sectors to manufacture?) and suppliers (e.g., what products to produce and at what price?). Third, as exhibited in Alibaba's Xunxi digital factory, new-generation technologies can considerably improve manufacturing operations (e.g., quality management and production planning) to make it more agile, leaner, and sustainable. Fig. 14.9 illustrates some typical Industry 4.0 technologies and their applications in the manufacturing operations (Frank et al., 2019).

5. Conclusions

This chapter has provided an overview of the transformative practices in the retail value chain in response to digital disruption. Three core areas have been examined—retailing, logistics, and manufacturing. The breadth of changes in the retail value chain have been reviewed, and key trends and tendencies of business reengineering taken by retailers amid the digital disruption are identified and illustrated with a comparative analysis of two platform-based retail giants in Western and Asian markets (i.e., Alibaba and Amazon). We discuss the impacts of digital transformation on business strategy, front-end retailing, and back-end operations (i.e., logistics and manufacturing) in the retail sectors. The emergence of platform-based retail ecosystems is highlighted. Our study contributes to both academic and practitioner knowledge by advancing understanding of the evolution and transformation of retail businesses driven by the digital technologies.

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Chapter 15

Digitalization in the textiles and clothing sector

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Abstract

Digitalization has advanced conventional textile and clothing supply chain (CSC) concepts, models, and practices by harnessing many emerging technologies and digital infrastructures. We discuss the impact of digitalization across the whole of the textile and clothing value chain. First, we provide an overview of the main factors driving digitalization in this sector. These include the growth of e-commerce and changing consumer preferences, the desire for increased speed to market from design concept to consumer, and the increasing imperative for more sustainable production and consumption. The impact of digitalization on CSCs is then discussed with regard to design and sampling development, sourcing, manufacturing and distribution, retail, returns, and reuse processes. Notable examples and insights are provided on different digital technologies that have the potential to transform the industry The potential for the adoption of circular economy principles enabled by digitalization, including innovative resale and sharing models, is also discussed. Finally, we outline a number of inhibitors and barriers that affect the pace of adoption of digital technologies in textile and CSCs. We highlight lack of access to available technology, economic viability, strategic development challenges, and lack of digital expertise, which currently constrain the growth of digitalization in the sector.

Keywords: 3D design; Artificial intelligence; Big data; Clothing; Digital tool; Digitalization; Industry 4.0; Supply chain; Wearable.

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1. Introduction

The persistent inability to automate many parts of the clothing supply chain (CSC) has resulted in low-cost and labor-intensive manufacturing that is largely forecast-driven and widely dispersed over space and time (Mustonen et al., 2013; UNEP, 2020). Production bases in CSCs, mostly located in comparatively low cost regions such as parts of Asia, North Africa and Central America, often create long lead times of up to 12 months. When combined with uncertain and volatile market demand, they result in large-scale inefficiencies, business risks, environmental and social problems in the production countries and substantial waste in the consumption countries. In an industry where the projected global market growth in value is expected to rise from 1.5 trillion US dollars (USD) in 2020 to about 2.25 trillion USD by 2025,[1] digitalization of the entire textile and clothing value chain—from virtual material design to electronic interaction with the final customer—is expected to lead to the rapid adoption of new technologies. This will result in the emergence of new industry players and business models that will begin to disrupt traditional CSCs, posing existential risks for traditional players. Use of big data, digital collaboration, online social interaction, and e-commerce are coming together to create, sell, or share a physical clothing product, or its digital twin over a digital environment.

Digitalization of the supply chain refers to complementing a physical system by digital connections between people and places, and the development of information systems by adopting and merging digital and physical resources for improved

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[1] https://www.statista.com/topics/5091/apparel-market-worldwide/#dossierSummary__chapter1.

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management (Ageron et al., 2020; McDonald, 2012). Strategic use of digital data combined with the use of advanced digital technologies such as machine learning, Artificial Intelligence, smart systems, etc., has the potential to enable an end-to-end alignment of digital initiatives with supply chain goals. It can improve productivity, reduce inefficiencies such as defects, waste and production lead time, and enable greater agility and visibility through short runs and small lot sizes (Nasiri et al., 2020; Raab & Griffin-Cryan, 2011). Digitalization can facilitate value creation and new business models in CSCs by enabling customer co-creation, predictive and remote monitoring and maintenance, virtual training, digital product twins, and "production-as-a-service" concepts.

In the textile and clothing sector, a number of key trends, driven by advances in digital tools and technologies, are contributing toward transforming the CSC landscape from analog to digital:

a. *Growth of e-commerce and changing consumer preferences:* Several recent studies (e.g., Guercini et al., 2018; Lorenzo-Romero et al., 2020) have highlighted that the growth of e-commerce is offsetting the reduction in use of off-line sales channels. A considerable proportion of the market is expected to migrate permanently to online channels in the coming years. Deloitte (2019) projects that the proportion of online purchases of clothing in several larger consumer markets such as China, United States, India, and Brazil could increase to reach 50%—70% of total sales by 2030. For clothing brands, the increase in online sales has the potential to reduce their cost structures through data-driven stock management and enable new fulfilment options including omnichannel, customization, click-and-collect, and drive-through collection (Gonzalo et al., 2020). Furthermore, innovative and personalized services in apparel e-commerce may ensure customer satisfaction and retention through value co-creation during the prepurchase phase; ensure added-value during the postpurchase phase of the shopping journey; and convenience in last mile delivery (Jain & Sundström, 2021).

McKinsey highlight that customizable apparel could account for 10%—30% of market share by 2030 (Gonzalo et al., 2020). Deloitte (2019) estimates that alternative e-commerce models such as online marketplaces, recommerce, subscriptions, and rentals could take as much as 9% share of the total by 2023 and 10%—30% share by 2030. For instance, recommerce or reverse commerce of selling of previously owned, presumably used products through online distribution channels attracts consumers for several reasons: it is more sustainable as it slows the rate of consumption of new products and materials, provides better value for money, and often offers a one-of-a-kind experience (Sularia, 2020).

b. *Speed to market:* As consumer habits change, the requirements and pressure for greater supply chain speed and flexibility will increase. Brands will need to accelerate speed to market, for instance, by adopting agile techniques that enable companies to reach the marketplace with products quickly, refining them iteratively based on consumer feedback. Time compression can be supported by digital interaction between the different supply chain actors and through digitalization of key business processes. For instance, compared to conventional sampling process in apparel product development, which can have a lead time of several months, virtual sampling using 3D design tools and Computer-Aided Design (CAD) systems can reduce the lead time to a few days (Chaudhary et al., 2020; Hsu et al., 2019). In another McKinsey study (Berg et al., 2017), a survey with apparel procurement officers indicated that the majority sought to reduce lead times by 2 to 8 weeks, and targeted a cost reduction of 2.5% was possible from implementing an integrated cloud-based system for centralized product development and procurement.

c. *Sustainability:* The digital shift in the textile and clothing industry promises not only to drive profitability but also significantly improve sustainability across all value chain stages (Brydges et al., 2020; Gonzalo et al., 2020). Digital technologies are found to have significant impact in driving the dematerialization of resource-intensive processes in traditional CSCs. For instance, clothing companies that have started using digital technologies such as 3D design, virtual sampling, and prototyping can optimize material consumption for physical sampling (Cobb et al., 2017), which can ultimately reduce carbon footprints (Xiong, 2020). In the production stage, digitally enabled on-demand production allows elimination of unsold clothes (Larsson, 2018), and when combined with digital tools such as 3D virtual fitting can be used to manufacture made-to-measure garments, thus eliminating both pre- and postconsumer wastes (Dissanayake, 2019). Other technologies, for example adding digital tags or Radio Frequency Identification (RFID) in the garment-making stage, can reduce the level of safety stocks needed, enable supply chain traceability, thus increasing the lifecycle of clothing by reducing preconsumer waste (Denuwara et al., 2019; Östlund et al., 2020).

In light of these trends, this chapter highlights the main areas of digitalization in CSCs, across the different stages of design, sourcing, manufacturing, distribution, retail and reverse logistics, and how these impact CSC performance, in terms of time compression, lowering environmental impacts, improving process integration, visibility, and customer orientation, as conceptualized in Fig. 15.1. In each section, we provide further elaboration of these impacts with specific notable examples of different digital technologies.

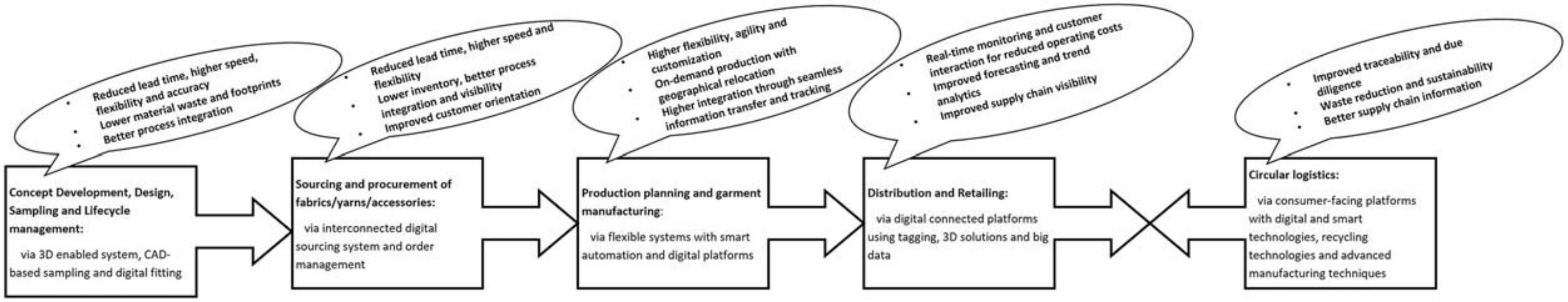

FIGURE 15.1 A digitalized process-based view of the clothing supply chain (CSC).

2. Digital clothing design and sample development

2.1 Product design, sample development, and product lifecycle management

Among the interconnected series of CSC activities, the product design and development stage needs involvement from various actors for different steps in the process, in particular for concept development, preparation of specifications, selection of materials, product development, and sampling. If the required skills, competencies, and tools are not well integrated across the different processes and business partners in the development cycle, the entire product design and development stage can be time-consuming, costly, and wasteful. Recent advancements in digital and virtual technologies support the optimum design, development, and product lifecycle management process (Braglia et al., 2021; Kasumoto, 2020; Lay, 2018; Luo & Yuen, 2005; Tsao et al., 2020; Weinswig, 2017, pp. 1−15). A key aspect of such digitalization is the transformation from conventional 2D-based style designing for making product sketches, to the use of 3D tools within the design process (Pal & Sandberg, 2017).

In 3D systems, garment design takes place in a virtual platform enabled with 3D tools and employs an integrated approach from draping and styling to 3D/2D synchronization. Such platforms include 3D drawings, 2D flat pattern design, fabric color and repeat controllers, and logo positioning (Lu et al., 2017; Weinswig, 2017, pp. 1−15). Unlike the conventional way of making adjustments to the initial designs through tailoring, in a digital design environment, simulations are made for every modification efficiently and speedily as it supports different sizing. These are concurrently updated to instantly generate detailed product specifications for the manufacture of the 3D designed garment. This system supports the costing process as it can concurrently update costs with the key textile suppliers and apparel manufacturers.

Leading clothing retailers such as Adidas, Nike, Under Armour, Victoria Secret, and Next have successfully applied such design technology with the development of latest software that facilitates 3D designs within the virtual platform (Kasumoto, 2020; Papahristou & Bilalis, 2017). Browzwear[2] offers software like Lotta for 3D fashion design and Clo3D[3] offers 3D garment visualization technology for direct 3D apparel design on a 3D human model to simulate the effect and the appearance of the apparel on the human body, avoiding repetitive fittings with physical models. 3D pattern-editing facilities, for instance, V-Stitcher 3D Style editing, enable direct style editing for fit improvement in 3D space, and projects the results directly on the pattern alteration in the 2D plane (Kasumoto, 2020; Papahristou & Bilalis, 2015).

Further, with the utilization of 3D body−scanning systems, digital body models are often created and new designs are simulated on such digital bodies. This facilitates the custom-design clothing segment if integrated with body measurement data using biometric technologies. Any modification can be accommodated easily without changing the first pattern. It is not required to develop the physical fabric or garment samples at the initial stage of the design process, thus avoiding repetitive fittings with physical models. The 3D fashion design systems with online interfaces take several sizes and fit them on a custom model to permit the fitting on of clothing online. It enables the designers to validate their design on a computer-generated or body-scan model, taking technical information such as fabric type, color, drape, tensile strength, shear strain, bending rigidity, and the effect of garment seams into account (Kasumoto, 2020; Papahristou & Bilalis, 2015).

Design and sample development are highly interrelated processes in the apparel sector. Digital 3D design impacts the sample development process by bringing more flexibility in the way that samples and prototypes are made and evaluated. Integrated digital 3D design systems allow garment manufacturers to incorporate manufacturing competency, for instance, in calculating fabric consumption, and cutting and sewing specifications, into the pattern development process, thus enhancing the accuracy. For instance, Nike designs the garments in a 3D-enabled system using an integrated approach in partnership with its main fabric and accessory suppliers as well as its main garment manufacturers (Kasumoto, 2020; Stangl, 2020). It then incorporates the insights and competencies of all these partners in the initial sets of samples, which are virtually developed and tried-on followed by making the required modifications and updating the entire system in the CSC. However, later samples from the fitting and approval stages are physically developed. In this context, Digital twins, that is a virtual model of the garment, play a vital role to enable successful control and communication in the physical sampling process and in the productive use of 3D design in the sample development stage. It allows data to be harvested to connect, update, and control the sampling process (Barraco, 2019), thus bringing more flexibility, speed, and accuracy into the sample development process.

Digitalized fashion design with 3D visualization and virtual sample development bring several key benefits to multiple partners in the CSC. These 3D tools for instance allow speedy design and development by reducing the physical sampling time due to virtual try-out at the initial stages of the design. This also has a significant impact on reducing design and

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[2] http://browzwear.com.

[3] http://www.clo3d.com.

development cost. Fewer physical samples are produced. Easy modifications and fitting can be performed in different sizes and styles without changing the original pattern, while maintaining an accurate correspondence between 3D changes and the 2D pattern. This relationship is essential for efficiency and accuracy in the fabric cutting process, which is one of the crucial tasks in apparel manufacturing. It reduces fabric and accessory waste and redundant samples. Other benefits include better integration with sourcing and manufacturing processes, and with fewer physical operations, it contributes to reductions in carbon footprint.

However, certain conditions are required for full-utilization of these benefits by all the partners in the CSC. Manufacturers, both upstream (textile) and downstream (apparel), need to cooperate with retailers and brand owners (Kanupriya, 2020; Majumdar et al., 2021) by investing in the required technology to get the maximum use from digitalized designing and 3D visualization. Furthermore, the lack of technicians with the required skills to use 3D design technologies with simulations is a bottleneck for acceptance of this advancement equally across the CSC (Kanupriya, 2020; Kasumoto, 2020). Thus, the development of the required skills through training is necessary (International Labor Organization, 2020; Sendlhofer & Lernborg, 2018), especially for designers, but also for sample development merchandisers in apparel manufacturing companies (Parschau & Hauge, 2020).

2.2 Wearable technology

In the clothing industry, convergence of textiles and electronics (e-textiles) is important for the development of smart materials that are capable of accomplishing a wide spectrum of functions, resulting in wearable technology (Stoppa & Chiolerio, 2014). These provide new avenues for developers to improve functions like heat regulation, impact protection, communication, and fire protection in multipurpose garment layering systems to suit the lifestyle needs of the wearer (Papahristou & Bilalis, 2015). Such wearables have computational and sensing requirements and are predominantly developed by using conductive materials (fibers, inks, and coatings) or by adding different types of sensors, antennas, and circuits to the clothing fabric. Typically, such smart wearable systems incorporate a number of different subsystems for sensing, actuation, control, power, and energy storage, tracking, and display (Fernández-Caramés & Fraga-Lamas 2018). Integrating IoT and electronics into clothing provide the possibility to offer several dynamic solutions in multifunctional, wearable electro-textiles for sensing/monitoring body functions, delivering communication facilities, data transfer, individual environment control, and many other applications (Izsak & Shauchuk, 2020).

For instance, interactive apparel has been developed by the University of Tokyo using conductive ink, which remains highly conductive even if stretched to three times its original length (University of Tokyo, 2015). It is employed by sports apparel companies, for instance, Adidas, Speedo, and North Face (Bertola & Teunissen, 2018) as it enables the measurement of muscle activity. Stanford University invented a textile coating fabric with conductive silver nanowires to boost a garment's thermal properties without impacting functionality and providing heat to the body in the coldest environment but still with same level of breathability as conventional fabrics (Bertola & Teunissen, 2018; Pendrill, 2015). Some of the commercial developments include Google and Levi's project Jacquard to make digitally connected clothing using a new kind of conductive yarn and woven multitouch panels that can turn standard clothing into interactive devices (Poupyrev et al., 2016). Ralph Lauren's smart T-shirt has embedded silver fibers and sensors that allow wearers to track biometric information, depth, movement, steps taken, calories burned, breathing, and heart rate. It allows tracking of the performance of athletes and provides real-time audio and visual feedback on foot placement, landing, and cadence, reducing the chances of injury (Gray, 2015).

Even though the importance of e-textile and wearable electronics is increasing and nearly 11% of textile startups in the EU-27 are working in this field (Izsak and Shauchuk, 2020), the market uptake is still at the infancy. A number of key aspects need to be further developed, such as comfort and fitting, durability aspects related to deformation and washing, battery power, energy harvesting, and hardware miniaturization (Fernández-Caramés & Fraga-Lamas 2018). Furthermore, new IoT architectures may be required to replace current cloud-based systems in certain scenarios like smart health where latency and communications have to be minimized to react fast to events. Only then can wearables realize their promise in the apparel sector.

3. Digitalization of clothing supply and manufacturing networks

3.1 Sourcing and procurement

Traditionally, in the textile and clothing industry leading retailers in the US and EU source from far-away countries in East and South Asia, North Africa, and Latin America, thus operating with long lead times, very large batches, and limited flexibility. Clothes manufactured in distant countries are generally produced in advance based on forecasts, and the sourcing process may start nearly a year in advance. It takes typically 2 months for shipping to the final destination from

Asia, i.e., a retailer's warehouse or distribution center in the United States or European Union. A high proportion of these upfront bought, traditionally sourced garments end up in the discounted racks of high-street fashion retailers. They may account for up to 33% of the entire assortment (Mustonen et al., 2013). Digital product lifecycle management including digital sourcing and production can shorten lead times. Physical inventory is replaced by information, including digital garment specifications, digital cutting patterns, and measurement charts.

Even though digitalized apparel sourcing facilitates end-to-end process management, and is one of the most significant developments in the current era, it is still in its infancy (Berg et al., 2017). Unlike the conventional approach, virtual product design and sample development facilitates the digitalized sourcing process. Once the garment design and initial sampling are finalized, the sourcing process is commenced through a digital system. Here, material and its suppliers, as well as the garment manufacturers, are selected using a digitally integrated approach. Retailers receive a price quotation digitally from garment manufacturers and textile suppliers, while the technical specifications finalized during product development are transferred digitally for checking the possibility of raw material supply and the ability of manufacturing according to the digital apparel specifications (Stangl, 2020). Suppliers are often graded based on their historical performance measured in terms of quality, reliability, flexibility, and compliance to sustainability practices. When retailers digitally call for a price quotation, these competency aspects are crucial for selecting the suppliers. Such supplier grades also have implications for quality assurance activities; for instance, if a fashion retailer sources from a supplier graded high, the quality of the fabric may not be checked by the manufacturers and instead directly fed into production by relying on the quality reports issued by the material suppliers. On the other hand, if an apparel manufacturer receives fabric from lowly graded suppliers, such supplies need to be checked for quality at a central place and only then can they be distributed across production locations. These grades and reports are maintained centrally in a digital platform by the retailers and are accessible to textile suppliers and to the apparel manufacturers.

Through digital platforms, retailers can sometimes scrutinize virtually a garment manufacturer's plants to assess its production competency and capacity (White et al., 2020, pp. 1—23). Once the prices, materials, and the production competency are finalized, the purchase orders are placed digitally for the given style, specifications, price, volume, and delivery dates. For instance, BizVibe[4] is one such leading digital sourcing platforms that provides textile professionals with seamless, efficient, and easy-to-use services for finding and connecting with other businesses and creating virtual communities for better supply chain management. It helps supply chain members to connect, engage, and make business deals more smoothly, quickly, and accurately by navigating the sourcing regions from the Far-East to Africa. FindSourcing,[5] Sqetch,[6] and FOURSOURCE[7] are other similar digital sourcing platforms where the buyers can search, filter, submit quotations, contact apparel suppliers directly, and receive offers via open database.

In such digitally integrated platforms, information flow is made seamless through the use of centralized cloud-based systems with information being secured for supply network partners, allowing access only to authorized partners, thus helping to provide real-time information visibility for all the supply chain actors. While this ensures more transparency and controllability for the retailers, on the other hand the suppliers are able to get market information in terms of preferred consumer styles, color themes, as well as production information in terms of potential production order volumes, sizes, and styles. Consequently, this can streamline supplier collaboration, enable quicker decision-making with less repetition and errors than in conventional sourcing. For instance, maru.co digitalizes the whole procurement process from quote to delivery with their turn-key supply chain technology (Sarkar, 2020).

Digitalized sourcing systems bring several benefits to business partners in the CSC, in terms of shortening lead times, increasing manufacturing flexibility, reducing the number of suppliers, streamlining the supply chain communication, minimizing errors, increasing transparency, and minimizing unnecessary inventories. It is worth noting the key factors that influence the successful use of a digitalized sourcing process with close relationship among the strategic business partners (Berg et al., 2017). All the strategic partners need to operate with a common goal of sourcing the apparel with high customer-orientation and flexibility for a reasonable price. Business partners should invest in the required technologies and business processes in order to improve efficiencies from beginning-to-end of the CSC rather than considering only their own ROI.

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4. http://www.bizvibe.com/.
5. https://www.findsourcing.com/.
6. https://www.sqetch.co/.
7. http://www.foursource.com.

3.2 Production planning and manufacturing

Digital tools, IT, and advanced manufacturing technologies (AMTs) have gained much prominence in the production side of the CSCs to ensure flexibility, responsiveness, and innovativeness (Izsak & Shauchuk, 2020). Flexible manufacturing systems (FMSs) based on AMTs such as CAD and computer-integrated manufacturing (CIM) have for a long time supported business processes in CSCs. For instance, clothing manufacturers have successfully deployed automation of several garment manufacturing operations, such as spreading, marker making, and cutting to select optimal raw material, generate cut-order plans, automatically match material patterns, and ensure effective means to cut multi-layered fabric stacks (Vilumsone-Nemes, 2018). Several companies such as Lectra[8] and Gerber[9] have been pioneers in offering such automated spreading, cutting, and pattern matching machines, together with advanced computerized systems for material requirements planning, material purchasing and inventory management. Additionally, with the help of automation, advanced fusing presses perform very sensitive fusing process to ensure high-quality fused composites, avoiding textile material shrinkage (Izsak & Shauchuk, 2020). Numerous innovations to innovate sewing and knitting processes, such as in gripping technologies, in handling cut pieces, in developing 3D seams or varying sewing configurations are also available in the market (Jana, 2018).

In recent years mechanization and "intelligentization" of manufacturing processes and supply chains have gained further prominence due to the emergence of Industry 4.0. Specifically, robotics, additive manufacturing, and IoTs are likely to impact and reconfigure future manufacturing setups to enhance supply chain performance (Majumdar et al., 2021; Manglani et al., 2019). Developments related to increasing digitalization of production and individual production technologies include Sewbot offered by SoftWear Automation,[10] a start-up that uses machine vision and robotics to create autonomous sewn goods worklines for home goods, footwear, and apparel. Fully autonomous technology may allow manufacturers to produce locally, moving the CSCs closer to the customer while creating higher quality products at a lower cost.

With the advent of such technologies, on-demand manufacturing systems in CSCs may be possible. Such systems need to include extensive automation, digital printing and cutting, and the potential for optimization of many different parameters, including material usage. Unmade is a UK-based global fashion software company that has radicalized the notion of FMSs through its cloud-based UnmadeOS[11]. This is an end-to-end digital platform to enable the production of customized products. It automatically connects the front-end co-design system with the manufacturer's full garment industrial knitting machines, thus enabling optimization, hypersegmentation of products to an order size of one, and the tracking of the customized products. This adds to the aspect of reconfigurability and agility in clothing manufacturing processes (Yin et al., 2017). In a similar way, Amazon has recently patented an on-demand manufacturing system designed to produce clothing after a customer order is placed. This computerized system is envisioned to include textile printers, cutters, and an assembly line, as well as cameras designed to take images of garments for placement in an e-commerce system in order to ensure cutting route planning, sorting and bundling, ironing, finishing, and packing, material transportation, and inventory management (Xu et al., 2018). Order aggregation from various geographic locations and coordinating apparel assembly processes on a large scale could add to the efficiency of such customized apparel manufacturing systems.

Another paradigm that is slowly transforming CSC is IoT. The use of Data Analytics and machine learning with IoT has the potential to empower decision-makers on manufacturing floors. Use of real-time information capturing technologies, such as RFID tags and sensors-based data communication networks, from different parts of textile and clothing manufacturing can transform the classical silo-based enterprise information system to an integrated IoT-centric architecture. Such integrated IoT systems for storing, processing, and distributing data can provide visibility within and between actors in the network, and support autonomous decision-making, quality control, and centralized order processing (Pal & Yasar, 2020). Avery Dennison, through its Janela technology rendering digital identity to garments in a 'phygital' (physical + digital) environment, and powered by Evrythng's IoT cloud-based Smart Products Platform, offers such a collaborative network. It has recently been adopted by Ralph Lauren Corporation to track each of these consumer interactions to provide brand and retail partners with valuable data and Analytics (Wnuk, 2020).

In the clothing manufacturing context, the interaction between several of these technologies like IoT, robotics, 3D printing, etc., is not only leading to a digital transformation but gives the potential to change the overall structure of CSCs

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[8] https://www.lectra.com/en/fashion.

[9] https://www.gerbertechnology.com/fashion-apparel/.

[10] https://softwearautomation.com/.

[11] https://www.unmade.com/unmade-os/.

and their governance. By enabling higher digital integration among various supply chain actors for seamless information transfer, more effective governance of clothing supply networks is possible. Several novel production models, such as "smart factory," micro factory, open and distributed manufacturing networks are already operational in the CSC context. For instance, Hugo Boss, one of world's premier luxury clothing manufacturers, has converted its largest production unit in Turkey into a fully operational "Smart Factory" since 2015 (Varshney, 2020). The key aspects of its Smart Factory are:

- **(i)** use of Smart Data for shop floor management and follow up of KPIs,
- **(ii)** real-time tracking of information around workers who work together on a certain line, and also data of all production lines, warehouses, inventory, etc.,
- **(iii)** use of robotics for hybrid production, and
- **(iv)** Augmented Reality/Virtual Reality (AR/VR) for operators' soft training, quality process integration, product information, and machine information.

Hugo Boss claims that their Smart Factory, running with a Digital Twin, Robotics, and AI, has led to large cost reductions, quick turnaround time, flexible processes, minimal complexities, easy retrieval of data at any given point of time, quality improvement, and productivity increases. The presence of multifunctional employees working with technology within cross-functional teams provides the opportunity to embrace such digital transformation.

Adidas also had a short-term success with its similar Speedfactory initiative,[12] with extensive use of automation based on robotics and new production technologies for flexibility and minimal human effort boosting savings and efficiency, and enabling faster development and prototyping of running shoes. What Adidas overlooked with the Speedfactory was the inherent complexity in footwear manufacturing due to the large number of process steps, typically ranging between 60 and 80, which led to higher process and labor costs. As a result, automating the complex footwear manufacturing process was not very cost-effective and was subsequently limited to production of only certain types of running shoes. Nevertheless, such concepts in CSCs have the potential to stimulate localized production by reducing intermediaries, providing flexibility, and setting the scope for strategic collaborations in certain business processes to support demand fulfillment.

One of the crucial aspects determining the success of Industry 4.0 in CSCs, beyond use of novel technologies, is open digital integration for seamless information transfer among the various players involved. This can support new manufacturing and design models based upon open networks of flexible, mini-factory lines with the know-how of making customized orders for different brands and deliver to the consumer (Pal & Sandberg, 2017). For instance, the Microfactory, coordinated by DITF (Deutsche Institute für Textil- und Faserforschung), showcases a completely networked and seamless digitally integrated production chain from design to finishing. In these digital manufacturing platforms, the brand owners can log into a cloud-based service portal potentially run by an e-commerce service provider who organizes the manufacturing networks and operates on a service charge basis.

Such open manufacturing concepts lay the foundation for collaborative supply chain structures (Srai et al., 2016), where the production of customized individual garments is realized in a flexible network of production units ranging in size from micro enterprises to SMEs. For instance, Make.Works[13] is a community of manufacturers, material suppliers, and workshops; factories can be found by browsing or searching using keywords related to processes, materials, and locations. This is followed by matching the order requirements to practical information from the manufacturers, such as turnaround times, minimum order costs, and previous clients for helping in evaluating whether that factory is appropiate for placing the order. Furthermore, such integrated digital supply chains and marketplaces act as a resource for a regional apparel industry to establish collaborative networks aimed at seamless integration, and fit well with the strategic directions prescribed under Regional Strategies for Smart Specialization (RIS3)[14] for regional job creation, competitiveness, and social sustainability in the European Union.

4. Digitalization of clothing distribution and retail formats

4.1 Distribution

As various independent parties (e.g., freight forwarders, third/fourth party logistic service providers, multimodal transport operators, carriers, and warehouse) are involved in the logistic process of CSC, the documentation, payment, and communication processes among such partners are highly dynamic and are, thus, challenging and complex

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[12] https://www.adidas-group.com/en/media/news-archive/press-releases/2016/adidas-expands-production-capabilities-speedfactory-germany/.

[13] https://make.works/.

[14] https://s3platform.jrc.ec.europa.eu/.

(Pal & Yasar, 2020). Consequently, there is a demand for highly flexible, speedy, and accurate information sharing systems with a common platform to store, share, transfer, and track the information, documents, and payments.

Information sharing systems connecting various independent parties across CSC is based on linking unique identifications of objects—tagged by means of RFID transponders or barcodes—with records in supply chain database management systems. In this process, Electronic Product Code Information services (EPCIS) by GS1 offers the most relevant industry standard.[15] Major retailers like the Metro Group in Germany, Marks & Spencer in the United Kingdom, and Wal-Mart in the United States have adopted this kind of tagging system with RFID technology and QR codes, for the purpose of tracking supplies (Azevedo & Carvalho, 2012). Furthermore, luxury brands such as Fendi, Max Mara, and Michael Kors are already integrating RFID in their products for tracking purposes, mainly to fight against counterfeits (Bertola & Teunissen, 2018). Inditex Group, owner of brands Zara and Massimo Dutti, tag every garment with an RFID microchip enabling the traceability of the products' movements from sourcing up to the points of sales. Consequently, it brings new items quickly into stores as its inventory management is 80% faster (Patwardhan et al., 2019). GS1 standards, including eCom and EPC-enabled RFID tagging at the item-level, have been reported through a Levi's pilot in 2010 to greatly improve inventory accuracy and stock flow, which ultimately drive sales (GS1, 2014).

EPC/RFID-enabled processes for garment tagging and tracking have further enhanced the scope to implement Internet of Things (IoT) as one of the most promising technological innovations in CSC (Pal & Yasar, 2020). Elements of IoT technology are used heavily in CSC for business processes such as inventory management, warehousing, and transportation of products, and for automatic object tracking. RFID and Near Field Communication (NFC) tags, which are within the scope of IoT, are used to track inventory and product movements within the CSC. By enabling the accurate tracking of goods, RFID can enhance value creation from multichannel logistics by supporting services such as reserve-and-collect and click-and-collect through providing an accurate view of inventory. However, standalone IoT application systems face security and privacy-related problems. In this context, blockchain technology has introduced an effective solution to the IoT-based information systems security. Here, RFID, NFC, and QR codes and other data capture systems are captured in the blockchain, enabling the logistics process to be more efficient and trusted through seamless data exchange, and also contribute to ensuring sustainability (Pal & Yasar, 2020). Furthermore, smart packaging, which has embedded tags and codes (e.g., QR codes) that contain information such as product provenance, or messages to logistics, is another digital innovation facilitating the access to precise information with tracking ability (Weinswig, 2017, pp. 1—15).

Despite the fact that some leading apparel retailers have initiated digitalized logistics practices in their CSCs, it is worth noting that the majority of logistic activities are still conventional in the clothing industry, especially when sourcing across long distances from the main consumer markets. Major apparel retailers still lack the presence of fully integrated digitalized logistics platforms, which would allow a complete shift in their business model through open and flexible communication with external or specialized tools and make use of data to optimize service levels (Bertola & Teunissen, 2018; JD Edward EnterpriseOne, 2021; Pal & Sandberg, 2017). In this regard, the luxury goods conglomerate, LVMH, has taken a step forward by trialing the use of its Aura blockchain platform with two other major luxury names—Prada and Cartier—to develop a single global blockchain solution open to all luxury brands worldwide, and enable direct-to-consumer access to product history and proof of authenticity along the product's lifecycle and transaction processes (LVMH, 2021). This further benefits the CSC in terms of smoothly tracking the movement of the luxury clothing from manufacturing and distribution, to the point of sale, thus contributing toward reducing costs, increasing inventory turnover, and creating higher customer satisfaction. Literature shows that implementation of the blockchain-enabled logistics network for clothing and fashion industry has the potential to drive environmental benefits, in terms of establishing mechanisms for reducing carbon emissions along CSC (Fu et al., 2018), and increase CSC visibility through smooth tracking of the movement of the products from textile to apparel manufacturers, through distribution and ultimately to the point of sale (Bullón Pérez et al., 2020).

4.2 Retailing

The growing popularity and transformative power of digital technology have fostered the rapid growth of fashion retail e-commerce. They aim to provide customers with diverse in-store experiences and the opportunity to view and select from a large digital product portfolio of the retailer through virtual online platforms (Guercini et al., 2018; Harale, 2021).

Such digital platforms offered by e-commerce fashion retail brands often include highly interactive image and web-based technologies that enhance customer shopping and purchase experience with the use of 3D animated videos, ultra-zoom functionality, fitting evaluation, and virtual try-on. With the exponential growth in such online commerce

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[15] https://www.gs1.org/industries/retail/apparel.

platforms, more and more consumers connect to the Internet through smart devices, resulting in large amounts of data being captured, managed, and processed by e-retailers. Fashion clothing value chains are becoming increasingly data-driven, deploying AI techniques in their online shopping platforms to determine consumer preferences, in order to perform predictive analytics (Giri et al., 2019).

Retailers can track sales, profile customers and market directly to individuals, and make appropriate and smart decisions with the help of data analytics. They provide better understanding of customer needs in terms of design and styles and also predict trends and demand through the use of "big data" (Park & Jayaraman, 2016; Thomassey & Zeng, 2018). Zalando—one of Europe's leading online fashion platforms—shows the power of harnessing AI beyond conventional areas of application such as in predicting seasonal demand. Algorithms are used to make subtle tweaks aimed at improving the shopping experience, such as using past orders to help customers select the right clothing size, and provide digital outfit recommendations in real time based on products that the customer has put in their "wish list" (Kung, 2019). Several other fashion retailers, like Zara, H&M, Macy's, have similarly made use of Big Data Analytics to understand consumer demands and trends, translating them into tangible designs and helping to plan product assortment lines (Silva et al., 2019). Trend forecasting giants such as Edited, WGSN, and Google Trends have also disrupted CSCs by using Big Data Analytics and Cloud computing applications to forecast fashion trends (ibid.).

The shifting nature of the fashion retail sector toward e-commerce business models has also enabled customers to participate online in the design of their chosen fashion products with a high degree of personalization. AI and Big Data Analytics is increasingly engaging fashion brands and retailers into a collaborative "co-design" process starting with customer's request of a garment via a virtual online platform, and a higher possibility to customize according to these preferences (Peterson, 2016). Several digital small-series fashion brands and platforms provide high product variety with an increased personalized shopping experience to the customers. They offer advanced, user-friendly interfaces to allow virtual try-on, and product image interactivity, thus enriching the browsing experience and incorporating the customer into the co-design process (Peterson, 2016; Plotkina & Saurel, 2019). Some brands also provide an online space where designers showcase images of the collection they are working on and consumers can contribute to, advise on, and get involved in the design process (Bertola & Teunissen, 2018). Then selected designs proceed for prototype creation in 3D visualizing platform.

Realistic virtual try-ons (VTO) and 3D fitting technologies created from a data core composed of a person's biometric data on body dimensions, as well as garment and fabric preferences (Guercini et al., 2018), can enable online garment customization and can work as a helpful tool in the planning process. Such VTO imitates the physical experience of trying on a garment as close to reality as possible, giving feedback regarding fit, size, and the behavior of the garment in physical activities. Specific examples of such digital technological advancements in fashion clothing retail include (Harper & Pal, 2018):

- Use of an Interactive Avatar that first gathers consumer biometric data using 3D body scanning tools in order to offer different functionalities such as rotation, movements, etc., to create 2.5D or 3D visualization of body types and the creation of digital twins.
- Additionally, 3D sales configurators and interactive rendering tools offer 3D illustration of the garment along with realistic and sometimes real-time updating of product customization of fabric drape, and simulation of properties.
- Virtual fitting is also an extended digital technology, which provides the possibility to simulate fit from 2D measurements. It is often used to compare sizes from well-known brands in order to find the right size for each garment.
- The most recent developments have been technologies like Augmented/Virtual Reality. Such technologies integrate the physical and digital reality and allow users to add a direct in-store experience. For instance, Uniqlo—a Japanese fast fashion giant—provides in one of its stores a magic mirror "Smart." While wearing the same garment, users can see in the mirror the different available colors and take photos to share via email or on the social networks, as well as having all of the product specifications.[16]

There are a number of developments beyond the growth of omnichannel in CSCs particularly in fashion retail. For example, in "webrooming," the shopping process starts with online browsing and then leads to buying in-store. In "showrooming," the shopping process begins with in-store browsing and then leads to an online purchase (E-commerce in the Nordics, 2017). Social media and mobile−commerce sites are also contributing significantly to the transformation of fashion e-commerce with new emerging players such as fashion bloggers and influencers (Guercini et al., 2018).

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[16] https://holition.com/work/uniqlo-world-s-first-magic-mirror.

Since consumers spend a considerable amount of time on different types of social networks and forums (Lorenzo-Romero et al., 2020), AI helps fashion retailers to tap into customers' online footprints on social media, for example, browser logs and historic behavioral data with predictive Analytics and text-mining, natural language processing, and machine learning (Zhong et al., 2016). This further helps to detect new customer trends and potential purchase decisions specific to their fashion choices (Luce, 2018, p. 142). AI is increasingly being used to improve customer relations and attend to grievances using voice assistants, social media avatars, virtual stylists, and conversational chatbots (Liang et al., 2020; Nash, 2019). These can enhance the personalized experience in platforms like Facebook Messenger, Skype, Slack, and Kik. Tommy Hilfiger has introduced its conversational chatbots in partnership with supermodel Gigi Hadid in order to make the shopping experience smooth and customized for browsing through styles and select an outfit (Arthur, 2016). For clothing retailers, AI has further enabled consolidating inventories for multichannel sales, such as for e-commerce and physical stores, reducing operating and warehouse costs and increasing profit margins (Guercini et al., 2018).

5. Digitally enabled clothing circularity

Lower prices and "fast fashion" habits have doubled clothing consumption globally between 2002 and 2015 and consumption is projected to rise to $2.1 trillion by 2025 (GFA & BCG, 2017). This has not only resulted in higher use of virgin natural and manmade fibers but has contributed to very significant increases in the annual total use of water and energy and in the amount of waste generated by the industry (Östlund et al., 2020; UNEP, 2020). Water use, energy consumed, and waste generated are projected to rise by 50%, 63%, and 62%, respectively, by 2030 (GFA & BCG, 2017). EEA (2019) estimates that currently about 91 million tons of clothing waste is generated annually, i.e., roughly 17.5 kg per capita. This has stimulated the adoption of circular economy principles and strategies at various levels aimed at designing products that are more durable, reusable, repairable, recyclable, and energy-efficient, as adopted within Europe's newly Circular Economy Action Plan (EC, 2020).

Recent advances in digital technologies have been highlighted in this regard in order to support the transition to a circular economy in CSCs, by radically increasing virtualization, dematerialization, and transparency (EMF, 2017). Emerging Industry 4.0 solutions and digital tools such as digital tracking and tracing technologies and blockchain can improve circular CSC provenance and transparency. IoT solutions can accelerate the transition toward a sharing economy. Digital platforms can improve circular CSC performance by enabling circular product design, recovery, re-commerce, and peer-to-peer sharing. All of these can help to underpin the transition to a circular economy in CSCs (Business of Fashion and McKinsey & Company, 2019).

One of the key areas in circular CSCs where digital technologies have gained great traction is in tracking and tracing to identify and recover materials. Several digital tools, such as RFID and other innovative tagging systems like digital passports, digital receipts, and smart labeling, are being deployed to trace and show the provenance in the CSC. These in turn have the potential to improve material reuse and recovery (EMF, 2017). Even though RFID has been available for over 2 decades to solve a range of problems unique to CSCs in various processes (Nayak et al., 2015), its application in solving circularity challenges is novel. With more accessible information about the product identification, content, and chemicals used, high volumes of sorting and recycling activities can become viable in the clothing industry. For example, the company Content Thread[17] have developed a digital thread that can connect with RFID technology to inform about the product composition for easy recycling. Such tracking solutions are supplemented by technologies for identification and detection of garments by composition, fiber type, color, etc., during sorting and recycling, using near-infrared (NIR) and ultraviolet—visible spectroscopies aimed at improving material scanning for automatic and easy sorting. FiberSort[18] is such a newly developed technology for automatically sorting large volumes of garments by fiber composition. An additional color scanner on the same system can also allow separation by specific color.

Other smart tagging solutions are also made available by brands for consumers and users in order to enable circular solutions beyond recycling, for instance, by providing maintenance information, repair instructions, or washing and storing tips to reduce wear and tear. IoT is being utilized by several companies to offer smart wardrobe services. These combine RFID tags and readers such as Bosch's new smart wardrobe[19] technology to offer recommendations on user behavior and to increase sustainability awareness among consumers and users. For instance, the Internet of Clothes' solution comprises of a washable RFID tag added to any garment and an RFID reader put on a wardrobe or a room door, which can register

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[17] https://globalchangeaward.com/winners/content-thread/.

[18] http://www.valvan.com/products/equipment-for-used-clothing-wipers/sorting-equipment/fibersort/.

[19] https://www.urdesignmag.com/technology/2019/01/10/bosh-bml100pi-ces-2019/.

TABLE 15.1 Summary of main digital technologies and the implications and barriers in CSC.

CSC stages	Main digital technologies	CSC performance implications	Key barriers to take into consideration
Product design and product lifecycle management	• CAD • 3D tools for apparel design, styling, and visualization • 3D body scanning • Virtual fitting	• Reduced design lead time • Reduced development cost • Ease of modifications • Better integration with sourcing and manufacturing processes • Reduced fabric and material waste and thus carbon footprints	• Technological limitations in replicating physical properties virtually • Lack of technicians with required skills for using 3D design technologies • Lack of investment by vendors
Sample development	• 3D design in the sample development • Virtual fitting • Digital twins and IoT	• Reduce physical sampling lead time and ensure higher flexibility, speed, and accuracy • Reduced carbon footprints	• High reliability on physical sampling at the end of the process • Collect and share data, and interconnect data sources
Electronic wearables	• Integrated sensors and IoTs • Conductive material (fabrics, coating, inks)	• Higher value products • Better data monitoring	• Technical features related to fitting, comfort, durability, battery life, etc. • High development costs
Sourcing and procurement	• Digital order specification and bill of materials • Digital sourcing platform	• End-to-end process management • Real-time information visibility • Reduced lead times, increased manufacturing flexibility and quality, reduced inventories • Increased customer orientation	• Lack of orientation of the strategic partners with a common goal
Production planning and manufacturing	• Flexible systems based on CAD, CIM • Robotics and machine vision, AR/VR • Additive manufacturing • IoT using RFID and sensors • Digital manufacturing platform, network, and marketplaces	• Smaller batch size and flexibility • On-demand, local production • Agility and customized product reconfigurability • Higher digital integration through seamless information transfer and tracking	• Manufacturing complexity due to the large number of process steps and the need for manual intervention
Distribution	• Peer-to-peer (P2P) platforms • Blockchain • IoT and Digital twins • Tagging systems, e.g., RFID, sensors, QR codes	• Real-time monitoring of transportation flows • Decentralized, secured data exchange for higher visibility	• Lack of transparent information sharing about the product's history and transaction processes • Lack of trust between SC actors
Retailing	• Digital e-commerce platforms • 3D fitting solutions, Avatars, virtual try-on, AR/VR • AI, big data, and cloud computing • M-commerce, S-commerce, chatbots	• Improved trend forecasting and predictive analytics • Real-time recommendation to consumers • Reduced operating and warehouse costs	• Limited user-friendly interfaces for co-designing personalized experience for consumers • Lack of decision-making based on advanced analytics • Limited smooth browsability and AI-based support
Circular economy and logistics	• Tracking and tracing technologies, e.g., RFID, digital passports, smart labels, etc. • IoT, smart wardrobes • Blockchain • Digital platforms for, e.g., selling/sharing, software-as-a-service, eco-design, material brokerage • Additive manufacturing, 3D printing • Digital sorting technologies, e.g., NIR	• Improved traceability and due diligence • Waste reduction and sustainability profile • Supply chain information gathering	• Limited design for circularity • Technological limitation related to traceability and separation technologies • Limited multistakeholder collaboration • Lack of consumer awareness

when clothes have been taken from the closet, how often are they worn, and when, and even reminding the wearer to wear "idle" clothes. This can enable a peer-to-peer sharing and renting of clothes that are used less, thus aiming to optimize the active usage lifetime of garments (Perlacia et al., 2017).

Blockchain is yet another digital technology that has gained attention for improving transparency and to provide sorters, collectors, and recyclers with reliable information on material composition of garments. London-based designer Martine Jarlgaard has partnered with digital company Provenance to use blockchain to successfully track the journey of an alpaca jumper from the farm to the finished garment (EMF, 2017). Under the ongoing United Nation's project on garment traceability, a similar blockchain pilot has been launched jointly by several luxury brands, including Stella McCartney, Hugo Boss, and Burberry in collaboration with several other value chain players, aimed at enhancing the traceability and due diligence in the cotton value chain to support a circular economy philosophy (UNECE, 2021).

The use of digital platforms with tools such as smart tags and blockchain is increasingly popular to improve circular performance of CSCs across different stages of the product lifecycle. Digital platforms such as Eon's global CircularID Protocol and Partner Network aim to utilize smart tracking and tracing solutions to create circular commerce for resale, rental, and recycling by enabling an end-to-end digital system for identification and management of garments.[20] Other digital platform—based solutions are more specific to address certain stages of circular CSC, such as Circular. Fashion's design tools, which offer Artificial Intelligence—driven decision-support for choosing the right materials and trims to design for optimal use in terms of longevity, adaptability, and material recyclability. Other digital platforms, offering either online tools or software-as-a-service, are increasingly becoming common in circular CSCs, such as the French ReFashion,[21] offering its members an eco-design platform to simplify and amplify the eco-design process.

Offering digital brokerage and marketplaces is another essential feature of several of these platforms, such as Reverse Resources, which aims at matching demand and supply for textile waste. They provide information to retail brands on where to get used clothes recycled after being collected via their take-back system, or where the recyclers can find new buyers for the recycled fibers. Beyond such recycling-based digital brokerages and marketplaces, the resale of used clothing has also been disrupted by the influence of digital technologies that offer innovative resale and sharing models focused on luxury second-hand or curation (EMF, 2017; Yrjölä et al., 2021). Online re-commerce for apparel is predicted to grow by more than 69% between 2019 and 2021, while the broader retail sector is projected to shrink 15% (Gilliland, 2020). The main "resale disruptors" curate product offerings, sell products via peer-to-peer marketplaces and augmented marketplaces. Online consignment and thrift stores for buying and selling high-quality second-hand clothes are offered by Depop, Vinted, eBay, ASOS Marketplace, Facebook Marketplace, and Etsy, etc. Each has its distinct product profile. For instance, Depop, beyond offering an online resale platform, can also be considered as a creative community marketplace and social app for buying, selling, and sharing fashion information and inspiration.

Advances in 3D printing or additive manufacturing of garments and footwear made from biodegradable polymers such as polylactic acid (PLA) have been taken-up by several small-scale designers, such as Iris van Herpen (Moorhouse & Moorhouse, 2017). The technologies present opportunities to incorporate design for disassembly and design for recyclability. For instance, additive manufacturing may allow the design of adaptable products that can be repaired, reused, and repurposed easily by removing or adding links, as shown in the Modeclix project where lined textiles were made through additive manufacturing of polyamide (Nylon PA12), which could be later deconstructed and reassembled (Bloomfield & Borstrock, 2018).

6. Conclusions

This chapter has provided an overview of the key digitalization trends that are observed in the contemporary textile and clothing industries from a supply chain perspective. Many digital tools are currently being used and have the potential to transform CSCs at various stages of product design and development, sourcing, manufacturing, distribution, and retail, and in reverse and return logistics, as summarized in Table 15.1.

Notwithstanding their potential, there are also many barriers that currently inhibit or prevent widespread digitalization of the CSCs (see Table 15.1). These are related to lack of available technology, economic viability, strategic development, and digital knowhow. For instance, several technological gaps persist, e.g., related to 3D design and retail, automation, wearable solutions, and circular economy technologies. These prevent reaching the desired quality and technical product features of clothing, such as in visualizing drape and fit in digital clothing twins, in rendering comfort and fit in wearables, and in replacing complex manual process steps in sampling and manufacturing, or in the sorting of used clothing.

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[20] https://www.eongroup.co/.

[21] https://refashion.fr/pro/en/about-refashion.

Furthermore, many digital processes have high investment and development costs making them economically less viable in their current state.

Lack of strategic collaboration also acts as a barrier along many CSC stages, for instance, in developing partnership to embrace 3D technologies in collaborative design and sampling stages, or in the end-of-life circular economy activities. The implementation of technologies such as blockchain and other advanced traceability systems requires transparent information sharing and trust-building, which is often absent in the CSCs driven largely by information asymmetry and the bargaining power of major supply chain actors such as retailers. It is crucial to develop standards, systems and architectures, and methods for digital data, data storage, data security, and its governance in context to CSCs. Digitalization is also crucial for improving sustainability of CSCs by integrating various innovative technologies (e.g., Blockchain, IoT, AR/VR), increasing consumer value and satisfaction, and reducing business process costs and creating more value for organizations (Ageron et al., 2020). In addition, as emerged in the study of Chkanikova et al. (2021). there is a need to develop the next-generation skillset to enable such digital CSCs and data handling, related to user experience testing, digital sample making and prototyping, digital marketing, and storytelling.

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Chapter 16

Digitalization in production and warehousing in food supply chains

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Abstract

This chapter discusses opportunities for digitalization in food supply chains, specifically in production and warehousing. A general description of food supply chains is provided as a backdrop to highlight digitalization opportunities. Findings are presented from a Norwegian innovation research project, DigiMat, that investigates if and how automation and Data Analytics can enable smart production planning and control (PPC) and smart material handling systems. Four cases are presented—two focus on production and two on warehousing. Case 1 illustrates how Artificial Intelligence and Machine Learning can enable smart PPC. Case 2 looks at how smart automation using collaborative robots and autonomous mobile robots can change the concept of production systems from production lines to flexible factory production networks. Case 3 illustrates how large datasets can be harnessed for dynamic planning of product storage location assignments in warehouses. Case 4 shows how emerging automation such as robotization can be integrated in warehouses, working with human order pickers in the fulfilment of orders. The conclusions reflect on the generic insights from the four cases, the challenges in designing and implementing effective digitalization solutions, and the lessons and suggestions for researchers and practitioners in engaging in such projects.

Keywords: Digital technologies; Food supply chain; Material handling; Production planning and control; Robotization.

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1. Introduction

Food products are classical examples of fast-moving consumer goods where supply chain actors may struggle to satisfy demand at high speed and with low costs. The various actors in food supply chains are continuously working toward digitalizing the information flow and making the decision processes smarter, combined with efforts to achieve higher flexibility and efficiency through the introduction of smart automation in the production and logistics systems. A key in realizing such advances is the access to and sharing of information (Ji et al., 2017).

Over the past decades, all stages in the food supply chain have had a strong focus on automating a large part of their operations with state-of-the-art technology (Moore, 2012). This has led to the creation of large datasets in operations, but the intelligent use of these datasets remains largely unexplored (Ji et al., 2017). There is also still a great potential to automate solutions for materials flows and materials handling, and to enable integration of these with smart planning and control systems.

Although digitalization through enabling technologies under the Industry 4.0 umbrella has demonstrated its positive impacts at the production level (Kagermann et al., 2013), some recent research projects and publications are showing the potential benefits also in extending these approaches to the supply chain level (Ivanov et al., 2018; Pfohl et al., 2015), in particular highlighting how the Industry 4.0 concept and emerging and disruptive digital technologies will enable the next-generation of food supply chains (Kayikci et al., 2020). Big Data Analytics, based on the abundance of point of sale (POS) data and other data collected both from within and outside the supply chain processes, have the potential to allow robust processing and analysis of information for different insights. This enables data-driven approaches and new opportunities in planning and control by facilitating real-time control of operations. Such approaches allow a higher frequency of

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replanning of production based on the collected data. This can also be integrated with data related to operator or manager decision-making patterns and experience (Oluyisola et al., 2020).

Other examples of digitalization and emerging technologies, such as Cloud computing, Artificial Intelligence (AI), Internet of Things (IoT), and collaborative robots (COBOTs), are making automation more flexible and easier to implement, in particular related to material handling activities such as transportation, picking, placing, and sorting. Thanks to these emerging technologies, automated solutions are becoming more and more *autonomous*, where decisions on how and when to perform tasks are made at a decentralized level (Fragapane et al., 2021). The availability of smart automation afforded by cheap and flexible technological solutions provides additional leverage. This is leading to disruptive changes in food production and logistics systems, where COBOTs and autonomous mobile robots (AMRs) can be integrated to create smart solutions (Fragapane et al., 2020).

The purpose of this chapter is to provide illustrative examples of how digitalization presents new opportunities in food supply chains. The cases come from an innovation research project in a Norwegian food supply chain, where the overall aim is to investigate if and how Data Analytics and smart automation can enable smart production planning and control (smart PPC) and smart material handling systems in food supply chains. In the following section, the research project is introduced. Next, key characteristics and some challenges for food supply chains are described as a backdrop for digitalization opportunities. This is followed by an introduction to four cases from the project and a detailed description of each case. Finally, in the conclusion section, some general insights and challenges encountered from the cases and the project are provided, along with some proposals for future research and development (R&D).

2. DigiMat—an innovation project between a food supply chain and academia[1]

In 2018, a consortium of actors in a Norwegian food supply chain initiated a 4-year innovation project called DigiMat, financed by the industrial partners and the Research Council of Norway. In the project, a producer, a 3 PL provider, and a wholesaler have joined forces with a consultancy firm, a leading provider of supply chain management software, and some of Scandinavia's leading researchers in computer science, food supply chains, PPC, and warehouse management. The overall objective of the project is to combine capabilities in digitalization and emerging technologies with logistics competence to develop new solutions for smart and efficient food supply chains.

The project was initiated by the leading partner Brynild AS, a family-owned Norwegian producer of chocolate, nuts, and sugar confectionary. Like many other food producers, Brynild competes by offering customers high-quality, branded, and safe products at reasonable prices. With its annual turnover of around €80 mill., Brynild is a relatively small actor that competes against large international actors with global and efficient high-volume supply chains. To increase its competitiveness, Brynild therefore seeks to improve its ability to run operations more efficiently, aiming to be better than competitors in meeting dynamic demand with minimum resource consumption.

The most prominent innovations resulting from the DigiMat project are (1) the exploitation of data captured and shared along the supply chain for development of *smart planning and control approaches*, and (2) the exploitation of emerging technologies in automation for development of *smart material handling solutions*.

The project uses design science as its overall research strategy. In this approach, research is driven by practical problems and specific solutions are developed, realized, and evaluated in close collaboration among company representatives and researchers (Van Aken & Romme, 2009). The researchers provide key competencies and development resources and act as drivers of the R&D activities. The industrial partners contribute with their knowledge, experience, and insights to practical challenges in discussions, development work, and testing of new solutions. The research process consists of four phases. In phase 1, the current situation is analyzed to identify problems, weaknesses, and improvement potential. This forms the basis for phase 2 where conceptual solutions are developed based on a study of available techniques and solutions. In phase 3, specific solutions are developed in close collaboration between researchers and practitioners. In phase 4, selected elements of the solutions from phase 3 are deployed and tested in the form of applications, demonstrators, and prototypes.

Data are collected using traditional case study techniques such as interviews, observations, site visits, and extraction of quantitative data from information systems. This is analyzed based on traditional qualitative and quantitative techniques and methods. Literature studies are used to augment solution design. Advanced modeling and simulation, as well as data-driven approaches, are used in development and testing of solutions. Although the solutions are and will be developed for the supply chain in the project, the knowledge, methods, concepts, and tools can be generalized to other food supply chains.

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[1] The reader can contact the authors for further information about the developments in the project and the latest achievements.

3. Characteristics of food supply chains

To understand the four cases and the digitalization opportunities, we introduce the typical actors and processes involved in food supply chains, focusing mainly on the processing and distribution stages. We outline some key characteristics that impact on the way production and warehousing is operated, planned, and controlled in this sector and we identify some current challenges for the actors.

Food supply chains encompass the growing, processing, and distribution of food products to consumers (Romsdal, 2014). The typical supply chain includes primary producers (of, e.g., meat, fish, vegetables, and grain), suppliers of other inputs such as packaging material and ingredients, an industrial production or processing unit, wholesalers and/or distributors, and finally retailers selling the products to consumers (see Fig. 16.1). Transport between the stages is undertaken either by the actors themselves or by independent transport or logistics companies.

Food supply chains deal with perishable goods, where the quality of products and raw materials deteriorates over time. This aspect places important requirements on the supply chain processes, where all time consumed in the supply chain, as well as the environmental conditions in processing, storage and transport, significantly influence product quality and safety, as well as the remaining shelf life of products, and on food waste.

Food products constitute a heterogeneous group of products, with differing degrees of perishability, supply uncertainty, and production lead times. The products are supplied to a variety of customers, in differing quantities and at different frequencies, and are sold in markets with varying degrees of demand uncertainty. The typical processes in industrial food production are receipt of inputs (raw materials, ingredients, packaging materials, etc.), processing, packing (often integrated with cutting and labeling), and delivery. Typically, there are three stock points; raw materials before processing, unpacked bulk products between the processing and packing stages, and end products packed in consumer packaging. The typical production processes and stock points are illustrated in Fig. 16.2.

Most food products are produced in batches, where raw materials and intermediates are accumulated and processed together in lots. The number of product variants may increase with each production step, where a moderate number of raw materials and other inputs are converted into a broad variety of finished products through a divergent product structure. The packing process is typically the point in the process where the products become customer specific, i.e., sized, packed, and labeled for a specific market or customer. Since production lead times in processing are typically much longer than customers' delivery lead time expectations, producers mostly use a make-to-stock strategy for production, and customer orders are filled from finished goods inventory. Simultaneously, large finished goods inventories lead to large amounts of waste if demand is lower than the amounts produced, and products can therefore expire in inventory before they are sold and consumed. Conversely, in situations where demand is higher than expected, producers commonly use overtime and other costly measures to avoid stock-outs and loss of goodwill with customers. In this context, warehouses are very important to decouple the actors in the supply chain. The main role is to keep products in inventory and then pick the products when a customer order is received. The activities involve receiving goods, placing goods in storage, and retrieving

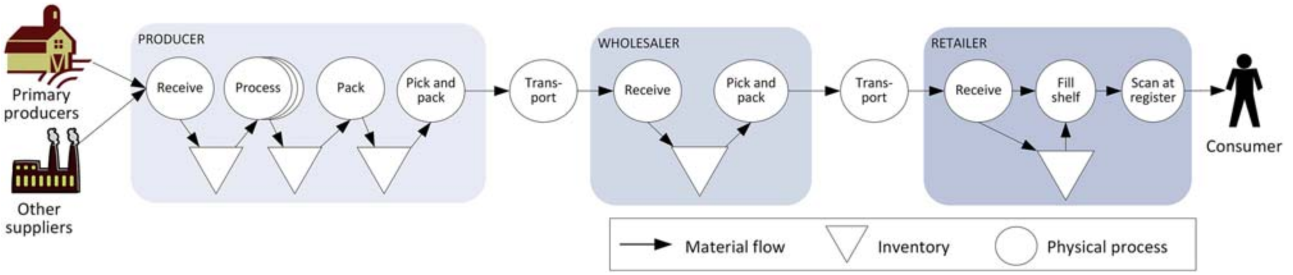

FIGURE 16.1 Typical industrialized food supply chain. *Adapted from Romsdal, A. (2014).* Differentiated production planning and control in food supply chains *(Ph.D.): Norwegian University of Science and Technology.*

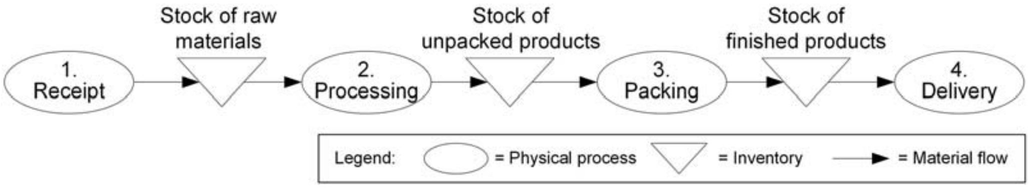

FIGURE 16.2 Typical processes and stock points in food production.

TABLE 16.1 Food supply chain characteristics.

Aspect	Description
Perishability and shelf life	High perishability, with shelf life constraints for raw materials, intermediates, and finished products.
Complexity	Varied product complexity, with mainly divergent product structure and increasing variety in products, packaging sizes, and recipes
Variety	High and increasing, particularly for promotions. High percentage of slow-moving items.
Product life cycle (PLC), innovation, and new product development (NPD)	Length of PLC decreasing. High risk in innovation and NPD, with a large proportion of new products failing in the market.
Volume and volume variability	Products produced and sold in high volumes, with increasing volume variability in downstream processes.
Market characteristics	
Delivery lead time and lead time variability	Varies by product, but generally wholesalers and retailers demand frequent deliveries and short response times. Producers mainly supply from finished goods inventory.
Demand uncertainty	Varying and increasing, largely caused by high and increasing frequency of promotional activities and price discounts. Strong presence of the bullwhip effect.
Inventory management and stock-out rates	Limited ability to keep stock. Periodic ordering. High and stable stock-out rates. Cost of lost sales often higher than inventory carrying costs.
Production system characteristics	
Production or make-to-order lead time	Product dependent, but generally long lead times and mostly forecast-based production planning principles.
Plant, processes, and technology	Adapted to low variety and large volumes. Mainly integrated and continuous production processes on capital-intensive equipment with long setup times and high setup costs.
Supply uncertainty	Some uncertainty, mainly caused by seasonality, annual production cycles, demand amplification, and economy of scale thinking, but generally high reliability for raw materials and other inputs.

Based on Romsdal, A. (2014). *Differentiated production planning and control in food supply chains* (Ph.D.): Norwegian University of Science and Technology.

the goods to fill customer orders. In producer warehouses, products are typically handled in full pallets, while in wholesalers' warehouses, orders from retailers are often picked from multiple storage locations and put on mixed pallets, which are subsequently delivered to individual retail stores or other customers. The key product, market, and production system characteristics of food supply chains are summarized in Table 16.1.

In the past decades, food supply chains in industrialized countries have experienced major structural changes, with the emergence of large industrial producers and brand owners and consolidation of the wholesale and retail stages. For instance, the top 10 food and beverage processors control around 90% of global sales (Clapp, 2021; IPES Food, 2017), while in Europe, the market share of the five largest grocery retailers is over 80% (FAO, 2020). Current logistics solutions are customized to deal with high product volumes, frequent deliveries, and consolidation principles. This enables actors to exploit economies of scale and achieve high-capacity utilization in their production and logistics systems.

However, despite strong integration and consolidation on some aspects, food supply chains are still fragmented, with many involved actors and limited cooperation, coordination and information sharing between supply chain stages. There are many stock points, and demand is aggregated between each supply chain stage. Thus, upstream actors' information about end customer demand is distorted, creating artificial demand variation also known as the bullwhip effect (Kumar &

Nigmatullin, 2011; Lee et al., 1997). The bullwhip effect makes forecasting and planning of production and warehousing challenging, and may ultimately lead to large inventory levels, excess capacity both in the production and distribution system, and large amounts of scrapping and waste (Lee et al., 1997). High levels of food waste remain a continuing concern (de Moraes et al., 2020; Mena et al., 2014).

A key challenge for actors in any supply chain is balancing supply with demand. The bullwhip effect and lack of information sharing makes forecasting difficult—particularly in food supply chains where demand is influenced by factors such as weather, seasonality, marketing campaigns, product launches, and promotions (Mena et al., 2011). Despite the use of advanced information systems that can record all transactions related to goods flow throughout a food supply chain, there are still major challenges to combine and streamline different data sources to enable Advanced Analytics and decision support in the planning and control of production and warehouse activities. For instance, with the huge amounts of heterogeneous data available today, food producers are struggling to identify which data are relevant in decision-making and how data should be made available to them in the form of actionable information (Allaoui et al., 2019; Ji et al., 2017; Verdouw et al., 2010).

Furthermore, supply chain actors often focus on internal optimization rather than supply chain optimization, and this is complicated by the lack of coordination and communication among supply chain actors (Mena et al., 2014). Retailers are continuously seeking faster replenishment and shortened cycle times to reduce their inventories. To respond to this, the supply chain needs closer coordination of production and distribution activities to avoid excessive inventories at the producer's warehouses (Bilgen & Günther, 2010).

The role of wholesalers and warehouses has changed dramatically over the past couple of decades due to the growing complexity and variety of products and customer orders (Lee et al., 2018). However, again, the lack of transparency of demand is a barrier to operational efficiency, further increasing response times to customers and increasing operational costs. In addition, manual operations still dominate in many material handling activities in production facilities and warehouses (De Koster et al., 2007; Sgarbossa et al., 2020a,b), such as the loading and unloading of machines and production lines, internal transportation, and order picking activities. This reduces operational efficiency and leads to difficulties in meeting customer requirements in an efficient way.

4. Introduction to cases

We present four cases and solutions that have been developed or that are under development in the DigiMat project: two cases in production and two cases in warehousing.

The first two cases focus on production. Case 1 illustrates how AI and machine learning (ML) can enable smart PPC and Case 2 looks at how smart automation using mobile robots is changing the concept of production systems from production lines to more flexible factory production networks. The two remaining cases focus on warehousing. Case 3 illustrates how the availability of great amounts of data, including POS data, can be used in the dynamic planning of assignment of products to storage locations, and Case 4 shows how emerging automation such as robotization can be harnessed and integrated in warehouses, working with human order pickers in the fulfilment of customer orders. The cases are summarized in Fig. 16.3.

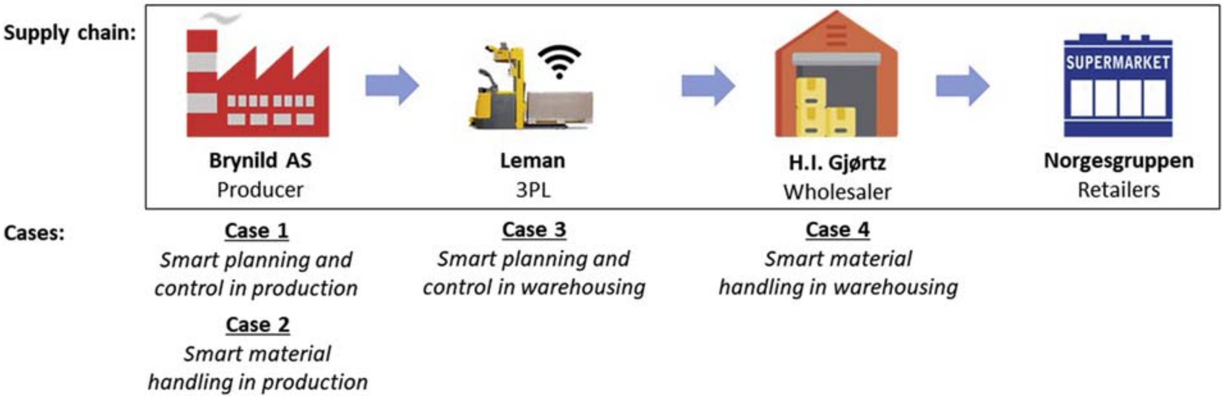

FIGURE 16.3 The DigiMat supply chain and the four presented cases.

Each case starts with an outline of the industrial motivation for the case topic and the objective for the case. This is followed by a general overview of digitalization opportunities to address the identified industrial challenges. Next, the results achieved in the companies to date and any expected future results are outlined. Finally, some reflections on limitations and implementation challenges are provided for each case.

4.1 Case 1—smart planning and control in production

Industrial motivation: The main supply chain actor in this case is Brynild. Despite the trends toward the digitalization of production and the recent push toward Industry 4.0, for many production managers in conventional industries such as in food production, the key issues essentially remain unchanged; how to improve the precision of the PPC processes that are used to manage operations. In Brynild, the production planning processes have low precision and planners typically use their experience to factor in a process deviation when planning production batches. Production control is not carried out in real-time and deviations are often discovered late. The large demand variations, combined with limited product shelf life and inventory costs, constrains the volumes that can be made to stock.

With recent advances in smart technologies for data collection and data analysis, Brynild sees an opportunity to collect data in real-time from the production system and use these data to generate insights that will (1) reduce the need for guess work in the short-, medium-, and long-term production planning, (2) harness the experience of the production planners, and (3) maintain near-real-time validity.

Case objectives: To develop a conceptual model for smart PPC that can guide Brynild in identifying digitalization opportunities to improve the performance of its PPC processes.

Digitalization opportunities: The requirement for real-time functionalities in PPC is a major challenge for conventional information systems such as enterprise resource planning (ERP) systems, manufacturing execution systems (MES), and advanced planning and scheduling systems. These systems are affected by the deviations between the captured data and processed information, and the reality in the production and logistics systems. The systems operate with data collected from a limited and standardized range of sources, such as production lines, machines, and material handling equipment. However, in many production systems and supply chains, several other factors heavily influence the result of a production plan. For example, in the food and beverages industry, the weather often affects not only the production but also the distribution and consumption rates of products. Being able to capture and use data from a broad range of sources therefore presents an opportunity for better PPC performance (Oluyisola et al., 2020).

With the emergence of digital technologies, there is an opportunity to evolve PPC systems so that they can address the current practical limitations and challenges that production managers continue to face (Strandhagen et al., 2017). Smart PPC aims to (Oluyisola et al., 2020; Bueno et al., 2020)

- **(i)** Use emerging technologies to enable the reduction of forecast uncertainty by using real-time demand and production system data.
- **(ii)** Enable dynamic replanning—allowing frequent updating and the ability to replan when there are changes or unplanned events happening in the production system.
- **(iii)** Capture the influence of an expanded set of factors, including environmental factors, especially for the process and semiprocess industries.
- **(iv)** Capture the experience of operators and production planners over time.
- **(v)** Predict short-term system parameter values and enable increase agility.

These aspects were used to identify opportunities for digitalization in Brynild.

Achieved and expected results: This case is currently in phase 2 of the research process. In the first phase, a number of improvement potentials related to PPC were identified at the Brynild. Then in phase 2, a conceptual solution for smart PPC was developed, starting with a conceptual description of the desired future state for PPC. As firms digitalize their production operations in the move toward Industry 4.0, they need to progress in stages (Schuh et al., 2017). Building on Schuh's framework, a multiphase, integrated conceptual framework for smart PPC was developed (Fig. 16.4).

The first stage of the model is the connected factory or production system. This stage involves computerization of processes and the connecting of production elements (de Man and Strandhagen, 2018; Klaus et al., 2000). Today's production systems have a multitude of electronic components and programmable logic controllers, thus allowing for more automation of the production processes. Increasing computerization means that all elements in a production system have a digital life and can therefore be connected to a digital industrial network in the smart factory. Connectivity can be achieved using auto-identification and data collection using sensor technologies such as radio frequency identification technology, beacons, and IoT devices (Liao et al., 2017). IoT connected sensors can, through IoT edge devices, interact with the

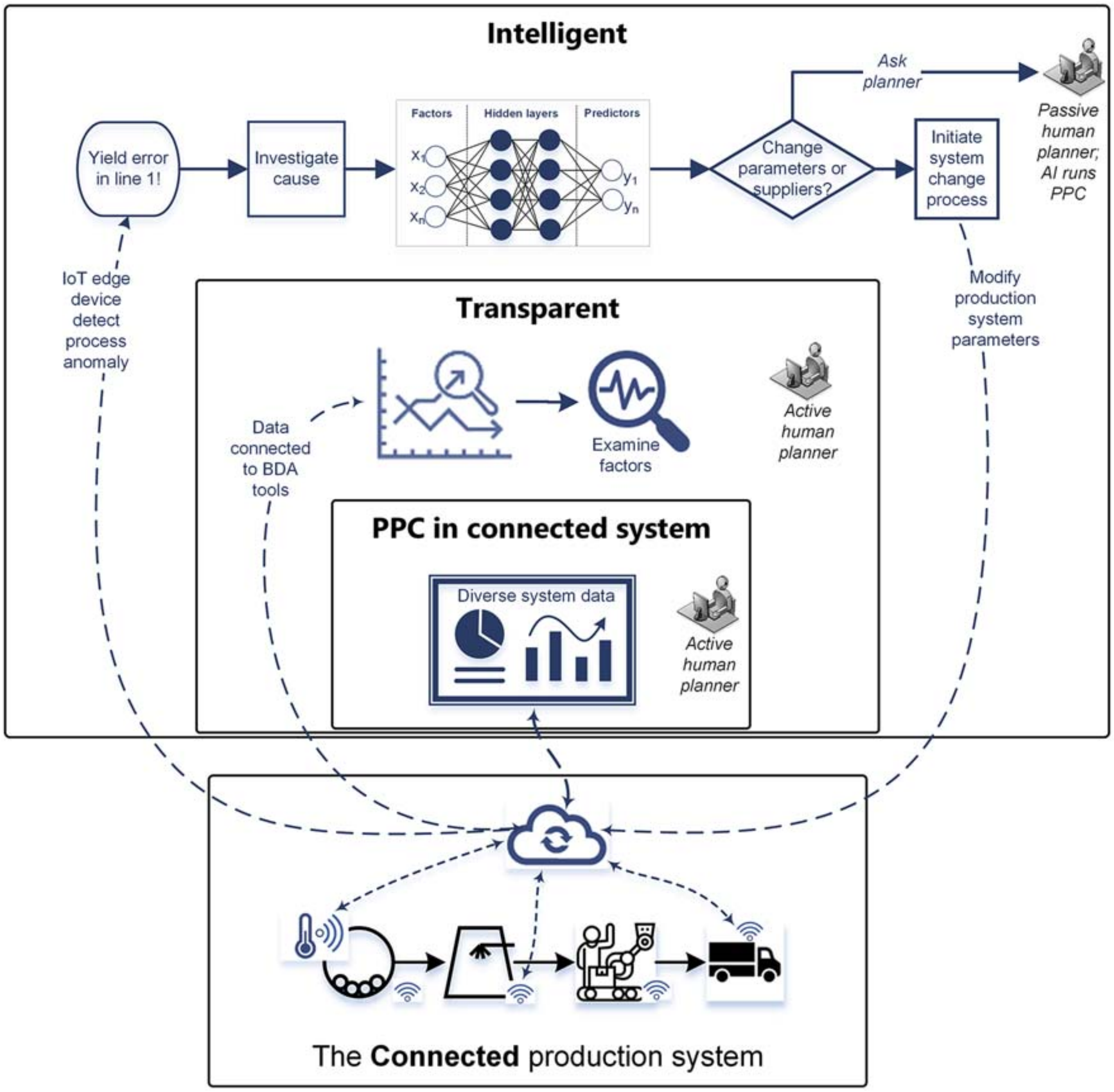

FIGURE 16.4 Conceptual model of smart PPC in a connected production system. *From Oluyisola, O. E., Sgarbossa, F., & Strandhagen, J. O. (2020). Smart production planning and control: Concept, use-cases and sustainability implications.* Sustainability, 12*, 3791.*

physical production system sending location and state, and compute requests, receiving data and instructions from services hosted on cloud infrastructure (Chen et al., 2018).

The next stage toward smart PPC is to enable transparent operations. When "things" are computerized and connected, it is possible to determine the exact location of products, routes traveled in the factory, status of machines and other resources, frequency of use, idle times, nonvalue-added time, etc. Digital models can also be made of the production system, and the components and final products moving through the production processes (Park et al., 2019; Schuh et al., 2017), and these can send action instructions to the production system (Kritzinger et al., 2018). The company currently experiences variation in process yield in all its production lines. If sensors can be installed to collect data from that line, it then becomes possible for a production planner to analyze the data to determine the sources and root-causes of this process variation so that planning precision can be improved (Kuo & Kusiak, 2019; Schuh et al., 2017).

The final stage is the intelligent factory. With the increasing research and wide application of ML and AI, there is potential for a machine intelligent, self-optimizing PPC systems that can handle all the applicable processes, process all data, and interact with planners from time to time as determined by the production managers. An intelligent factory combines data from several sources about itself and its environment to learn and autonomously predict events, which may influence its performance regarding set goals. In production, that implies being able to predict production delays, supplier delays, reduction in demand, etc., to avert performance failure. Recent industrial interests in ML have led to significant advances, which make these technologies and methods more feasible now for PPC than previously.

Limitations and challenges in implementing digitalization: Brynild has recently implemented several automation projects such as using robots in packaging and palletizing and using visual control and dashboards. One such initiative is the use of dashboards on the production lines, which provide direct access to data from the line, thereby providing the planner real-time access into the status of the processes. The company is currently implementing a digital system that collects data from production lines and sends it to a data warehouse where Analytics tools can be used to harness the data and generate meaningful insights.

Despite these efforts, the development and use of smart PPC solutions that use Analytics and ML remains challenging. The main challenges toward the realization of this concept at the company are costs, internal IT capacity, and management interest. For example, the complexity of the existing ERP system and cost of modifying and upgrading the ERP system and other enterprise data systems constrain the use of Analytics and ML for PPC. For this reason, managers in the company currently prioritize projects that further harness the functionality that the current ERP system offers. When used appropriately, Big Data Analytics can enable transparency of process performance, critical materials, and critical paths, estimate delays per supplier, process material yield, and other factors affecting the behavior and output of the system. However, as observed in this case, the use of such technologies still requires a production planner who is highly skilled in production planning and data analytics methods to take an active look at the data, process and analyze it, and make appropriate decisions.

4.2 Case 2—smart material handling in production

Industrial motivation: The main supply chain actor in this case is Brynild. The company has already implemented some elements of smart automation in its production system, including COBOTs in a couple of palletizing stations and automated guided vehicles (AGVs) in the internal transportation between two production processes. The company now wants to investigate the potential benefits of using COBOTs also for loading workstations and of using AMRs for more flexible transportation of products in the entire factory in order to increase the flexibility and the efficiency of the production system.

Case objectives: To develop innovative smart intralogistics solutions and study their impact on flexibility and efficiency in the food production system.

Digitalization opportunities: Production systems need to be both flexible and efficient to deliver the right variety of products over time and at the right cost. Digital technologies can contribute to improving production flexibility and efficiency. Discrete manufacturing was the first in applying and exploiting these technological developments (Lin et al., 2019), while examples in process industries, such as in food processing (e.g., confectionary, chocolate, dairy, ice cream, and baked goods), are still limited even though these innovative technologies have the potential to greatly improve the flexibility and productivity of their processes. Production systems in the food processing sector are mainly composed of production lines with high productivity, specifically adapted for processing of a single product or small product family. The system usually consists of several workstations connected by conveyors. The system is characterized by high production volume, low product variety, dedicated and inflexible equipment, fixed routings, long changeover times, and fixed layouts typical of production lines.

In a traditional production line, the actual throughput and utilization rates of each stage rate are limited by the bottleneck of the entire line, which also defines the maximum throughput rate. When production mix increases, more changeovers are needed—which requires stoppage of partial or entire lines and reduction of the overall equipment effectiveness (OEE) of each machine and so of the entire system (Muchiri & Pintelon, 2008). Further, in such systems, the sequence of production stages is fixed and dependent on the sequence of the workstations, not allowing any further combination of stages more than the one the lines have been designed for.

Thanks to the advent of digital technologies, such production systems can improve their flexibility through the application of smart automation and robotization in the material handling. Early applications of automation and robotization in material handling in the food industry were related to activities like packaging, palletizing, wrapping, and transportation of full unit loads (Fragapane et al., 2020). With the availability of cheaper technologies, developments in computational power, increasing battery storage capacities, AI, and many others digital technologies, a new level of automation and robotization in material handling equipment has been reached—notably with the introduction of (1) COBOTs and (2) AMRs. COBOTs are a type of robot which can interact and collaborate with human operators in a shared operational space. Due to the possibility to use them without any safety fence or physical cages, they are slowly substituting industrial standard robots in the material handling of light items (Litzenberger, 2019). AMRs are industrial robots that use a decentralized decision-making process for collision-free navigation to provide a platform for material handling, collaborative activities, and full services within a bounded area (Fragapane et al., 2021).

Achieved and expected results: The case is currently in phase 4 of the action research methodology. In phase 1, the company and researchers carried out a detailed mapping of all material handling activities in the production. This was combined with an extensive and critical analysis of the state of the art of available technologies. Based on this, the company installed and implemented some COBOTs for more efficient loading of semifinished products into packaging workstations. These were previously performed manually, with potential ergonomic risks for the operators. The implementation cost was relatively low and allowed for a quick return of investment (ROI) compared to traditional robotic solutions. Moreover, the COBOTs can work closely with human workers due to the high level of safety they can guarantee, allowing very flexible and reconfigurable solutions.

The potential application of AMRs was investigated through a multiscenario analysis to understand their flexibility and their impact on the other activities. The analysis of the literature was combined with the experience of the authors from similar projects, leading to the development of a novel concept for material handling in production systems where AMRs allow many-to-many machine connections (Fragapane et al., 2020).

Fig. 16.5 illustrates how smart automation in material handling has turned the fixed production lines into a "factory production network." By introducing networks where AMRs are utilized for smart material handling between production lines, a one-to-one fixed connection is no longer required, and all products can be sent to all lines in the subsequent production step. In this way, the number of lines used in each production phase can be reduced since they are not affected by the bottleneck of the system where they were included before. The OEE of the entire factory production network is thus higher compared to the OEE of the production lines. In this way, the number of machines in each production step can be adjusted more easily to the actual required throughput.

AMRs can also perform collaborative activities such as loading and unloading, palletizing, labeling, and others. This means that their use is not limited to the transportation activities so that they can serve as additional resources in feeding the production lines. In such cases, COBOTs are mounted on the AMRs, allowing them to work as a "third arm" or assistant for the machine and operators. In other cases, COBOTs can be installed directly on the production lines where they perform loading and unloading activities.

The potential benefits of integrating production lines into factory production networks, especially for the semiprocess industry such as in the food sector, include

- *Scalability:* thanks to relatively cheap technologies and the flexibility of the smart automation in material handling, which does not require significant supporting infrastructure, the installation downtime is short, requiring limited maintenance and potentially quick ROI.

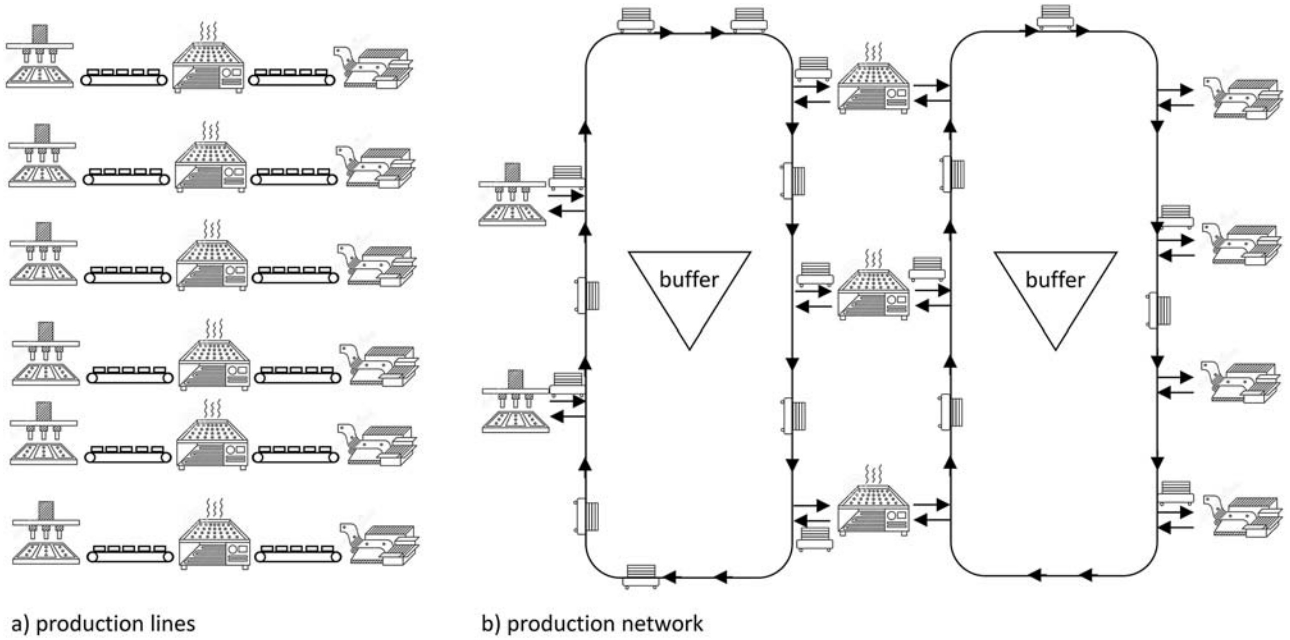

FIGURE 16.5 (A) Fixed production lines versus (B) factory production networks.

- *Proactivity and dynamicity:* the many-to-many connections play a central role in making the system more flexible, allowing multiple combinations and configurations of the system, which can easily be adapted to changes in demand profiles across the product portfolio and changes in production plans. There is also a potential extension to a cyber-physical system where different production plans can be simulated to allow PPC to become more proactive and dynamic.

Brynild has started their journey toward smart material handling in their production systems, and the preliminary results show that the implemented solutions increase the flexibility of the system while maintaining its high efficiency.

Limitations and challenges in implementing digitalization: In this specific case, the implementation of COBOTs in Brynild has been quite simple due to the maturity of the technology and the limited needs for physical infrastructures and changes in the layout. The implementation of factory production networks in the company is still limited by the factory layout and the IT infrastructure necessary to integrate the new intralogistics system with the current production workstations. However, such factory production networks have already been implemented in other cases in the food sector, where there were not such limitations.

4.3 Case 3—smart planning and control in warehousing

Industrial motivation: The main supply chain actor in this case is Leman, the 3 PL provider that operates Brynild's finished goods warehouse. Leman receives the full pallets of finished products from the producer and fulfills the orders received from the wholesalers, both with full and mixed pallets. A key challenge is that the picking frequency of each product is affected by its demand in the market, which in food supply chains can be very variable and uncertain. Thus, Leman wants to investigate how smart planning and control can enable more efficient, flexible, and reactive operations in the warehouse. In this case, the focus is on how to allocate products dynamically in the storage area.

Case objectives: To analyze the state of the art on the storage location assignment problem (SLAP) and to develop dynamic solutions based on data-driven approaches.

Digitalization opportunities: Warehousing operations include not only receiving products, storing, and retrieving them but also order picking, and shipping. Among these, movement and traveling not only are necessary activities but are also the main source of waste in a warehouse (Bartholdi & Hackman, 2019, p. 13).

The storage policy selection is an important planning and control lever for reducing the time spent in traveling. The SLAP is the process of assigning products to the available storage locations in a warehouse after being classified according to predefined criteria. A common criterion is the frequency with which the products are picked. This should be reflected in the storage location they are assigned. Most of the research and methods to solve SLAP are focused on classification of products based on static and known demand. They usually do not consider the cost of implementing a new storage assignment, fluctuational order patterns, incoming and outgoing material, or re-locations (Bartholdi & Hackman, 2019, p. 13). Warehouses typically change their storage assignment annually due to introduction and phasing out of products, but the storage assignments also might become outdated earlier due to demand fluctuations in product volume and mix. An emerging topic of research is investigating more dynamic policies for product classification and storage (Li et al., 2016).

One of the ways to do this is by having a dynamic variant of the class-based storage policy (Li et al., 2016). This policy allocates the products among, typically, two or three classes, and for each class a set of locations within the storage area is reserved based on the common ABC inventory classification method. A possible approach to create a dynamic variant of this traditional class-based storage policy is changing the classification of products based on the daily number of order lines instead of using historical demand, typically yearly (Li et al., 2016). In the dynamic classification, each product could be allocated to a different class and consequently also a different location. In this approach, the additional time incurred by relocation must be compared to the potential savings obtained by the change, considering the time capacity of the warehouse. In literature, observations from a simulation using data from a case study indicate that when reshuffling time increases, the order picking time decreases, and vice versa (Li et al., 2016).

Another policy for dynamic class-based storage has been introduced by Zuou et al. (2020). Here, K-means-clustering is used for classification based on a broad set of features and data, utilizing data mining techniques. This approach led to an improved classification used to optimize storage policy. From this method, Kheybari et al. (2019) also examined how factors influence a product's importance, such as demand rate, lead-time, and availability. Multicriteria decision-making can be used to support the classification.

Achieved and expected results: This case is currently in phase 4 of the research process. In all food supply chains, large amounts of transaction data are generated along the supply chain. In this case, Leman investigates how POS data captured in retail stores can be combined with other types of data to develop a storage policy with dynamic product classification.

In this way, classification can be changed before the demand increases and triggers some interventions in the warehouse. The approach uses time series analysis to forecast demand and inventory level—thus estimating how the classification will change based on multiscenario analysis. This is done for all the products arriving to the warehouse in a specific period of analysis (from a few days up to a week). Then, using multiscenario simulation, the products are allocated to the available locations based on the previously defined classification. The simulations include all the operations in the warehouse, including movements from the reception to the storage, movements from the picking to the shipment—thus properly assessing the effectiveness of different assignments.

This results in a predictive and prescriptive approach where the movements and relocation of products in the warehouse are performed in advance of the demand changes. The frequency of classification changes is an important aspect to consider to avoid relocations that are not valuable or that have a negative impact. The method is still under development. In further work, the analysis will be aligned with classification related to promotional campaigns and seasons such as Christmas and Easter.

Limitations and challenges in implementing digitalization: The main limitations in this case are related to the validation and implementation of the proposed dynamic approach. The use of simulation software for production and logistics systems can help in validating the results and in evaluating the robustness of the dynamic solutions. However, a validation with data collected from the field needs to be carried out to confirm the benefits of dynamic solutions. Moreover, warehouse management systems (WMSs) are common IT software that support all the operations in warehouses but many of them are still based on manual product classification in their databases. A possible way to overcome such limitations temporarily is to implement the dynamic approaches in an external module where the archive of products with their classes can be updated dynamically and uploaded to the WMSs when required. This solution can then be easily implemented in most of WMSs, integrating it with the other standard modules.

4.4 Case 4—smart material handling in warehousing

Industrial motivation: The main supply chain actor in this case is the wholesaler H.I. Giørtz. The company is working closely with the Norwegian technology company Currence Robotics, which develops and manufactures robots for the warehouse industry. The innovative robots are currently being implemented in selected distribution centers in the supply chain to increase the efficiency of picking operations and reduce the ergonomics risks for operators in the warehouse. Through the study, both H.I. Giørtz and Currence Robotics wish to understand how to effectively implement such a robotic system in current warehouses and the factors to consider when designing the warehouse operations.

Case objectives: To develop an innovative approach to guide warehouse managers in the implementation of the new robotic system.

Digitalization opportunities: Bartholdi and Hackman (2019, p. 13) identify order picking as the most labor-intensive warehouse operation. An order picking system includes the process of retrieving items from the designated storage location to satisfy the customer demand, and accounts for up to 55% of warehouse costs. Picking items from storage locations involves repetitive lifting of large and heavy items, sometimes from hard-to-reach places, potentially leading to fatigue and injury for the order pickers. In recent years, automation has reached new implementation levels, with major e-commerce players such as Amazon and Alibaba investing heavily in the development of new automated warehouses (Boysen et al., 2019). However, developing a fully automated warehouse requires huge investments and entails high risks. This is particularly true for small to medium-sized warehouses that are not able to automate to the level of large, centralized warehouses at this stage.

As an alternative, partially automated warehouse solutions have emerged through the development and application of robot pickers for grocery warehouses (Azadeh et al., 2019; Sgarbossa et al., 2020a,b). These can work side by side with manual order pickers, resulting in an easily scalable solution that can be implemented with considerably less investments than fully automated warehouse solutions. However, since partially automated warehouses still operate with manual pickers, it is important to also consider the impact such solutions have on the human factors, including mental, physical, psychosocial, and perceptual aspects. Consideration of these aspects in the design of these solutions can also improve the overall performance of the order picking system (Grosse et al., 2017; Sgarbossa et al., 2020a,b).

Currence Robotics' new picking robot is called Grab (patent pending; see Fig. 16.6). The robot is currently being implemented in some grocery distribution centers and can work in existing warehouses using the current shelf layout.

Grab consists of a robot arm mounted in a standard AGV that can operate in most warehouses without any major changes in layout and infrastructure. To pick items from the warehouse, the robot arm has a vacuum gripper that can lift items up to 30 kg. The current gripper has some limitations in the type of products and packaging types it can pick because it needs a flat surface to grip the items. A range of different gripper options are under development and will be gradually

FIGURE 16.6 Grab by Currence Robotics (patent pending).

introduced as optional upgrades, most probably with a "tool change" interface and functionality. Currence Robotics aims to significantly increase the amount of pickable items over the coming 2—3 years. To the best of our knowledge, the Grab is the first solution that can be implemented easily in a picking-from-pallet warehouse. Moreover, the Grab can pick very heavy items and large picking orders, typical of grocery warehouses.

The Grab uses a vision system consisting of several cameras and sensors to locate pallets and individual products in the warehouse and to identify placements for the items on the pallet on the AGV. The output from the vision system guides the robot's arm movements. The Grab can receive picking orders from the WMS similar to manual order pickers in the current warehouse. On the picking tours, the robot fills a single pallet, which is subsequently placed in a decoupling buffer area so that operators can complete it with the remaining part of the order. The Grab can pick from both ground floor and second shelf (to about 3 m high, see Fig. 16.5) and can currently stack about 1.5 m tall pallets (expected to increase to 2 m tall pallets within 2 years). Due to safety, the robot is not able to drive as quickly through the warehouse as order pickers on forklifts. The picking time for the prototype system in the case study is about 60 s per item (expected to be reduced to about 40 s in the industrialized version, within 1 year). To make up for the lack of speed, the Grab can work almost the entire day and at low operation costs compared to human order pickers. This results in a comparable number of items picked in one workday. Our estimation indicates a 50% reduction in expenses related to this operation.

Achieved and expected results: This case is in phase 4 of the research process. To implement the Grab, the researchers have, in collaboration with engineers from Currence Robotics, developed an approach based on warehouse zoning; one zone for the robot and one zone for human pickers. The Grab zone will contain products that can be picked by the robot arm and typically the heavier products to create the bottom layers of the pallet. The second zone is traditional manual order picking from the pallet area, where humans will perform the picking of smaller products to fill the pallet (using a relay picking method). In this way, the performance of the picker-to-part order picking system is optimized using warehouse zoning with robots and operators by estimating the optimal zone size and buffer capacity.

Two objective functions have been introduced to drive the zoning process: a combined ergonomic index for the operators and the total cost of robots and operators, as, respectively, the ergonomics and economical assessment of the solution. The problem has been modeled as a mixed-integer linear program and solved with a heuristics approach based on genetic algorithms. Then, a simulation of daily operations has been performed to study the dynamic behavior of the system.

Using the zoning approach, the warehouse managers have gained an understanding of how products should be allocated to the two different zones, the relationship between the size of the zones and the number of robots and operators, and the impact on the capacity of the decoupling buffer.

In other cases, if the size of orders and warehouses are limited, an alternative approach is to keep one unique zone where Grab and operators work together, sharing the space but picking different products according to dedicated assignment policies. In this case, Grab can pick all the heavy products, which will be used to create the bottom layers of pallets, in one route. Then the pallet will be passed to the operator who will complete it with the remaining products in another route.

Limitations and challenges in implementing digitalization: The current limitations of this case are related to the validation of the approach developed for supporting the Grab implementation. All the results obtained by the optimization approach and simulation have been discussed with the Currence Robotics' engineers and the warehouses' managers. As soon as the system is installed and operating in a steady state, the solution and its performance will be validated with data collected from the field. Questionnaires are currently being used to assess the ergonomics aspect of operators before and after the implementation. This will allow validation also of the ergonomics objective function.

5. Conclusions and future research perspective

Digital food supply chains are evolving as digitalization technologies continue to see advancements and as food industry actors continue to experiment with various use cases. In the DigiMat project and the associated supply chain that is presented in this chapter, several digitalization subprojects are discussed that are in different stages of completion. These include smart PPC at a producer, smart material handling with the use of AMRs, and use of COBOTs at the producer, and smart planning and control and new robotic solutions for material handling in warehouses.

The variety of cases discussed in this supply chain is an indication of both the amenability of the attributes of food supply chains to digitalization and the challenges that can be encountered in designing and implementing effective digital solutions in existing supply chains.

Attributes such as short product shelf life, intense competition, repetitive batch production processes, and the fact that these products are mostly made to stock has led to increasing digitalization and automation of processes and supply chain control over the last few decades. This in turn presents an opportunity for the use of several digitalization technologies to enhance the efficiency of these supply chains.

From the cases, a number of significant challenges for companies in the transition toward digitalization can be observed, including:

- *Value of data:* the quantitative value of sharing and using data for digitalization in production and warehousing is still not fully known. Thus, it is difficult for supply chain actors to agree on the distribution of costs and risks associated with capturing, storing, processing, and sharing data.
- *Which data to use and share:* we still do not know exactly which data are useful in the digitalization of production and warehousing. Challenges remain related to issues such as capturing too much data, not enough data, not the right data, and incompatible data formats.
- *Cost of technology:* companies may be reluctant to invest in digitalization technologies due to both the upfront investment and the hidden costs of technology associated with the need for maintenance, upgrades, higher-skilled employees, etc. They may also find it difficult to choose and prioritize between technologies.
- *Infrastructure:* realizing the potential benefits of digitalization requires investments in infrastructure, e.g., for data capture in processing lines and automation of physical processes. In addition, there are challenges associated with integrating the different technologies.
- *Resistance in moving from conventional enterprise systems*: Organizations may have invested significantly in conventional information systems, including ERP, MES, and WMS systems. The benefits achievable from adopting and integrating further digital technologies need to be clear and demonstrable.

Consequently, future research in this area can address some of the practical implementation challenges for these technologies. For example, many forecasting methods were available before the exploration of Big Data Analytics and ML for forecasting. However, while initial methods used patterns in demand data and at best a few additional variables in most conventional forecasting algorithms, ML algorithms take this to a new level with the ability of deep learning algorithms to "see" patterns through a multitude of variables and use those forecasts in a more proactive way with prescriptive approach in PPC. Future research could also investigate the development of new inventory and warehouse optimization methods to take advantage of new data-capturing opportunities made possible by IoT sensors and cheaper scalable computer processing power that Cloud computing enables.

A final consideration is the extent to which emerging technologies can solve challenges in production and warehousing in food supply chain. In such advanced fields, a strong collaboration between industrial partners and research institutes is the main reason for the success and impact of such cases. An important lesson from this initiative is how to approach such projects. It is necessary to have a clear mapping and overview of the industrial challenges in order to highlight which of them are solvable simply by applying proper operations management approaches and which ones are likely to benefit from the implementation of digital technologies. Collaborations are necessary in implementing such digital solutions in order to fully understand the challenges, the limitations of technological solutions, as well as their additional potentialities. This requires new methodologies to assist researchers and practitioners to tackle the problems in a rigorous way, avoiding just following the latest trend in the industrial revolution's history.

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Chapter 17

Automotive supply chain digitalization: lessons and perspectives

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Abstract

Supply chain (SC) digitalization in the automotive industry is an old story but one that raises many contemporary strategic issues. The objective of this chapter is to better understand the complexity of SC digitalization and gain greater insights into its dynamics. We combine a historical overview of the evolving process of SC digitalization in the industry with the analysis of a specific case: one car manufacturer's ongoing SC digitalization journey. The evolution of automotive SCs and their digitalization falls into five main historical eras. Digitalization has an impact on all SC management processes from the design of cars to their end-of-life. It is a complex, multifactor, multilayer, and multiactor coevolving process. Digital technologies are a major factor of change but are also combining with other macro trends in the sector. Today's automotive sector has become a complex ecosystem with new players and stakeholders. External factors interact with SC digitalization strategies, resulting in multiple projects involving heterogeneous stakeholders. We highlight the complexity of the decision-making processes on whether to adopt specific technologies, and the strategic, organizational, and operational challenges they bring. We note the changes affecting the future of mobility solutions, which in turn will affect SC digitalization in the sector.

Keywords: Automotive industry; Car manufacturer; Digital technologies; Digitalization process; Supply chain digitalization

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1. Introduction

The automotive industry is important from an economic point of view. It contributes to a significant portion (3.65%) of global GDP and is a strategic industry in many regions (e.g., Americas, Europe, Asia) and countries (e.g., in China, United States, Japan, Germany, India, Korea, France, and the United Kingdom). In 2019, the automotive industry accounted for nearly 10% of world trade (ACEA website[1]). In Europe it represents 7% of the EU's total GDP, 6.7% of all EU jobs, and 11.5% of manufacturing jobs (ACEA[2]). The automotive industry has always been considered a very interesting sector to study from the perspectives of operations management, logistics, and supply chain management (SCM). It is one of the sectors that has significantly influenced thinking and ways of working in supply chain and operations management. The digitalization of SCs in the automotive industry is an old story but raises many contemporary strategic and operational issues, in particular for the major OEMs and brand owners. The automotive industry is therefore an important area to study the SC digitalization process, both at the industry and company levels.

The aim of this chapter is to better understand the complexity of SC digitalization and gain insights into the dynamics of this process. Section 2 presents an overview of SC digitalization in the automotive sector, which is a decades-long, multilayer process driven by multiple factors and it is still in progress. In this section, we show that the historical trends in this worldwide industry and the evolution of its SCs are intertwined with their digitalization. Each era of SC digitalization we identify shows more and more SC processes being affected by digitalization and, thus, both aspects need to be

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[1] <https://www.acea.be/press-releases/article/global-auto-manufacturers-call-for-resolution-of-wto-impasse> Accessed 24.05.2021.

[2] <https://www.acea.be/automobile-industry/facts-about-the-industry> Accessed 24.05.2021.

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considered holistically. The adoption and appropriation of Information and Communication Technology (ICT) and digital technologies (DTs) at the company, SC, and sectoral levels has an impact on what automotive SCs comprise, how they manage physical, informational, and financial flows, processes and activities, and what their information systems (IS) and information management processes consist of.

Section 3 analyzes the case of SC digitalization at a major car manufacturer—the Renault Group. We give an overview of the context and explain the reasons why SC digitalization has been a strategic issue for this company since the beginning of the 2010s. We look at their SC digitalization strategy and the way it has and is evolving through different kinds of interacting projects. This section details the experience gained from recent and ongoing projects aimed at developing SC traceability and end-to-end SC visibility to create value for stakeholders. Increased digitalization both upstream and downstream seeks to improve SCM and add value. We present the results, feedback, and lessons from the digitalization process. The case shows that increased SC digitalization leads to unexpected issues and raises significant new questions. We consider current and future challenges for this company's SC at the strategic, organizational, and operational/technical levels and their combined dynamics.

In combination with other factors, SC digitalization transforms the nature and participants of automotive SCs. It "complexifies" SCM, and poses new problems and challenges. Our analysis of automotive SC digitalization indicates future challenges for the automotive sector as it undergoes transformation. The study has relevance for researchers in this domain and also for other sectors.

2. Overview of SC digitalization in the automotive sector

Digitalization and SC digitalization are sometimes presented as something new. However, a historical perspective at the macrolevel shows that automotive SC digitalization is not a new phenomenon and has many antecedents. It is a decades-long complex process driven by multiple factors and actors, and it is still in progress. This section presents automotive SC digitalization across five eras, identified on the basis of the research experience of one of the authors, the examination of several literature streams and evidence of some automotive SCs.

To the best of our knowledge, no existing publication traces the overall evolution of automotive SC digitalization. To understand this complex process, we have conducted a broad literature review and examined papers on the evolution of the automotive industry (e.g., Wells & Nieuwenhuis, 2012), its SCs and global value chains (GVCs) (e.g., Sturgeon et al., 2008, 2009), automobility (e.g., Janasz & Schneidewind, 2017), SC digitalization (e.g., Büyüközkan & Göçer, 2018; Ivanov et al., 2019), production systems (e.g., Yin et al., 2018), and SCs, logistics, and SCM (e.g., Fabbe-Costes & Nollet, 2015; Hines, 1999; MacCarthy et al., 2016). We identify five eras of automotive digitalization emerging from our review of the different and separate streams of literature. Our study is supported by data triangulation from multiple nonacademic sources.

2.1 Era 1—Industry 2.0 and fragmented operations digitalization—1950–1970s

Since the 1910s, the automotive sector has been behind many innovations, firstly in production management (Yin et al., 2018), with a powerful "initial combination of product technology and process technology" (Wells & Nieuwenhuis, 2012, p. 1685). Auto manufacturers began to internationalize in the 1920s, shipping completely knocked down (CKD) vehicles to offshore assembly plants (Sturgeon & Florida, 2000). However, most research on the history of the automotive sector at an international level (e.g., Sturgeon et al., 2008, 2009) dates the major changes back to the second world war. Before that time, the industry was mainly nationally based. Car manufacturers served their domestic markets and were vertically integrated, running the entire process of designing, producing, and selling cars.

As documented by Sturgeon et al. (2008, 2009), the internationalization of the automotive industry developed substantially after the second world war and was directly linked to the strategies of companies seeking to expand and countries pursuing industrialization. Having a local presence was the only way for automotive firms to penetrate markets that were expected to expand rapidly. Political pressures on international automakers to "build where they sell" encouraged the dispersion of final assembly. Most automakers expanded their manufacturing networks to conquer new markets, even though this was sometimes costly because of the narrowness of the market and the local competition they sometimes encountered.

Digitalization in the automotive sector began with production automation during 1950–70—"rigid automation" according to Veltz (1986, p. 71). First used in factories in the 1960s, robots have also played a key role in digitalizing SCs since that time. However, automotive SC digitalization truly developed in the 1970s with the introduction of mainframe computers and the widening role of computerization in business and industry. As plants are at the heart of the automotive sector, a computer-based manufacturing system to better control and optimize production management was the first step in SC digitalization.

In the 1970s, new international commerce rules (GATT), introduced to balance trade at the industry level, led to increasing flows of vehicles, parts, and technical equipment at the international level. Due to too narrow local markets, taxes on imported finished cars, limited local sourcing opportunities, and the need to maintain a certain level of production in plants, more complex supply chain flows developed. Most car manufacturers were forced to feed their overseas plants with exported parts, sometimes with CKD vehicles, and to bring finished vehicles back to the home country or ship them to third countries. The trend of offshoring and international division of labor developed at that time (Sturgeon & Florida, 2000).

The oil shocks that occurred in 1973 and 1979 powerfully impacted the automotive industry. The sudden rise in oil prices hurt American and Western car sales because of their high fuel consumption. They had also begun to face the growing popularity of compact Asian car models with lower manufacturing costs, lower fuel consumption, better quality, and more variety in terms of end product (Savary, 1995; Sturgeon & Florida, 2000). With the democratization of car ownership and increasing traffic density, safety also became an issue. The development of road infrastructures lead to the introduction of speed limits, which also changed the car market. Many American and Western car manufacturers faced financial difficulties at the beginning of the 1980s and some even declared bankruptcy (McKinsey, 2005). This marked the beginning of major waves of industrial restructuring that have been ongoing ever since (Sturgeon & Florida, 2000).

2.2 Era 2—toward internal and local SC digitalization (local integration)—1980s

2.2.1 Toward manufacturing integration

In the early 1980s, because of increasing competition, it became clear to automakers that their SCs needed to be rationalized. Many emerging markets did not develop as expected so car manufacturers had to concentrate production in regional hubs and reexport from there. More mature markets were becoming replacement markets with intensified competition between manufacturers (Savary, 1995). Competition, as well as more volatile markets, led car manufacturers to develop more flexible and responsive production systems. This was achieved in the 1980s with Industry 3.0 technologies (Yin et al., 2018) such as Computer-Aided Manufacturing (CAM).

The main impacts of production automation and computerization in the automotive industry in the early 1980s were to introduce "real-time"/"delayed time" systems and operations (Veltz, 1986, pp. 73−74), impacting processes and activities (e.g., some data processing activities carried out overnight in batch mode). This led manufacturers to rethink the relationship between employees and machines as well as between organizations and systems, and to realize that automation and computerization produce a flow of information about processes and activities, which could open avenues for increased visibility and greater control over operations. By the 1980s, automation and computerization already resembled a "patchwork" (Veltz, 1986, p. 75) of old and new technologies.

In the mid-1980s with the development and diffusion of personal computers and more powerful mainframes, combined with the development of dedicated programs and ICT, digitalization rapidly covered all aspects of manufacturing: from product design (with Computer-Aided Design/Manufacturing systems, CAD/CAM) to industrialization, production and maintenance, and the management of inventory, upstream and downstream. This supported the credibility of Computer-Integrated Manufacturing (CIM), promoting integrated data management of the product−process life-cycle (Veltz, 1986, p. 75).

2.2.2 Toward local integration of supply and distribution logistics

As noted by Sturgeon et al. (2008, p. 302), since the mid-1980s, the world automotive industry "has been shifting from a series of discrete national industries to a more integrated global industry." Companies that were internationalizing both upstream (supply) and downstream (distribution) also discovered the potential benefits of sourcing and producing in emerging countries (e.g., China, Brazil, India) in particular to reduce costs and offer low-cost models to mature markets. Such offshoring strategies provoked a "political backlash" (Sturgeon et al., 2009, p. 14) in countries (e.g., United States, France) and macroregions (e.g., Europe) that were facing national sovereignty issues about this industry (Frigant & Zumpe, 2017).

Internationalization strategies led to increased competition between car manufacturers, who sought cost domination. The logistics of vehicle distribution became an important issue and the quality of delivery services became a factor of differentiation. The generalization of modular design (Sanchez & Mahoney, 1996) and the use of CAD/CAM also led carmakers to further develop outsourcing. They began to focus on vehicle assembly, buying parts from suppliers, which raised the problem of upstream logistics.

In the 1980s, computerization began to affect every kind of operation, including logistics operations with dedicated software such as warehousing or transportation management systems. More and more off-the-shelf management software packages were adopted by companies in the automotive sector, mainly aiming at process optimization and cost reduction. This proliferation of different IS became problematic and raised the need for system and database integration to improve systems interoperability.

To face increasing competition in all markets, car manufacturers focused on their core business of design and assembly, and developed relationships with industrial and logistics suppliers (Sturgeon & Van Biesebroeck, 2011). This vertical disintegration (outsourcing of noncore activities) that began in the mid-1980s led to logistics coordination and standardization issues in managing upstream and downstream SCs. International standardization bodies emerged to improve the efficiency of the industry at the regional level and enhance the competitiveness of companies (e.g., Odette[3] in Europe in 1984, Fabbe-Costes et al., 2006). These focused on developing consensual standards, initially regarding the overall logistics process but that extend today from the design phase through purchasing, production, vehicle distribution, and aftermarket servicing to final recycling. In the 1980s, as observed by Christopher (1992), competition in the automotive industry was no longer just between companies, but between supply chains.

With the adoption of principles and tools from the Toyota Production System and lean management in North America and Europe in the mid-1980s, and given the context of more outsourced operations, it became clear that SC performance in the 1990s would depend on better coordination of manufacturers and their suppliers upstream and downstream (Sturgeon et al., 2009). New technologies were expected to support this improved "partner congruence" (Angeles & Nath, 2001) and develop partners' "bridging capabilities" (Takeishi, 2001) in interorganizational SCs.

2.3 Era 3—toward extended interorganizational SC digitalization—1990s

2.3.1 Regionalization and interorganizational process digitalization and traceability

The WTO liberalization of commerce in the 1990s and early 2000s established regional free trade agreements that facilitated the management of regional upstream and downstream SCs (e.g., European Union, NAFTA, ASEAN, Mercosur). These resulted in a regional reorganization of the car industry (Sturgeon & Van Biesebroeck, 2011). Car manufacturers outsourced more and more to suppliers, developed horizontal cooperation at the regional level, and rationalized their network of assembly plants. Competition was not only between SCs but also between industrial regions, in particular between Europe, North America, and Japan. The roles of regional organizations in Europe (Odette), North America (AIAG[4]) and Japan (JAMA[5] and JAPIA[6]) were important in improving performance in each region (Odette website[7]).

In the late 1980s and early 1990s, one very important technology had a tremendous impact on logistics and SCM: Electronic Data Interchange (EDI) using local and/or wide area networks (LAN/WAN) (Bensaou, 1997; Angeles & Nath, 2001). Automatic computer-to-computer communication using a standardized language, whether a company's own private language or one designed under the umbrella of Odette, AIAG or JAMA and JAPIA (see AIAG website[8]), enabled rapid data exchange, thus boosting intra- and interorganizational processes, in particular routinized data exchange between manufacturers and first-tier suppliers, customers, and Logistics Service Providers (LSP). EDI facilitated the rapid adoption of Just-in-Time (JIT) strategies between automotive assembly plants and their first-tier suppliers that began to predominate from the early 1990s (Fawcett & Birou, 1992).

EDI had a significant impact on all processes in the sector, including design, purchasing, production, and logistics. Standardization not only concerned the language used for sharing data but also the ways of identifying and coding "things" in processes (Fabbe-Costes et al., 2006): parts, logistics units, cars, etc. Continual developments in electronic miniaturization and lower costs led to the adoption of many new technologies and applications to capture, memorize, compute, and share more real-time data in and about SCs, leading to improved SCM. Standardization bodies have developed standards to support this trend (e.g., for reusable logistics units with barcodes and/or RFID to improve closed-loop SCs to feed plants). Consequently, the traceability of physical flows could be developed, from upstream in the chain to downstream. Linked to

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[3] www.odette.org.

[4] AIAG: https://www.aiag.org.

[5] JAMA: Japan Automobile Manufacturers Association. http://www.jama-english.jp.

[6] JAPIA. Japan Auto Parts Industries Association. www.japia.or.jp.

[7] <https://www.odette.org/about-us/> Accessed 24.05.2021.

[8] <https://www.aiag.org/supply-chain-management/materials-management/electronic-data-interchange> Accessed 24.05.2021.

total quality management and the lean approach, traceability systems could provide a clearer picture of flows and processes, more visual management (a key lean principle), ease and reduce the cost of product recalls in the case of nonconformance, and help to identify dysfunctionality in the SC.

2.3.2 Digitalization of global integrated enterprise information systems and the emergence of modular design

In the 1990s, the diffusion of enterprise resource planning (ERP) systems answered the call for enterprise IS integration, but more importantly database integration. These systems echoed the management information system (MIS) concept developed by Davis and Olson (1985). An MIS seeks to facilitate global reporting and include decision-making modules, leading to the command and control of a company's internal SCs by computers. Adopting ERP systems was supposed to improve competitiveness, thanks to standardized internal processes, unified databases, and the centralization of data and decision-making (El Amrani et al., 2006). However, in contrast to business and management software, engineering systems remained largely separate until product data management databases helped to facilitated convergence (Gielingh, 2008).

The extensive deployment of CAD and Computer-Aided Engineering in the early 1990s led to increasingly digitalized car design, allowing for multiregional development on a worldwide scale and for codesign with partners, in particular first-tier suppliers. This made it easier to adopt a "project management" approach (Midler, 1994). This management mode fitted well with the development of modular design and changed the relationship between carmakers and their suppliers (Frigant & Zumpe, 2017; Sanchez & Mahoney, 1996; Sturgeon & Florida, 2000).

2.3.3 Extended interorganizational SC digitalization and just-in-time

The penetration and success of Japanese car manufacturers—Toyota in particular—in Europe and North America increased competition. Benchmarks revealed differences with Japanese carmakers in terms of production and SCM systems (Liker, 2004; Ohno, 1988), robotization of plants, logistics, supplier relations (Bensaou, 1997), and customer relationship management. In the 1990s, JIT and lean management became popular "innovative" methods (Fawcett & Birou, 1992; Womack et al., 1991) that changed manufacturing, logistics, and SCM in the automotive sector, as well as in many other industries, eventually becoming the dominant management paradigms.

Heightened competition put pressure on car manufacturers. Thanks to modular design, they developed mass customization, allowing greater product variety and adaptation of models to local markets in order to differentiate products from their competitors. Innovation was seen as a new winning strategy. Suppliers became more and more involved in the development and the production of components and functionalities in the 1990s, and took on a larger role in the design process itself (Frigant & Zumpe, 2017). Given the tight integration required in the design and production of complex subsystems, suppliers followed car manufacturers to the locations where they set up their plants, leading to the emergence of global suppliers (Sturgeon et al., 2009). Automotive supply clusters appeared in many regions of the world, in particular in emerging markets. "Because of deep investments in capital equipment and skills, regional automotive clusters tend to be very long-lived" (Sturgeon et al., 2008, p. 304), with enduring B2B relationships (Wells & Nieuwenhuis, 2012).

Car manufacturers not only outsourced the production of components and subassemblies but also transport and logistics. In Europe, most of them turned their transport and logistics department into a subsidiary and began to challenge its performance, comparing it with other LSPs both in upstream and downstream SCs. The role of LSPs in the automotive sector became more and more important, especially upstream to feed assembly lines operating on JIT principles. They developed new "comanufacturing" services in warehouses near assembly plants (Fulconis & Roveillo, 2009). Industrial suppliers and LSPs ended up working for various car manufacturers, leading to a complex web of SCs (Fabbe-Costes, 2004). Most large industrial suppliers and LSPs colocated with manufacturers, leading to the internationalization of suppliers and the globalization of the car industry. Henceforth, it was possible to imagine planning the design, supply, manufacture, and delivery of vehicles on a worldwide level, seeking the best options to design, produce parts, and assemble vehicles to meet demand expectations. More and more horizontal collaborations emerged (Savary, 1995) not only between car manufacturers but also between suppliers, resulting in the cross-design of car platforms to standardize the "hidden" base vehicle, reduce parts variety, and rationalize the supplier base, while using late point postponement to increase end-product variety and customize the product as late as possible (Hsuan Mikkola & Skjøtt-Larsen, 2004).

2.4 Era 4—total integration and interconnected SCs digitalization—2000s

A major shift in SC digitalization occurred in the 2000s with the growth of the Internet (Gereffi, 2001; Seebacher, 2002). The Internet facilitated communications between SC members, in particular via web-based EDI to connect suppliers and customers beyond the first tier, including SMEs. Intranets and extranets made it possible to share data more easily and securely between internal and external SC partners. Internet-based interorganizational systems (IOS) developed in the automotive sector and their use has had an important impact on SC processes, structure, relationships, and competitiveness (Chi et al., 2008).

B2B marketplaces began to develop in order to structure interorganizational automated or semiautomated workflows and standardize processes, in particular with first-tier suppliers. Some car manufacturers (e.g., Toyota) launched their own "private" web-based portals using their own standards (Fabbe-Costes et al., 2006), which helped to structure and gain better control over their supplier base and improve process performance (design, order, deliver). Initiatives to create multicarmaker Internet portals such as the Covisint experience (Gereffi, 2001) complexified IOS and revealed complex interorganizational SC governance issues related to lack of trust and fear of increased power imbalances between members (Chatterjee & Ravichandran, 2013). In the 2000s, some first-tier suppliers were emerging as "mega-suppliers" (Frigant & Zumpe, 2017), i.e., global companies that were gaining power in automotive SCs, with carmakers increasingly dependent on them for specific subsystems and technologies.

Changes were not limited to manufacturers' upstream supply chain. Some of the most important impacts of the Internet have been in the downstream distribution channels. Distribution and sales began to change in the early 2000s with the emergence and development of e-commerce. Although the automotive sector lagged behind other sectors, a multichannel and even omnichannel approach to car distribution has developed, putting coherent customer relationship management at the core of the sales strategy. E-commerce for selling or renting cars caused an important change in the way manufacturers manage the distribution of vehicles. Some tried to sell cars online, while others used their websites only to present their cars and inform customers. Car manufacturers were initially puzzled by, and are still thinking about, how to manage multichannel distribution worldwide. Omnichannel automobile distribution strategies are still under development (Deloitte, 2016). The second-hand market and the way cars are used also began evolving with C2C platforms (peer-to-peer) and the development of the so-called sharing economy (Janasz & Schneidewind, 2017) with new digital intermediaries (e.g., UberCab, blablacar).

With more and more electronic devices and software integrated in them, every car was becoming a sort of memory bank of its own history in terms of design, production (what parts were assembled from which batch), usage including accidents and breakdowns, and logistic support for maintenance. This is important for after-sales service, for the second-hand market as well as for the reuse of parts (e.g., remanufacturing). The introduction of Product Lifecycle Management software reduced the gap between engineering and management IS and helped to digitalize vehicle life-cycle management (Cao et al., 2009).

2.5 Era 5—Industry 4.0, full SC digitalization—from the 2010s

The beginning of the 2010s was a turning point in digitalization, both for manufacturing with Industry 4.0 (Yin et al., 2018) and for SCs, improving the integration and interoperability of engineering systems with enterprise management systems, sharing common databases along the entire value chain (Ramos et al., 2020). Recent papers (e.g., Ivanov et al., 2019; Núñez-Merino et al., 2020) list the many "new" DTs having an impact on SCs, sometimes with a mix of emerging, mature, and even previously "obsolete" technologies (Núñez-Merino et al., 2020). According to recent reports by consultancies (e.g., McKinsey, 2020; William Blair, 2018), digitalization will profoundly change the automotive industry and SCs. While, as in previous eras, the use of DTs will lead to major changes in the automotive sector, many other factors (Fabbe-Costes & Colin, 1999; MacCarthy et al., 2016) will combine to influence how today's automotive SC will evolve with further digitalization.

2.5.1 Digital technologies and electronics in vehicles

The most important shift, which will have a tremendous impact on SCs, is the ever-increasing use of electronics in cars. Today, cars include more and more electronic components for various purposes: advanced safety sensors, operating systems, geolocation systems, driver assistance systems, and entertainment devices. As foreseen by McKinsey (2016a): "in the future, cars will become computers on wheels." The digitalization of cars and the way they are used is having a major impact on automotive SCs, from vehicle design, production (including more and more electronic components), distribution, and logistics support, up to end-of-life. Digitalization makes it easier to capture and use data from the vehicle, creating the potential for new services to develop. In some sectors such as media, SC digitalization has led to a full virtualization of products and services. In the automotive sector this is not the case. Nevertheless, DTs have a great impact on cars, the way they are marketed and sold, and the way cars can be used. Digitalization opens avenues for thinking differently about various mobility service offerings including cars.

2.5.2 Opportunities to develop new services and rethink the automotive product–service system

SC digitalization offers opportunities to develop new services not only in after-sales services (Verstrepen, 1999, pp. 538–545) but also in the area of car sales and the financing of car ownership, insurance (dynamic insurance pricing uses driving and vehicle data), maintenance, and the logistics support for this activity (spare parts management and delivery to maintenance service providers). Such product-related services may lead car manufacturers to develop new alliances with other sectors or to enter new sectors.

Connected and geolocated cars could allow manufacturers to capture data about their use. Records related to cars, drivers, and other passengers' behavior also allow new virtual services such as driving aids, entertainment, and travel aids that car manufacturers could develop through diagonal alliances. Other important issues concern insurance related to driving behavior, compliance with traffic regulations that could lead to tickets being issued automatically or modifications made to road signs or traffic regulations. Thanks to machine-to-machine (M2M) communication, many predictive systems could interact to prevent accidents, automatically collect tolls or parking fees, and encourage drivers to adopt more sustainable driving practices (McKinsey, 2019).

2.5.3 Pressure to achieve total traceability and end-to-end visibility

In logistics, the introduction of bar codes, RFID and IoT everywhere (on logistics units, parcels, certain strategic parts, cars, means of transport, warehouses, etc.), combined with systems to capture data and networks to transmit them, has led to an endless quest for total, real-time, precise traceability. Connectivity between automated machines, robots, IoTs, and computers (M2M communications) also contributes to achieving total traceability of operations and SCs. In addition to using traceability systems for quality control, safety, fighting counterfeit products, and proof of compliance, data are seen as a new 'gold mine' for optimization and innovation, thanks to data mining, deep learning, and other Artificial Intelligence (AI) tools (Ivanov et al., 2019; McKinsey, 2019).

2.5.4 New SC governance issues

The automotive sector has had to face many challenges and crises since the 1970s. The 2007–10 global financial crisis had a significant impact on the demand for vehicles and was one of the first to reveal how complex and intertwined SCs are and how interdependent SC members are (McKinsey, 2019). While it was relatively easy for carmakers to temporarily shut down plants, such a response might kill off their suppliers. The demise of suppliers would result in a loss of competencies and resources that would in turn damage the carmakers. It became clear that solidarity was key to their common survival (Yao, 2014). The governance of SCs was at the top of the automotive agenda from that time, changing the nature of relationships between automotive SC members.

However, the proliferation of DTs does not in itself solve the twin dilemmas of decentralization/centralization and the hierarchy/autonomy concerning decision-making in SCs and SC governance, as was the case with marketplaces in era 4. Powerful actors are still tempted to centralize data and build "control towers" that give them overall SC visibility, so they have access to all relevant data for their strategic purposes.

2.5.5 New cars and the future of automobility

Another recent evolution that will significantly shape the future of the automotive sector and its SCs concerns how people view their mobility and their relationship with cars (Janasz & Schneidewind, 2017). Owning a car is no longer a status symbol and often not a necessity. Sustainability issues and regulatory pressures on car usage are also changing the market. The sharing economy and the access economy (ride hailing, hourly car rental apps) have inspired new ways of "consuming" cars. New services are emerging, with newcomers to develop them.

2.5.6 Complex and risky ecosystems

Besides economic crises, other events and trends have impacted the automotive sector and the way of making cars. Environmental issues arose with the oil crises (1973 and 1979) and further developed in the 1990s with concerns about recycling, air quality, and pollution (CO_2, NOx, etc.) leading manufacturers to look for alternative energy sources (electric, hydrogen). Traffic safety also led them to explore ways of making autonomous vehicles. These innovations have had important impacts on the sector and its SCs. The automotive sector has become a complex ecosystem with new stakeholders, and automotive SCs are now interrelated with, and dependent on other SCs (e.g., electronic components and battery SCs). Newcomers, some of them digital-natives, are entering the car market, disrupting the industry's equilibrium (McKinsey, 2016b). Tech players are becoming more and more important (e.g., in-car infotainment systems).

The automotive industry is global, complex, and highly competitive. Through mergers and acquisitions, companies have sought to secure a powerful place in the world market. Car manufacturers are worldwide companies with complex and interconnected supply chains, resulting in a web of SCs. Fierce competition exists among car manufacturers, who nevertheless cooperate in many domains (e.g., in the arena of battery technology). Sustainability issues and changes in mobility are increasing the complexity of the ecosystem. It is therefore more than ever necessary to have an understanding of the big picture of the automotive sector, the interdependence between its SCs, and the key drivers of their evolution.

Digitalization impacts every SC process: car design (both the design of the cars themselves and the way they are designed), the sourcing of components and upstream SCM, production, distribution, sales, after-sales service, as well as all the services related to car usage and maintenance. Digitalization also impacts remanufacturing and end-of-life processes. These interrelated processes, as well as their digitalization, accelerate with the use of electronic components, DTs, ICT, and IS. Every new technology is viewed as an opportunity to improve SC performance and add value through the transformation of product-service systems (PSS), car manufacturing, service delivery, and the overall product life-cycle. Products, processes, and activities are also increasingly tracked and traced and the data (records) from traceability systems are used to gain in SC visibility. In particular, car manufacturers want to know what is happening in their SC, to improve connectivity across the supply chain, and to be able to foresee and react quickly to any change in the SC environment. They also want to improve their business model in terms of benefits for customers, end-users, the company's shareholders and stakeholders, and society.

Digitalization not only offers many potential benefits (reduction of fuel consumption, improved security and safety, etc.) but also raises critical environmental issues (increased consumption of energy and rare metals, problematic end-of-life for some components), as well as new risks (cybersecurity, random failures) and ethical questions related to personal data ownership and use. However, as documented by Wells and Nieuwenhuis (2012), the automotive industry is slowly moving toward radical changes.

2.6 The coevolution of information systems and automotive supply chains

The automotive sector has been an innovator and leader in computerization, EDI development, and tracking-and-tracing systems, and has integrated every relevant new DT in its business operations and in its cars. Car manufacturers have improved the management of their SCs in a context of increasing worldwide competition with high uncertainty. The evolution of ICT and other DTs, their adoption, and use in automotive SCs has led to a continuing evolution of SCs. Table 17.1 summarizes the above discussion across each of the five eras identified for automotive sector digitalization.

Every new technology era offers new opportunities and new challenges for SC managers to turn visions into reality (Fabbe-Costes, 2000, chap. 9). As noted by Scott Morton (1991), the adoption of technology has transformed processes, operations, roles, and even strategies and business models. The coevolution of the automotive sector with the digitalization of its SCs has made the big picture more complex, resulting today in a new ecosystem with diversified actors and complex interactions. Table 17.2 summarizes the key points of each evolution.

Many questions that seem new (e.g., how to achieve better traceability with a technology such as blockchain) are actually reincarnations of old ones (Fabbe-Costes et al., 2006). Many questions persist and reemerge in every new technology era. However, since technologies are evolving and changing very quickly, it is often difficult to learn from experience and capitalize on knowledge. The continuing journey of SC digitalization with many different technologies, at different levels, results in a multilayered patchwork of technologies and systems combining old technologies (because of lock-in effects) and newer ones. IS strategy, planning and development is thus still a major challenge for automotive SCs.

3. Lessons from the SC digitalization of a car manufacturer

SC digitalization at the sector level presented in Section 2 is the result of strategic decisions by one or multiple actors. The major car manufacturers have influenced the digitalization of automotive SCs strongly, sometimes by imposing their technological and organizational choices (e.g., EDI combined with JIT) on their suppliers. The increased digitalization of their SCs has supported their globalization, vertical disintegration by outsourcing noncore competencies and subcontracting production, while continuing to undertake design, assembly, and sales. Digitalization and the adoption of multiple technologies have helped car manufacturers to maintain control over more and more complex worldwide SCs. Thanks to SC digitalization and process redesign and streamlining, some car manufacturers have obtained high SC performance with improved interorganizational supply chain integration. Today's SC digitalization era not only offers new opportunities to

TABLE 17.1 Overview of SC digitalization in the automotive sector.

Eras		Era 1	Era 2	Era 3	Era 4	Era 5
Decades		1960–70s	1980s	1990s	2000s	From the 2010s
What is (cumulatively) digitalized?		Plants, manufacturing, operations	Design, decision-making, management	Product and information flows, tracking and tracing	Info sharing, communications, retail and sales	SC governance, product-service system, car monitoring, self-driving (autonomous cars)
What “new” technology is adopted for what purpose?	Operations	Computers (mainframe), automation, robots	Electronic digital computers, personal computers	GPS, LAN/WAN, barcodes	Internet (intra + extranet), RFID	IoT + LPWAN, API, blockchain
	Design		CAD/CAM	PDM	PLM	Data-driven PLM
	Management	In-house programs, hierarchical databases	Software including expert systems, relational databases	ERP, EDI	Web, web-EDI platforms and portals, SRM (B2B), CRM (B2C)	Cloud + data lakes + big data, deep learning, artificial intelligence
Factors impacting automotive SC evolution (other than digital technology)		Free trade agreement (GATT), oil crises (1973, 1979)	Increased competition in all markets, mature market penetration and domination by Japanese carmakers	Toxic emission standards (Euro 1 and 2), increased consumption in developing countries, WTO agreements	Newcomers (Tesla), development of pure private Chinese and Indian carmakers, sustainability regulations (car end-of-life), financial crisis	Newcomers (Google), C2C platforms, Fukushima, COVID, smart programs (e.g., smart cities), mobility evolution, energy (renewable)
Main automotive manufacturers’ strategies		Manufacturing internationalization to conquer new markets	Cost domination, offshoring (in China, Brazil, India), standardization, outsourcing noncore business	Diffusion of JIT, lean methods, modularity, differentiation, B2B collaboration	Innovation, mergers and acquisitions, mass customization, rationalization of regional clusters	Alliances (horizontal, vertical, diagonal), innovation (more radical), sustainability, new business models (value creation change)
Main SC changes		Production (globalization), fragmented industry, isolated optimizations, complex flows	Production and maintenance (cost reduction), logistics (flow optimization cars and pans), IO coordination	Cars (modularity), production (OEM), logistics (comanufacturing), regional clusters, “local” SCM	Distribution (e-commerce), B2B marketplaces, globally engaged suppliers (first-tiers OEM and LSPs), global SCM in complex SCs, SC governance issues	Distribution and sales (omnichannel), After-sales service, reverse logistics, cars (electric + digital), risk management
Automotive SC ecosystem		Car manufacturers + consumers + garages	+ Industrial suppliers + Transport providers + Standardization bodies	+ Logistics suppliers + Software and IT service suppliers	+ Other service providers (for after-sales services and other services)	+ Electronics suppliers + start ups + GAFAM + public sector (cities)

TABLE 17.2 Key points of the coevolution of automotive SCs and their digitalization.

Configuration and management of automotive SCs	Development of digitalization in the automotive sector
Intertwined national (country), regional (continent) and global levels. Complex relationships between car manufacturers, industrial suppliers, dealers and logistics service providers, which are expanding to include new stakeholders. Coopetition between car manufacturers working with the same suppliers and sharing resources in regional clusters with worldwide relationships. The industry resembles a web of SCs, now also extending to other sectors. Complexity is leading to greater interdependence and emerging phenomena in the automotive ecosystem. Many interconnected factors linked to technological innovations are driving the evolution of automotive SCs.	Multiplication of “new” technologies and systems combined to control operations. From islands of automation, robotization, computerization, etc. to total digitalization. SC digitalization combines different technologies at different levels that must be able to operate with each other. Need for system interoperability to improve flow management in SCs and SCM. Importance of standardization bodies and techno-suppliers. Every new technology era leads to new benefits (use of technology), but poses new problems. Automotive SC digitalization is a decades-long multi-layer process driven by multiple factors and is still in progress.

car manufacturers but also raises many new challenges. This section focuses on the analysis on the recent and ongoing digitalization of a specific car manufacturer's supply chain.

For the first author, this study is one of the latest in 30 years of research in logistics and SCM, several of which were spent in the automotive industry in France. She regularly collaborates and interacts with the manufacturer—The Renault Group—at the center of this study. To understand better the complexity and the dynamics of contemporary SC digitalization, a much closer collaboration was initiated at the end of 2018 for a period of 3 years. Consequently, the second author was able to participate in more than 20 projects concerning the process of SC digitalization, in particular those aimed at developing traceability and SC visibility to create value. As the company produces and distributes vehicles around the world, its digitalization process is undertaken on an international scale, prioritizing uniform deployment at the European level. The same scope—Europe and worldwide—was used for this case study. Internal company data were collected to support the analysis. These data come from observations, note-taking, semistructured interviews, consultation of internal confidential documents, and, for some projects, from action research. We monitored new business developments and emerging research and also engaged in foresight thinking on the evolution of the automobile industry and its SCs. All of the data collected have contributed to documenting the study reported in this chapter.

3.1 Understanding the SC digitalization strategy and processes of a car manufacturer

The car manufacturer we studied is one of those that were in the market before the Second World War. It has succeeded in maintaining a leading role in the automotive world to the present day. The digitalization of its upstream and downstream SC has largely followed the evolution described in Section 2. It is evident that SC digitalization has been and continues to be a dynamic and complex coevolution of many factors, among which technology (with continuous innovations) plays a key role. In Europe, the company has played a leading role in adopting new technologies and, in concert with local and regional standardization bodies, in creating conditions that are propitious for their diffusion across SCs and throughout the automotive sector.

Since 2010, many factors have converged to initiate a new and important period of change in the company and its SC digitalization. The 2007–08 financial crisis called for SC reorganization to improve agility, a lesson confirmed by the impact of the Fukushima crisis in 2011 and, more recently, by the COVID-19 pandemic. Notwithstanding the complexification of upstream and downstream flows in the SC, exacerbated by various alliances with other SCs, new technologies were expected to support the development of powerful SCM decision-making systems.

The development of electric vehicles has meant that manufacturers have had to find new suppliers (e.g., for batteries) and meet new requirements. Online sales of spare parts has given rise to counterfeiting issues that called for increased upstream traceability. The introduction of more and more electronic devices in cars (seen as potential sources of breakdowns), combined with changes in city mobility and the way cars are used, is perceived not only as a threat but also as an opportunity to innovate and to respond to sustainable development issues (e.g., energy consumption, product end-of-life, and greater security and safety). Increased competition, exacerbated by newcomers in the sector (e.g., Tesla), has forced existing manufacturers to innovate and maintain firm cost control on operations. Societal and regulatory issues continue to require greater compliance with more and more standards, norms and regulations (e.g., concerning CO_2 emissions, due diligence in SCs, certification of the origin of certain raw materials, and extended producer responsibility). All of these issues demand more traceability and SC visibility.

Although this car manufacturer has a good track and trace system, a number of shortcomings were identified—not enough coverage (some "gray" zones), not precise enough (some uncertainties), not reliable enough (concerns about data quality), not homogeneous enough (difficult to combine data from the different systems), and not sufficiently flexible and user-friendly to adapt to and meet new information needs. Like other long-established car manufacturers, it has had to deal with the heterogeneity of a "patchwork" of IS systems and technologies that combine different legacy IS, sometimes with well-known lock-in effects (Jahre & Fabbe-Costes, 2005): technologies that are so-well integrated are difficult to change, requiring challenging trade-offs to be made.

It was considered strategic to boost digitalization to improve traceability and overall SC visibility, to build a shared digital platform to work with the ecosystem, and to create value for SC stakeholders. New technologies, such as RFID, IoT, AI, and blockchain, were seen as an opportunity to improve the visibility of their supply chain both upstream and downstream, in particular to see into "black boxes" such as the flows, activities, and processes handled by industrial suppliers, LSPs, and dealers, and to gain better knowledge about the evolving use of cars.

The company has engaged in the exploration and use of any DT that could open strategic opportunities by boosting SC digitalization. This initiative has been cross-functional, involving every department in the company, but especially in supply chain and in sales. It has led to multiple projects with different purposes and ambitions. Fig. 17.1 outlines the manufacturer's overall SC digitalization process including the main decision-making points, based on our analysis.

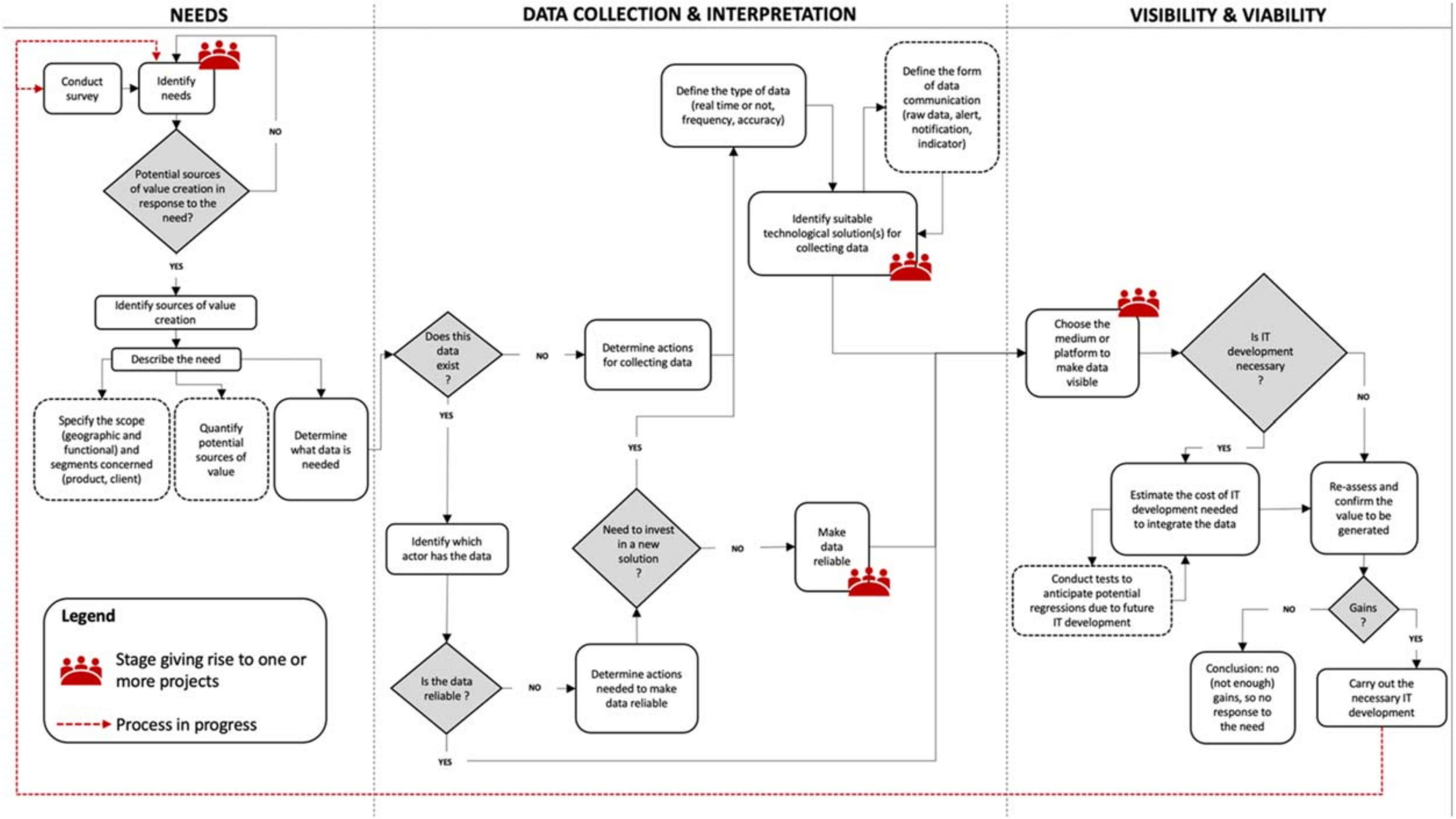

FIGURE 17.1 Model of the manufacturer's SC digitalization process.

With the aim of meeting the company's supply chain strategic objectives and more broadly those of its strategy, the digitalization process is made up of the three distinct stages shown in Fig. 17.1. The first stage focuses on defining needs, the second on collecting and interpreting data, and the third on making these data visible and ensuring the viability of the response to the need. The company adds digital bricks in the IS and the SC, sometimes including "new" IT adoption. The process begins with a diagnostic survey carried out among the various internal actors of the company's supply chain to identify their needs. The articulation of needs is an essential step in the digitalization process. Generally, needs are expressed in the following way: "As an x, I need y for z." The first condition is that whoever expresses a need must describe the sources of potential value that could be derived and/or generated through the company's response. The next step is to define the specifications for the need and potential response. An essential precondition for moving forward with the process and on to the second stage is identifying what sort of data will be required.

The second stage of the process focuses on the data required to meet the need. There are several different actions depending on the answer to the following question: Does these data already exist? If it cannot be found in existing internal or external systems, they have to determine the sort of action needed to collect it. It will be necessary to define the type of data as well as how they want the data to be communicated in order to identify suitable technological solutions to answer the need. If the data exist, it will be necessary to identify the owner of the data, access to it, and assess its reliability. If the data are not sufficiently reliable, they will have to determine whether they need to invest in a new solution to increase data reliability. In this case, the next step is to identify the nature of the data. Whatever actions are to be implemented to meet the need, all of them lead to the third and final stage of the process.

Once they have determined which type of software will be used to interpret and share the data (e.g., Excel, Dashboard, visibility platform), it is necessary to assess whether any IT development will be required. If so, the next step is to estimate the cost of such development and to anticipate any potential IT regression (software testing conducted to ensure that any additions or modifications do not adversely impact existing internal or external IS). The last stage of the process is to reevaluate and confirm the value that will be generated by the company's response to the need. If these financial investments do not generate a net gain for the company, no action will be taken to respond to the need.

Currently, this is an ongoing process. It has given rise to multiple projects aimed at responding to needs expressed by actors in the manufacturer's supply chain. Whether successfully completed or not, these projects have different ambitions and have been launched at different stages in the digitalization process. We identified three categories of projects as well as interactions between these different categories (see Fig. 17.2). Projects with a strategic purpose (A) are aimed squarely at meeting the main objectives of the company's supply chain strategy and these were launched at the beginning of the process, during the needs identification stage. These strategy-oriented projects influence and shape projects launched at later stages of the process, particularly those aimed at modifying and improving existing supply chain processes (B). When conducting projects with a strategic focus, actors often want to modify certain business processes (link 1a). In seeking to improve these processes, they contribute directly to meeting the objectives of the original strategy-oriented projects (1b). Projects in the third category (C)—tools and technological solutions—may be launched either in response to the objectives of the strategy-oriented projects (2) or process-oriented projects (3) and may in turn have an impact on some of the latter (4).

Initiated during the second part of the process, multiple projects seek to improve existing tools (particularly in the area of data reliability) and to deploy new technological solutions. These are generally used to capture the data required to

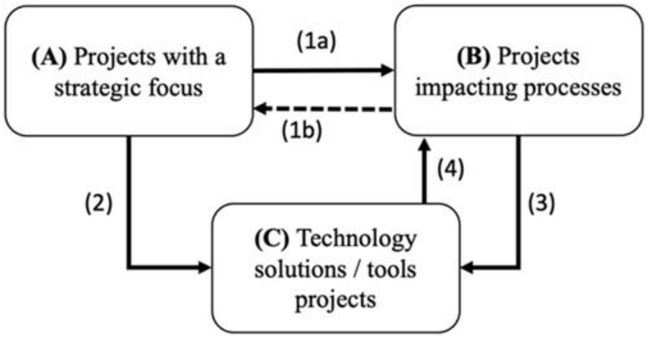

FIGURE 17.2 Interactions between project categories.

respond to the needs previously identified. The collection of new data is a complex stage, involving the combination of existing and new technologies. For the same need, some data can be extracted from existing systems, while other data will be collected through the implementation of new solutions. This combination is indispensable, given the existing constraints: multiple actors involved in the digitalization process, multiple IS and interfaces, multiple activities, technological geographic coverage, and keeping existing systems running. Clearly, the digitalization of the manufacturer's supply chain cannot rest on the development of a single technology.

The above-mentioned constraints also affect the last part of the process and raise critical questions about data sharing among the different actors, given that their objectives may diverge (cf. Fabbe-Costes et al., 2020). This is not surprising since the digitalization process combines bottom-up and top-down forces in the company and involves shareholders and stakeholders. The goal is to collect, interpret, and share the data in a useful way, bearing in mind that the person requesting the data is not always the owner.

In summary, SC digitalization is a complex ongoing process even at the company level and is directly related to the company's overall strategy. SC digitalization entails the simultaneous implementation of many intertwined projects with different ambitions. SC digitalization requires the coordination of strategic projects and issues, organizational changes and process reengineering, and different technical choices. The process may further complicate the multilayered IS patchwork with the introduction of heterogeneous technologies of different types and ages.

3.2 Lessons from the SC digitalization process experience

The SC digitalization case study provides lessons on digitalization in the automotive sector. Increased SC digitalization reveals unexpected issues and raises new questions at the strategic, organizational, and operational levels.

3.2.1 At the strategic level

Identifying "real" needs: SC digitalization is linked to strategic questions, which is why the SC digitalization process begins with the identification of needs. Our analysis of the ongoing process over 3 years, as well as the examination of documents on projects from the beginning of the 2010s, show that there is an endless loop of needs and solutions (see Fig. 17.1). There are always new needs!

Technology and capability gaps: Automotive SC digitalization leads car manufacturers to discover a "new world" far from their traditional industrial culture: "The skills that automotive companies need are significantly changing" (Forbes, 2021). There is a need for new competencies to understand technologies, foresee their potential use and impact in the SC, and make the strategic choice whether to adopt them or not. The question of whether to outsource these competencies, make alliances, or integrate them in-house is of great importance.

Powerful technology providers: Pressure from powerful actors from the tech world linked to data management such as blockchain and the Cloud that seek to participate in the automotive industry as service suppliers, or even enter the industry themselves with autonomous cars in some cases, could lead to new dependencies and the risk that manufacturers become locked into solutions and lose their power in the market.

New risks: More generally, digitalization requires SC risk managers to expand their SC risk management (SCRM) to include new risks such as the risk of obsolescence or cyber risk. These relate not only to IS but also security risks regarding IoT all along the SC, including cars themselves. It also creates new vulnerabilities (e.g., electronic component shortages), raising questions on whether it is still possible to manage SCs in the event of IS breakdown or unavailability.

New services: The increasing amount of DT and equipment integrated into vehicles makes it possible to offer new services (Genzlinger et al., 2020; Spring & Araujo, 2009), but this also creates new needs in terms of SC digitalization, right up to the end-of-life of cars. What will be the role of car manufacturers in new data-driven services? Can they develop more services linked to the usage of cars based on data (e.g., car sharing, predictive car maintenance) and can they capture the value created through this type of service? How can car manufacturers shift to this type of product-service model? Can car manufacturers become platform companies? According to (Deloitte, 2020), "Shared mobility will increase the utilization per vehicle and shift ownership from private customers to fleet operators."

Societal issues: SC digitalization leads car manufacturers to consider a wider ecosystem and to scan a wider space for threats, opportunities, pressures, and risks. With SC digitalization, societal issues that have always been important (e.g., driving safety) are changing in nature. Digitalization also generates new societal issues (e.g., privacy protection) with new dangers to avoid (e.g., cybersecurity). On the other hand, societal issues may present opportunities to develop new PSS in the automotive industry (Mahut et al., 2017).

3.2.2 At the organizational level

In the automotive sector and in the case company, SC digitalization has an impact on all SCM processes: car design, the sourcing of components and upstream SCM, production, distribution, sales, and all the services related to car usage and maintenance. It also impacts remanufacturing and end-of-life. The use of DT, ICT, and IS accelerates processes and increases their entanglement. It develops their tracking and tracing, and the data from traceability systems are used to make further progress in terms of increased productivity, performance, and value.

New data requirements: Almost every new need expressed at the strategic level leads to the conclusion that the company needs more data. The data requirement depends on actors' needs and the technical capabilities of the solution: if the technical solution does not gather all the data, an additional solution will be required to collect the missing data. For example, if an ETA (estimated time of arrival) is needed for vehicle delivery, it may need to be calculated with already available data (start/end date of transport) and new data (GPS coordinates of the transport truck and/or the vehicle itself).

Better use of existing data: The company has discovered a lot of unexploited sources of data (e.g., data related to vehicle location, quality, or usage gathered by different tools). Some new technologies such as the Cloud and data lakes facilitate data gathering from existing tools, while others, such as data mining, AI, and deep learning, help to better exploit them.

Internal collaboration challenges: SC digitalization makes the SCM processes ever more interrelated, necessitating more collaboration between functions and departments in the case company. It also means that the downstream SCM processes and logic need to be better connected with the upstream SCM. In the car manufacturing sector these different logics and behaviors have not been well integrated historically—different departments may not be used to sharing their knowledge (Fabbe-Costes et al., 2020).

Loss of control: Changes in processes due to digitalization can impact organizations and structures as well as people's day-to-day jobs. This is not a new revelation (cf. Scott Morton, 1991), but the pace of change is accelerating, as well as the number of new technologies introduced, leading to the feeling of losing control over the SC because of unstable and unfinished digitalization.

Data ownership and data access: SC digitalization has led to a tremendous amount of data being captured all along the SC. The question of who owns the data, where it should be stored, who may access it, and what they may do with it are major issues. These are not new questions (they emerged with EDI and B2B marketplaces) but now affect organizations much more widely and their importance needs to be appreciated.

SC governance: Governance of SCs, governance of IOS, and governance of data are intertwined, and more complex with the widespread prevalence of today's DTs. The centralization/decentralization debate is also reemerging (cf. power issues linked to emerging control towers).

Patchwork problems: The new SC digitalization does not eliminate the problem of the patchwork of IS. It is still difficult to consolidate data, in particular to access and feed certain data into specific systems at the intra- and interorganizational levels. A process-oriented "urban planning" approach (i.e., borrowing concepts and methods from city planning) to IS in digital SCs is still a challenge (ANSSI, 2021; Cigref, 2021).

Visibility or fog: More technologies do not necessarily provide more visibility. Some supply chain actors may still be reluctant to be more transparent, which may explain why some automatic track-and-trace projects have failed. Many car manufacturers have not increased SC visibility much in their multi-tier upstream and downstream SC since the EDI era, in particular in relation to SMEs.

Managing SC digitalization projects: Digitalizing an SC is an endless project, with no definite beginning and end (cf. Fig. 17.1). How can one conduct a process that combines numerous subprocesses with many interrelated projects at different levels (as described in §.2.1 and in Fig. 17.2) with multiple actors within the company and in the ecosystem? Rapid technological developments offer new opportunities every day and new technologies to test. There is clearly a risk of prioritizing DT opportunities over real business needs.

3.2.3 At the operational/technical level

Increasing SC digitalization has a significant impact on the day-to-day work in SCs. There are enduring questions about human−machine relationships, human−AI cooperation or competition, and the risks of giving algorithms and machines control over SCs.

Sensemaking: Technology is supposed to give managers more SC visibility, thanks to performance dashboards, detailed KPIs, overviews of flow circulation, stock levels, and other management IS. However, because of the complexity of the SC and its management, problems of sensemaking—understanding the big picture and the importance of every individual contribution—will continue to remain.

Technical constraints and hurdles

- *Geographic coverage constraints*: associated with both technology (e.g., communication networks) and international location choices (e.g., with regulatory differences).
- *Reliability of data*: Coverage constraints associated with uncontrollable external factors (e.g., concerning traceability of international transportation, the weather can affect the quality of data transmission or can even be the cause of unreliable data such as inaccurate location data).
- *Interoperability:* Constraints due to the technological "patchwork." It is more and more difficult to create links between different systems in an IS infrastructure. Multitechnology interfaces are complex and increase the risk of IT "regressions" during development. Interdependency between heterogeneous IS modules makes IS maintenance and upgrading more difficult, and requires more competences.
- *Cybersecurity and regulations*: Constraints related to anticipating cybersecurity risks as well as future regulations concerning data management (e.g., GDPR in Europe).

In summary, SC digitalization is a complex emerging process combining bottom-up and top-down forces in a company and involving shareholders and stakeholders. Strategic, organizational, and operational issues interact and must be considered together. For example, SC digitalization projects undertaken to bridge boundaries (Takeishi, 2001) between a car manufacturer and its logistics services providers will encounter governance issues (strategic level), interoperability difficulties (organizational level), and concerns about data quality (technical level). The result is that technology does not always ensure greater data reliability. Interoperability issues remain complex and IOS remain problematic to run. It is very important to be sure of the quality of the data produced, in particular whether it reflects what is really happening. Is the image provided by the IS consistent with reality? But it is also very important to be sure the data are relevant to the needs of actors. High quantities of data do not guarantee their relevance.

4. Conclusions

This overview of the development of SC digitalization in the automotive sector offers important lessons and opens many questions for further study, both for academia and industry. SC digitalization is not an end in itself. It is only desirable because of what it offers. Value creation, including in terms of sustainable SCM, is therefore crucial. It is important to digitalize for valid reasons and not to give in to trends or copycat behavior, nor to give in to pressure from dominant interests. We focus on the main results of our research (the What, Why, and How of digitalization) and conclude with future perspectives and some philosophical thoughts.

4.1 What?

- Given that SC digitalization combines numerous heterogeneous interconnected technologies that complement each other and have to interoperate, SC digitalization is a complex process that calls for a long-term perspective to understand technology evolution.
- SC digitalization eras are linked to the adoption and diffusion of some disruptive technologies, combined with existing ones, leading to cumulative solutions, which in turn open new strategic perspectives.
- SC digitalization comprises three intertwined facets: digitalization of operations (manufacturing, transport, logistics, service operations), digitalization of the design of the PSS (cars, services), and digitalization of the management of SC processes.

4.2 Why?

- Digitalization has been and still is a powerful SC game changer, but it is not the only factor explaining SC evolution and it interacts with many others (Fabbe-Costes & Colin, 1999; MacCarthy et al., 2016). SC digitalization phenomena need to be considered as embedded in a global complex and changing environment.
- SC digitalization combines macro trends at the sector level with individual company decision-making at the strategic, organizational, and operational levels. The micro and macro levels influence each other. Powerful SC actors can be SC digitalization influencers.
- Whatever digitalized SCs are at a given moment is temporary. The different "stages" of SC digitalization cannot be seen as "models" or compulsory stages to achieve. While they can help to compare SC digitalization paths or stories, they do not indicate what to do. There is no "one best way"!

4.3 How?

- SC digitalization is a coevolution process. DTs offer "solutions," and implementing them in SCs should help to better manage those SCs. However, they influence and affect the topology, structure, and governance of the SC ecosystem. In turn, the ecosystem evolves, raising new data needs and spurring new SC digitalization efforts.
- SC digitalization is not a single big project with one-shot decision-making. It results from many interacting projects addressing many questions at different levels.
- SC digitalization does not solve all problems and is not a simple journey. It combines heterogeneous technologies, each with a different level of maturity. Learning in each era is important: some old questions are still of high relevance.

During every era of digitalization, a change in SC governance has been predicted. But has it really changed? Problems of dependence, unbalanced power, information asymmetry, reluctance to share information, opportunism, and partner congruence, persist. Technologies are never "magic bullets." It may be time to change both the vision of what an SC is and how DTs may help to govern SCs in a more sustainable way. SCs are complex adaptive systems that may be viewed as a kind of "commons." Pooled SC resources should therefore be collectively managed. SC digitalization should help to develop polycentric governance (in line with Ostrom, 2010) of data and of SCs.

Every step of increased SC digitalization raises questions about the right focus, level and scale of analysis, and the work needed to improve SCM, especially in global IOS. Digitalization requires organizations to adopt and use many different technologies at different levels of the SC. Increased digitalization is often an opportunity to get more detailed data, enabling a more fine-grained analysis. However, instead of always looking at the more detailed level, which may lead to precise but wrong decisions, it is also necessary to adopt a multiscale, multilevel unit of analysis approach and to adopt a local/global multiview dialogue (Fabbe-Costes et al., 2020).

Digitalization has always been viewed as a way of improving SC performance, getting better control over space and time, reducing uncertainty, and increasing responsiveness to any hazard. SC digitalization can be viewed as an opportunity for logistics and SC managers to achieve their goal of more JIT. Customer-driven processes, deployed on an ever wider geographic scale, adapting to their environment and providing strategic outputs for SC stakeholders (Fabbe-Costes, 2000, chap. 9). But increased SC digitalization brings new risks (e.g., cyber risks), new uncertainties (e.g., concerns about data accuracy), and new factors of vulnerability (e.g., linked to IoT battery life, random electronic failures, electronic component sourcing). Is it a vicious or virtuous circle?

Since the beginning of SC digitalization, there has been more and more automation in physical operations (e.g., handling in warehouses), information communication (e.g., EDI), and also in decision-making. Workflows and decision-making systems are infused with practices and management rules which are (sometimes unconsciously) applied via the IS. The IS sets the limits of what can and must be done. Virtual control by IS, which has been denounced for years, is more relevant than ever (Lechaptois, 2020). The latest technologies result in rules so complex that few may understand them or be able to challenge them. This can be risky in volatile, uncertain, complex, and changing environments.

SC digitalization is a never-ending journey that may render futile the search for stability in the SC and its management. This forces us to reconsider the stable vision offered by many SCM books and to accept that the dynamic of the system is in reality permanent change due to internal or external forces. Digitalization thus calls into question the maturity models offered by consultancy organizations and academic publications. SC digitalization challenges the limits of a "command and control" approach to SCM. Many companies are still working with the legacy of CIM and MIS paradigms. It may be time to abandon the modernist dream and learn how to "dance with the supply chain" (Wieland, 2021).

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Chapter 18

Digitalization of the international shipping and maritime logistics industry: a case study of TradeLens

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Abstract

This chapter assesses the potential implications of global trade process digitalization for the international shipping ecosystem by analyzing a prominent industry-wide emerging solution—TradeLens—a platform jointly developed by A.P. Moller Maersk and IBM. TradeLens is an open and neutral industry digital platform that provides end-to-end visibility across the entire shipping processes and is powered by blockchain technology. We discuss the complexity of the shipping process, the number and types of actors involved, and the critical documentation that is required for the movement of cargo by ship. The motivations and opportunities for increased digitalization of shipping processes are noted and the impact on business models and operations are highlighted. The research combines multiple data sources to identify the key challenges in the maritime industry and to analyze the capabilities of TradeLens, and its diverse use cases. A SWOT analysis of TradeLens has been conducted to identify its strengths, weaknesses, opportunities, and threats, including the provision of a rich data environment, ease of integration, and enabling secure document handling. The case study analysis provides new empirical evidence about the potential implications of digitalization for the shipping industry as a whole and the main actors in the international shipping ecosystem.

Keywords: Blockchain; Digitalization; Maritime logistics; Shipping industry; TradeLens.

1. Introduction

The international shipping and maritime logistics industry is the glue that connects the different actors across global supply networks. Maritime shipping is the main mode of transport for around 90% of the goods traded globally (OECD Ocean, 2021). The international shipping industry has grown proportionately with the increasing globalization of businesses and the dispersal of supply chains. Here, we analyze a pioneering case—TradeLens—a solution that provides an open and neutral digital platform for the whole of the international shipping industry. We first discuss the motivations for increased digitalization in international shipping and then discuss the opportunities the sector provides for the digitalization of shipping processes, business models, and operations.

To appreciate the complexity of shipping processes and the number of parties involved in the maritime shipping operations, we describe a general shipment scenario in Fig. 18.1. At a very high level, the shipping process starts with the booking confirmation from the ocean carrier based on the submitted booking request and shipping instructions. Depending on the logistics service used, this process can be initiated by the exporter, importer, or a third-party logistics partner (3 PL). Upon the receipt of the empty containers, the cargo can be stocked at the ports or exporter's facilities. Once the containers are filled, customs clearance processes start, which are typically managed by a customs broker. Depending on the type of cargo and the contract terms, several certificates can be requested, and an inspection can take place for the cargo. The customs clearance processes can also differ across countries. Once released from customs, the containers are then loaded onto the vessel. After the vessel's departure, the original bill of lading (BOL) is created by the ocean carrier. The BOL is a

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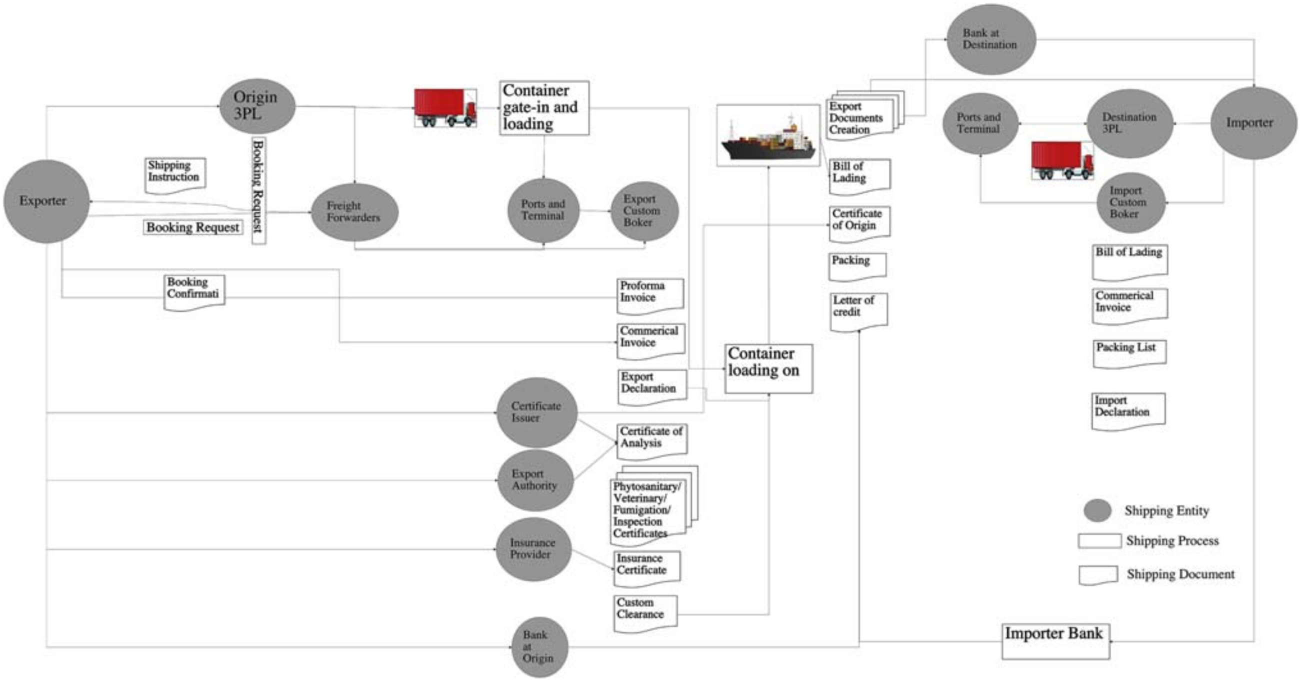


FIGURE 18.1 Overview of high-level shipping processes. *Credit (Authors).*

legal contract that includes the cargo information and the agreed-upon terms and conditions between all the parties involved in the cargo transport (Irannezhad & Faroqi; 2021, pp. 1−19; Vector, 2020). BOL is the most important document in the shipping process. BOL acts as proof and title of ownership throughout the shipping processes. It provides a piece of evidence that the shipper has released the consignee's goods to the carrier for transport. It is the main document that enables the consignee to receive the cargo at the point of arrival (Vector, 2020). BOL acts as an official evidence of cargo information that can be referred to in the case of disputes. The BOL is also an important document for the payment cycle between the sellers, buyers, and their banks (Irannezhad & Faroqi; 2021, pp. 1−19). In cases when there is a lack of or limited trust, the BOL may be handled by a bank, which issues a letter of credit (LoC) and ensures that payment is settled before enabling the importer to release the cargo (Tsiulin et al., 2020).

In addition to the significant number of steps and parties involved in the shipping process, the processes are mostly manual, requiring a tremendous amount of paperwork, and significant time goes into documents creation and exchange (Yang, 2019). Documentation is a key part of maritime transport (Papathanasiou et al., 2020). On average 30 documents are exchanged to process one shipment (Cargo Smart, 2018). The industry suffers from a lack of innovation and limited digitalization of its operations and logistics processes (Jović et al., 2019). However, digitalization presents concerns since there have been several cyber-attacks in recent past years in this industry (Cimpanu, 2020). Additionally, information sharing, visibility, and transparency have been viewed as a threat to competitiveness (Papathanasiou et al., 2020).

All of these challenges have led to significant inefficiencies evident across shipping ecosystems that have affected the performance of all parties involved. Beneficiary cargo owners (BCOs) and logistics partners (2, 3, and 4 PLs) struggle to estimate shipping times, which affect their supply chain planning and management processes (Pradi & Rios, 2020). The lack of visibility of shipping processes leads to increased costs for BCOs and logistics partners, including increased demurrage costs and truck waiting costs when cargo is delayed and/or updated information is not received about their cargo upon arrival (Pradi & Rios, 2020). This limited visibility can force BCOs to increase cargo stocks to mitigate any disruptions or delays, and/or pay for more free time in shipping bookings to minimize extra demurrage and detention costs. Also, limited trust between buyers and sellers has led to the involvement of banks in the shipping processes, which lengthens the process and contributes to the delays and extra costs. Other supply chain partners and logistics partners also struggle from these challenges as it affects their performance, costing, and customer service.

Similarly, customs brokers, customs authorities, and ports and terminals also suffer from this limited visibility in their planning processes and resources allocation. 60%−70% of cargo vessels' port time is spent in berth in the European region as port operators lack visibility on vessel arrival time, which contributes to significant inefficiencies (Hvid Jensen, 2020; Lind et al., 2019). It is estimated that more than $5 billion could be saved in reduced fuel and idle time if vessels traveled optimally (Hvid Jensen, 2020). Having more visibility into when vessels will arrive can lead to early planning, optimized resource allocation, significant cost savings, and reduced environmental impact.

The digital transformation that has taken place in industries such as the retail industry with e-commerce will expedite its adoption in the shipping and logistics industries sooner rather than later (WEF, 2016). Moreover, the recent pandemic has forced organizations across the globe to move into the digital world to sustain their business. This has also forced the shipping industry to transform its traditionally inefficient and lengthy shipment processes through digitalization.

There are several opportunities for digitalization in the industry. Digitalization and information and communication technologies can facilitate collaboration in the maritime industry (Feibert et al., 2017). In their joint report with Accenture, the World Economic Forum (WEF) has identified five themes for the digital transformation in the logistics industry: (1) Digital information services where data services like control towers and Analytics can reduce costs and improve efficiencies, (2) Digital logistics services that enable growth across borders through the development of cross-border platforms, (3) Digital delivery capabilities that create more options for deliveries, (4) Circular economy to promote more sustainable product life cycles and reduce the environmental impact of the industry, and (5) Shared logistics capabilities like warehouse and transport, leading to better utilization of assets. Logistics digital transformation benefits are estimated to be around $1.5 trillion of value gained by the logistics players and $2.4 trillion of value in societal benefits (WEF, 2016). In the maritime industry, manual document handling slows logistics and reduces the potential value of containerized freight by 15%. This value can reach up to $1.8 trillion per year and can be claimed back through the digitalization of global trade processes (TradeLens, 2021a).

In this chapter, we assess the impact of digitalization on the maritime industry with the use of a case study analyzing one of the pioneers in developing a shipping industry−wide digital solution. TradeLens is an open and neutral industry digital platform that provides end-to-end visibility across the shipping ecosystem and is powered by blockchain technology. This case study helps in understanding the impact and implications of digitalization for the maritime shipping ecosystem.

We start by describing the research methodology and data sources. A brief introduction to TradeLens is presented, followed by examples of several TradeLens use cases. A SWOT analysis has been conducted to critically identify the key strengths, weaknesses, opportunities, and threats of TradeLens. This enriches the discussion about the implications of the digitalization of the shipping processes for the many different shipping entities and its potential in overcoming the existing challenges in the industry. We conclude the chapter with a brief discussion about the case study work, limitations, and recommendations for future research.

2. Methodology

To understand and analyze the impact of digitalization on the shipping industry, we first take a broader approach to identify the key challenges and the level of digitalization in the shipping industry using the existing literature. Then, we take a narrower approach where we conduct a case study and investigate one of the most prominent current industry-wide digital solutions in the shipping industry, namely TradeLens.

Conducting a case study enables in-depth understanding of the complexity of the shipping processes and the different characteristics of the shipping ecosystem in a real-world context. Yin (2018) defines a case study based on two aspects: scope and features. In terms of scope, a case study is defined as "an empirical method that investigates a contemporary phenomenon in depth and within its real-world context especially when the boundaries between phenomenon and context may not be clearly evident. (P15)" In terms of features: "A case study copes with the technically distinctive situation in which there will be many more variables of interest than data points, benefits from the prior development of theoretical propositions to guide design, data collection and analysis, and relies on multiple sources of evidence with data needing to converge in a triangulating fashion. (P15)"

To analyze TradeLens, both publicly available data and internal documents have been examined, and with the expertise of the authors, a thorough analysis and discussion have been conducted on the potential implications of digitalization on the shipping industry. Several use cases have been presented to identify the key capabilities and potential benefits of TradeLens, followed by a SWOT analysis to identify the key strengths, weaknesses, opportunities, and threats of TradeLens. SWOT analysis is a common strategic tool for business researchers and practitioners. In SWOT, the internal strengths and weaknesses, and the external opportunities and threats are identified, which set the ground for strategic planning and decision-making (Helms & Nixon, 2010). Besides strategic management and market research, SWOT analysis has been adopted for different purposes in the literature including analyzing planning support systems (Vonk et al., 2007), and the adoption of information technology in the healthcare industry (Helms et al., 2008). In the context of

TradeLens, SWOT analysis provides insights into its key strengths and weaknesses, its main capabilities as a digital solution, and the opportunities and threats from having such an industry-wide solution in the shipping industry.

This approach has helped to provide both theoretical and empirical lenses on the impact of digitalization on the different entities in the shipping ecosystem.

3. Digitalization in the maritime industry

Gartner's IT Glossary define digitalization as "the use of digital technologies to change a business model and provide new revenue and value-producing opportunities; it is the process of moving to a digital business" (Gartner, 2021).

Digitalization in the maritime industry varies across the shipping ecosystem (Pradi & Rios, 2020). Higher levels of digitalization can be found in ship design and shipbuilding with the use of Artificial Intelligence and unmanned vehicles (Sanchez-Gonzalez et al., 2019), developments in robotics for vessel inspections (Milella et al., 2017; Ortiz et al., 2014), and use of big data to study ship navigation (Isenor et al., 2017), optimized vessels routes (Li & Huang., 2017), and advanced ports management (Fernández et al., 2016). Industry 4.0 and the Internet of things (IoT) have also revolutionized some aspects of the shipping industry by enabling better container and vessel management and tracking (Choi et al., 2018; Katayama et al., 2012). However, there are concerns related to the security of radio frequency identifiers (Fernández-Caramés et al., 2017). Having solid security tools and processes are essential for digitalization, yet still, the area of digital security in the maritime industry is one of the least researched topics (Sanchez-Gonzalez et al., 2019).

Taking a supply chain perspective, the maritime industry has been poorly connected to the end-to-end supply chain (Voorspuij & Becha, 2021). The majority of entities in the maritime ecosystem work independently and only interact closely at certain times to achieve individual aims (Feibert et al., 2017; Lind et al., 2015). There is a lack of horizontal and vertical integration of digital solutions in the maritime industry. Digitalization is fragmented across a limited number of processes that serve certain logistics entities. Most developed solutions do not promote information sharing with other actors in the shipping ecosystem (Feibert et al., 2017; Lind et al., 2015). The INTTRA Ocean Trade Platform, for example, is one of the largest digital platforms that enables the booking and tracking of shipments and includes more than 20,000 carriers, logistics service providers (LSPs) and Freight Forwarders (E2open, 2021). INTTRA provides visibility for standard shipping journey milestones (i.e., Empty pick up, Gate in, Vessel load, Vessel departure, Vessel arrival, Vessel unload, Gate out, Returned), and can be integrated with other logistics systems through EDIs or APIs (INTTRA, 2021). INTTRA data present the common level of visibility provided by most ocean carriers with limited to no visibility in the ocean leg. The platform provides main logistics execution updates without connecting to other entities like ports and terminals, customs authorities, and/or financial authorities. However, these entities are closely engaged in the processing of shipments, require access to shipping data and documents, and can affect the execution of logistics and cause shipment delays.

Lind et al. (2015) stated that the shipping industry has not yet experienced the digital transformation that enables information sharing to improve efficiencies and reduce costs. They addressed the need for a digital transformation that enables the different participants to control access to their data but also meets the level of information sharing required by the industry. Most of the shipping processes are manual and paper-based and involve multiple parties in lengthy validation and authorization processes, which have had an impact on the shipping time and costs (Liu et al., 2021). Digitalization in this industry has been introduced at a slower pace compared to others (Sanchez-Gonzalez et al., 2019; WEF, 2016).

The industry lacks standards for the shipping data that are shared across the supply chain (Yang, 2019), and information is scattered across multiple systems. There is limited visibility across the shipping processes. All of these combine to make lengthy inefficient processes and contribute to the high costs of delays (i.e., detention and demurrage), and poor customer service (i.e., responding to customer inquiries, meet delivery requirements, etc.). These pain points are common across all parties in the shipping ecosystem from BCOs, LSPs, ocean carriers and authorities. The industry has been subject to fraud especially in customs clearance processes (Segers et al., 2019), and to several cyber-attacks that hit its top players (Cimpanu, 2020). This has raised concerns related to the security of currently used digital technologies for shipping data sharing and documents exchange. However, the emergence of blockchain technology is providing opportunities to address these issues.

Blockchain technology promises to revolutionize the shipping industry (Bavassano et al., 2020). Blockchain is a distributed ledger shared in a peer-to-peer network that contains an immutable digital record of transactions that are timestamped and stored in blocks in chronological order. Each block is identified with a cryptographic key (i.e., hash), and points to the block that preceded it in the network (Christidis & Devetsikiotis, 2016; Crosby et al., 2016). The security and transparency provided by the blockchain network provide great potential to tackle the outstanding challenges in the shipping industry. Smart contracts are programmable codes that are executed automatically once the predefined contract conditions are met (Wang et al., 2019). Their use can enable the automation and digitalization of shipping processes, which brings the potential for transformative capabilities to the shipping industry (Lambrou et al., 2019).

Blockchain enables end-to-end visibility across the supply chain (Verhoeven et al., 2018; Wamba & Queiroz, 2020). In their research, Zhou et al. (2020) have categorized four application areas for blockchain in the shipping industry: (1) managing shipping operations and movement of cargo, (2) managing shipping transactions without the need for intermediaries, (3) facilitating marine insurance by ensuring vessel status data immutability and timestamped records, and (4) managing ship registry processes by having a valid, traceable, and immutable record of the ship containing all its details and certifications. In maritime logistics, Papathanasiou et al. (2020) identify four main advantages from using blockchain − (1) use for documents exchange which will lead to significant savings in time and costs by eliminating intermediaries and resource-intensive paperwork, (2) use for containers utilization and efficiency by having a tracking record for the containers on the blockchain, (3) enabling intelligent transportation by providing accurate data about vessels location, speed, etc., that enables the optimization of travel routes, and (4) capturing, verifying, and reporting container weight, which is a requirement for the International Maritime Transport regulation: Safety of Lives at Sea—Verified Gross Mass (World Shipping Council, 2015). Despite the potential benefits of deploying blockchain in the shipping industry, most research discusses blockchain application in the shipping processes on a high level (Tsiulin & Reinau, 2021). Very little research investigates the implications of adopting such a technology on the shipping ecosystem (Bavassano et al., 2020). There is also a need for empirical research that provides insights into the different areas of blockchain application in the maritime supply chain (Yang, 2019; Liu et al., 2021). In practice, many blockchain-based solutions have been developed in the maritime industry including Insurwave, CargoX and TradeLens (Lambrou et al., 2019). However, there is a lack of research that investigates state-of-the-art blockchain applications in specialized fields like maritime logistics (Tsiulin et al., 2020). In this research, we aim to address these gaps by providing empirical insights into the implication of digitalization enabled by blockchain on the shipping ecosystem by studying one of the most prominent industry-wide digital platforms, TradeLens.

4. TradeLens: a blockchain-enabled digital solution in the shipping industry

4.1 Background

With over 35 million containers processed, over 16 million documents published, and almost 2 billion shipping events tracked at the time of writing this chapter (TradeLens, 2021b), TradeLens has become one of the largest digital platforms in the market that provides end-to-end visibility across all shipping processes. Starting with the booking confirmation, TradeLens enables every party involved in a shipment, including shippers, freight forwarders, ocean carriers, customs authorities, ports and terminals, and financial services, to obtain visibility and tracking of shipments events and documents at every stage of the shipping process based on their role in the shipment.

TradeLens began as a joint venture between the giant A.P. Moller Maersk and IBM. Soon after the development of the solution, TradeLens has been introduced as an industry-wide solution based on a collaboration model between all ocean carriers. The solution is now owned by a separate A.P. Moller Maersk company called GTD Solution Inc. (GTD stands for Global Trade Digitization) and IBM.

Digitalization is at the core of the Maersk Group. The company has developed several digital solutions including Maersk Flow and Maersk Supply Chain Management to provide customers with digital tools for shipment tracking, management, and visibility (Maersk Flow, 2021). Having management support has eased the initiation of many blockchain projects (van Hoek, 2019), and TradeLens is no different. Maersk top management support has been an important factor for its success in leading digital transformation within the shipping industry.

Transparency is at the core of TradeLens, and as an industry-wide solution, the company has published sufficient information to understand the TradeLens architecture, the integration process, and the permission model (TradeLens Documentation, 2019). TradeLens has three layers: (1) the Ecosystem, which encompasses all the network members who provide, share, and access data through TradeLens, (2) the Platform, which is the medium where all these data are shared and is accessed through open APIs, and (3) the Marketplace, which is an open platform that enables TradeLens and third parties to launch specific and customized applications on top of TradeLens (Fig. 18.2). Having a layer like the Marketplace promotes innovative solutions to be developed and published to an industry network, which can accelerate their adoption. This brings opportunities to foster digitalization and to advance solution developments. The use of open APIs to integrate with TradeLens has eased the process of onboarding new members and integrating with their existing systems without the requirement for additional investments (TradeLens, 2021b).

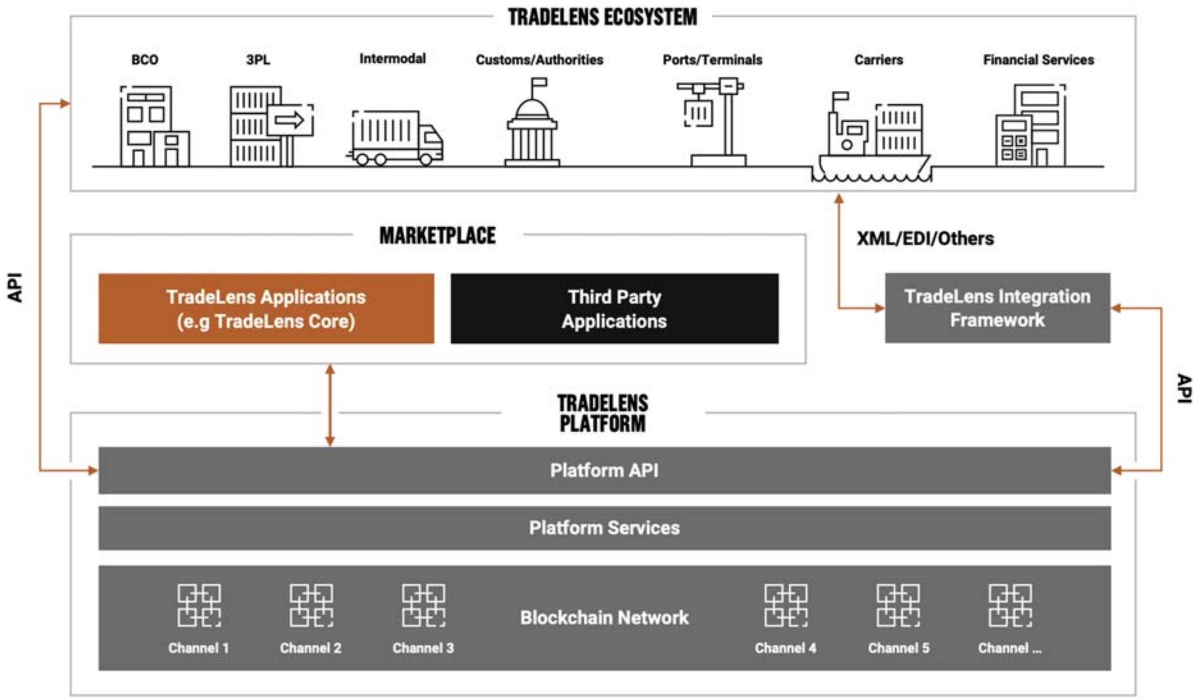


FIGURE 18.2 TradeLens solution architecture. *Reproduced from: TradeLens Documentation. (2019).* Solution architecture—TradeLens documentation. *Retrieved 27 January 2021 from: https://docs.TradeLens.com/learn/solution_architecture/.*

In terms of governance, TradeLens has designed a detailed permissioned model that provides access rights to the relevant parties based on their role in the shipment process (see TradeLens Data Sharing Model, 2020 for more information). For standardization and interoperability, TradeLens adopts the supply chain reference model from UN/CEFACT (TradeLens, 2021b). The use of blockchain technology comes into play for ensuring the security, immutability, and traceability of trade documents (TradeLens, 2021b).

TradeLens enables a high level of visibility and transparency and provides a rich data environment for all parties to utilize for continuous improvement. More than 130 shipping events can be captured on TradeLens including shipment, consignment, transport equipment, transport plan, and other generic events (TradeLens Documentation, 2019). We categorize TradeLens' events into five categories: (1) estimated, planned, and actual events for container filling, stripping, and movement, (2) Customs inspection and release events, (3) BOL creation and submission, (4) Cargo weight capturing, and (5) Transport equipment environment conditions.

4.2 TradeLens use cases

We briefly describe examples of TradeLens use cases below and identify TradeLens key capabilities and potential benefits in Table 18.1.

(1) **API Integration:** TradeLens uses open APIs to connect with its users. This eliminates the need for additional hardware investments and saves significant IT resources and costs. Data from TradeLens can automatically feed into existing EDI systems enabling users to have access to near real-time data about their shipment. Access to the platform is controlled through federation authentication (i.e., open ID connect and OAuth2) and data sharing is secured by a blockchain-based permission model (TradeLens Use Cases, 2021a).

(2) **Customer Service:** The availability of all shipment data on a single platform in near-real time, saves an enormous amount of employees' time spent on manual tracking of shipments. This time can then be utilized in improving customer service and experience. The near real-time data accessibility enables better and timely customer service. TradeLens provides accessibility to estimated, planned, and actual shipping events, which can be used to improve shipping planning and logistics processes and to respond proactively to changes in shipment schedules. This is especially important for freight forwarders and LSPs who compete in providing services (TradeLens Use Cases, 2021b).

TABLE 18.1 TradeLens use cases, key capabilities, and benefits.

Use case	Key beneficiary	TradeLens key capabilities	Potential benefits
1. API integration (TradeLens Use Cases, 2021a)	All parties	**(1) Ease of integration:** With the use of open APIs, supply chain partners can easily connect to the TradeLens platform without any hardware investment requirement. **(2) Security:** TradeLens is supported by IBM Cloud. Federation authentication is based on Open ID connect, OAuth2 to control access to shipment data. The blockchain-based permission model ensures documents' security, traceability and immutability. **(3) Automation:** TradeLens enable business processes actions to take place on the platform. Different data formats including EDI feeds can feed automatically into the platform from existing infrastructure systems.	• Save IT resources and costs required for setting and maintaining EDI systems. • Access and share near real-time data about shipment events, documents with other supply chain partners worldwide.
2. Customer service (TradeLens Use Cases, 2021b)	LSPs, Freight forwarders	**(4) Single platform for all shipping data:** TradeLens provides a single platform for all shipping data, events, documents that are shared among permissioned participants. **5) Near real-time data accessibility:** All permissioned participants get access to shipping data in near real-time. Permissioned participants can get notified of changes in the shipment status as they occur. **(6) End-to-end supply chain visibility:** More than 130 shipping events can be captured in TradeLens. TradeLens provides an unprecedented level of visibility that reduces uncertainties and enables accurate invoicing across the supply chain.	• Better customer service by responding timely to customers' inquiries. • Utilize time for searching carriers' websites and fetching shipment information to focus more on improving the customer experience. • Proactively respond to changes in shipment schedule. • Evident record of shipping events that can be used to resolve disputes.
3. Customs declaration (TradeLens Use Cases, 2021c)	Customs brokers, customs authorities	**(7) Digitalization of customs declaration workflow:** TradeLens enables all involved parties to share customs required documents as soon as they are available in a single platform. **(8) Automate filling of documents:** The broker system can automatically extract structured data from packing lists and commercial invoices using TradeLens open APIs. **(9) Secure document versioning:** Blockchain technology enables traceability of changes in documents versions.	• More efficient process by saving time and efforts to assemble all required documentation for customs declaration. • Reduce errors by keeping track of documents versioning and access information from a single source. • Proactively prepare for customs clearance by tracking shipping events.
4. Processing letter of credit (TradeLens Use Cases, 2021d)	BCOs, financial services	**(10) Document digitalization:** With TradeLens, digital documents are shared and secured using a solid permissioned model which reduces errors, speeds up document exchange, and optimizes workflow processes. **(11) Secure trade documents exchange:** TradeLens APIs can be connected to customers' systems enabling secure document sharing from its source to authorized parties. **(12) Digitalization of letter of credit workflow process:** TradeLens enables information sharing and transfer of LoC documents between authorized parties.	• Quick transfer of LoC documents through TradeLens platform. • Reduce time and costs related to lengthy and time-consuming LoC processes and couriering of documents. • Prevent LoC delay that can lead to detention and demurrage. • Reduce risks of documents fraud and forgery with the use of blockchain.
5. Verify bill of lading (TradeLens Use Cases, 2021e)	BCOs, financial services	**(13) Instant validation of entities:** Authorities and banks can instantly verify customers' identities by accessing all required documentation through TradeLens (i.e., bill of lading). **(14) Eliminate fraud:** Ensure and secure documents authenticity with the use of blockchain.	• Recorded and digitally signed transactions. • Automate the verification and validation processes. • Reduce errors, streamline processes, and improve efficiencies. • Reduce the cost and time of printing and couriering documents.

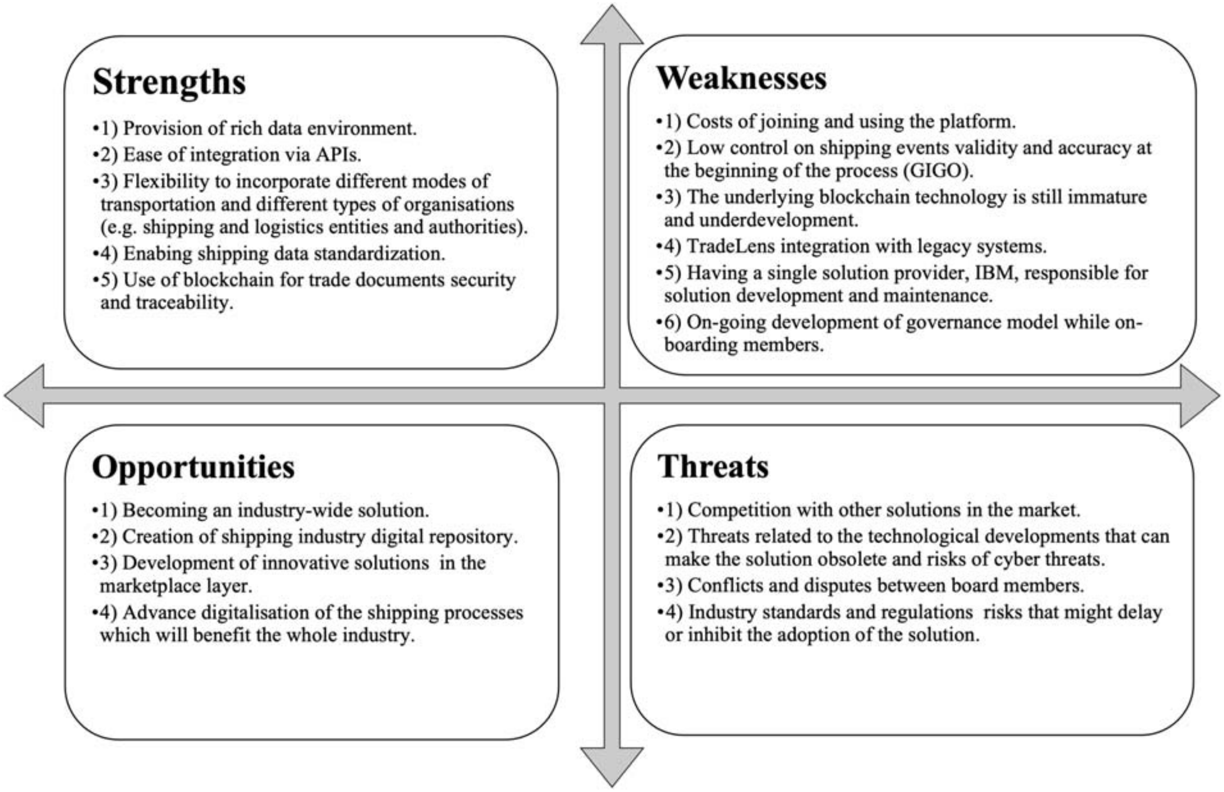
(3) **Customs Declaration:** TradeLens enables all participants to share shipment documents in a secure manner. The use of blockchain enables the tracking of document versioning. Customs brokers can get access to the required shipment document as soon as they become available, which saves time and effort to assemble all required documentation for customs declaration. Getting all the documents from a single source along with the tracking of document updates reduces the potential errors that are frequently encountered in traditional lengthy and manual customs processes (TradeLens Use Cases, 2021c).

(4) **Processing of Letters of Credit:** Issuing and processing letters of credit is one of the bottlenecks in the shipping processes. These processes are time-consuming, expensive, and demand secure information and document sharing. TradeLens provides a secure platform for information and document sharing that can be connected directly to its customers' systems. With the use of TradeLens, authorized participants can access required documentation directly from its source, which expedites the LoC processes, minimizes errors, and leads to better customers services (TradeLens Use Cases, 2021d). It can also prevent delays, which can result in additional costs of demurrage and detention.

(5) **Verify Bill of Lading:** TradeLens can enable the instant verification of customers through the platform. The use of blockchain ensures the authenticity and traceability of documents. Authorities can access all the required documentation to verify customers and the originality of documents. In the case of financing requests, banks can instantly verify the BOL by connecting to TradeLens through open APIs and accessing the latest published BOL to ensure its authenticity (TradeLens Use Cases, 2021e).

4.3 TradeLens SWOT analysis

Fig. 18.3 presents a SWOT analysis for the TradeLens solution considering its internal strengths and weaknesses as a digital solution and the external opportunities and threats it faces from the shipping industry ecosystem and market environment. We discuss each SWOT element next.



Strengths

- 1) Provision of rich data environment.
- 2) Ease of integration via APIs.
- 3) Flexibility to incorporate different modes of transportation and different types of organisations (e.g. shipping and logistics entities and authorities).
- 4) Enabing shipping data standardization.
- 5) Use of blockchain for trade documents security and traceability.

Weaknesses

- 1) Costs of joining and using the platform.
- 2) Low control on shipping events validity and accuracy at the beginning of the process (GIGO).
- 3) The underlying blockchain technology is still immature and underdevelopment.
- 4) TradeLens integration with legacy systems.
- 5) Having a single solution provider, IBM, responsible for solution development and maintenance.
- 6) On-going development of governance model while on-boarding members.

Opportunities

- 1) Becoming an industry-wide solution.
- 2) Creation of shipping industry digital repository.
- 3) Development of innovative solutions in the marketplace layer.
- 4) Advance digitalisation of the shipping processes which will benefit the whole industry.

Threats

- 1) Competition with other solutions in the market.
- 2) Threats related to the technological developments that can make the solution obsolete and risks of cyber threats.
- 3) Conflicts and disputes between board members.
- 4) Industry standards and regulations risks that might delay or inhibit the adoption of the solution.

FIGURE 18.3 TradeLens SWOT analysis.

4.3.1 TradeLens strengths

The TradeLens platform aims at connecting the shipping ecosystem and presents a powerful digital solution that has the potential to transform the shipping industry. The emergence of such platforms will play a significant role in bridging the gap in the industry, reducing inefficiencies, enabling shipping data standardization, and fostering collaboration. TradeLens provides access to a rich data environment by capturing more than 134 shipping events that enable an unprecedented level of visibility that goes beyond the ocean carriers (TradeLens Documentation, 2019). Flexibility and ease of integration are key strengths of TradeLens. The use of open APIs enables quick and near real-time integration with existing systems without the need for additional investments. The platform is capable of incorporating different modes of transport (e.g., rail), and different types of organizations in the shipping ecosystem regardless of their size, location, or existing systems. The use of blockchain technology for secure trade document exchange and traceability ensures the reliability and security of TradeLens. Blockchain enables the provision of a secure, traceable, and immutable platform, allowing information sharing in a decentralized manner (Christidis & Devetsikiotis, 2016).

4.3.2 TradeLens weaknesses

The success of TradeLens relies on its adoption by as many participants in the shipping ecosystem as possible. This will determine its ability to provide a rich data environment and end-to-end visibility. Participants incur costs to join and use the platform. This might influence the adoption of the solution by the mass ecosystem participants.

TradeLens has no control over the data accuracy and validity at the beginning of the process (e.g., shipping events). The quality of the data cannot be guaranteed as the platform mirrors what the different participants input into the system and may, therefore, be affected by the GIGO (garbage in garbage out) principle. However, the platform has a sophisticated permissions model that controls who shares what information and with whom, which holds each participant accountable for the data they provide (TradeLens Documentation, 2019). It operates with a continuous data improvement focus, where data performance is constantly monitored, and actions are taken with each network member as the primary source to ensure data improvement in terms of accuracy, timeliness, and business logic.

Some of the key technical weaknesses of TradeLens include the immaturity of the underlying blockchain technology. TradeLens uses blockchain for tracking and managing shipping documents. Blockchain capabilities have been proven to work in a variety of applications in financial services, manufacturing, and SCM and logistics (Kshteri, 2018). However, the technology is still in its developmental stage and is still evolving (Glaser, 2017). This evolution, although it holds great promise for improving shipping industry processes (Lambrou et al., 2019), can also be considered a weakness and a risk to use an immature and continuously evolving technology as the underlying technology for an industry-wide solution. Another technical challenge is the integration of TradeLens with legacy systems, which may not necessarily work with open APIs. It can be argued that this is a legacy systems dilemma with technological development but is still worth addressing. Finally, TradeLens is maintained and developed by the accredited and respected IBM technology corporation, but it is a single IT company, which potentially subjects the platform to have a single point of failure.

The development of TradeLens started in January 2018, and the solution has been evolving since then, incorporating feedback and lessons learned. Similarly, the governance model of TradeLens has changed from a joint venture between Maersk and IBM to a collaboration model including other giant players as part of the "TradeLens Collaboration Board" (e.g., MSC, CMA-CGM) (TradeLens, 2020). Further changes in the governance model can take place with the development of TradeLens (e.g., the launch of TradeLens marketplace layer). Changes in governance models need to be managed carefully and effectively (WEF, 2021) to avoid serious drawbacks.

4.3.3 TradeLens opportunities

TradeLens has the potential and the capabilities to become an industry-wide digital solution, especially with the majority of the top ocean carriers now being part of it (i.e., Maersk, MSC, and CMA-CGM, Hapag Lloyd and ONE) (TradeLens, 2020, 2021c). TradeLens can enable the creation of a shipping industry-wide digital repository that connects all participants in the global shipping ecosystem in a single platform. Having a shared digital Global Trade Identity (GTID) has been recommended by the WEF as one of the key facilitators for digitalizing logistics processes (Hvid Jensen, 2020). It reduces costs and the resources required for identifying and managing multiple digital identities. Moreover, the marketplace solution provides a platform where innovative solutions are announced to the whole TradeLens network. The availability of the platform encourages the development of such innovative solutions, which can benefit the industry as a whole. TradeLens promotes the digitalization and automation of shipping processes, which can potentially transform the whole shipping industry and result in higher performance and efficiencies.

18.3.4 TradeLens threats

TradeLens is subject to several threats including the availability or future development of competing solutions that might affect the mass adoption of TradeLens. Furthermore, as with all digital solutions, TradeLens faces the risks of technological developments that can make it obsolete and of cyber threats. These risks also hold for the use of emerging blockchain technology.

Other potential risks include conflicts and disputes between TradeLens board members that might affect the success and sustainability of the solution. There must be a clear conflict and dispute management process that is agreed upon by all board members to sustain the solution. Finally, for TradeLens to be a global industry solution, it will have to fit in with the complex and changing regulatory frameworks of the different countries. Lack of supportive regulations and standards can inhibit or delay the digitalization of logistics processes and the use of blockchain technology (Bavassano et al., 2020) (Fig. 18.3).

5. Impact of shipping industry digitalization on the shipping ecosystem

We discuss how digitalization enabled by blockchain technology can impact each of the different entities in the maritime shipping ecosystem based on our analysis of the TradeLens platform.

(1) **Ocean carriers**: Ocean carriers are the main transporters in the shipping industry (OECD Ocean, 2021). They are involved in the majority of the shipping processes from the time of booking the shipment to the creation of BOL and the release of shipment at destination. Therefore, they play a major role in the digitalization of the shipping industry and are the most impacted. Several digital solutions such as INTTRA (2021), Icontainer (https://www.icontainers.com/), and Freightos (https://www.freightos.com/) have been developed to facilitate the booking and tracking of the vessel schedule from/to the berth in a port. However, shipment document handling has remained an area with little digitalization until the emergence of blockchain. Blockchain provides a secure digital platform to optimize the laborious, lengthy, and expensive shipping processes. Combined with the use of IoT, blockchain can also enable the secure tracking and monitoring of containers and vessels (Lambrou et al., 2019). The digitalization enabled by blockchain can impact the ocean carriers operations by (1) enabling secure document sharing through which ocean carriers can share sensitive documentation like the BOL in near real-time with all authorized participants, resulting in significant time and costs savings, (2) enabling secure tracking of vessels and containers that can lead to better container management and vessel route optimization, and (3) providing a verifiable and valid way of submitting required information like cargo weight to authorities (Papathanasiou et al., 2020). All of these can support ocean carriers in improving internal efficiencies and delivering optimal customer services. However, to obtain all potential benefits, ocean carriers may need to make major changes to their internal processes to enable digitalization and the development of new business models.

(2) **Shippers and Beneficiary Cargo Owners (BCOs):** As the main initiators of the shipping process and being the cargo owners, shippers and BCOs are significantly impacted by the level of shipping process digitalization and the visibility provided. The digitalization of shipping processes enables information sharing, improved efficiencies, and reduced costs (Lind et al., 2015). Blockchain-based digital solutions enable end-to-end visibility and traceability across the supply chain (Verhoeven et al., 2018; Wamba & Queiroz, 2020). At the supply chain level, better visibility and traceability leads to improved supply chain planning and management and better response to supply chain risks and disruptions (Kshetri, 2018). For in-house logistics processes, digitalization improves efficiency and reduces paperwork. TradeLens, for example, enables secure and automated information and documentation. Cargo information can be accessed by all supply chain partners providing end-to-end visibility and a rich data environment to optimize logistics processes (TradeLens Use Cases, 2021b). Streamlined shipping processes benefit BCOs by reducing costs and lead time for document handling and preventing detention and demurrages.

With the use of IoT and blockchain, monitoring of cargo and container temperature and moisture levels in real time has become possible (Lambrou et al., 2019). This also helps BCOs and shippers to ensure the proper transportation of sensitive goods and avoid potential losses (i.e., nonconformance, damage, etc.). On a higher level, having an industry-wide digital solution like TradeLens provides a single platform through which BCOs can connect directly with the shipping ecosystem and get near real-time visibility to shipment progress. This enables BCOs to assess the performance of the different parties and have better insights to inform their logistics strategy whether it is in-house logistics or outsourced logistics services. Hence, digitalization can enable benchmarking, information sharing, and performance measurement in the shipping industry (Feibert et al., 2017).

(3) Freight Forwarders and Logistics Service Providers (LSPs): The impact of digitalization on freight forwarders and LSPs can differ depending on their size and local environments (Bavassano et al., 2020). For smaller parties, digitalization in the logistics industry can leverage their capabilities to compete in the global market (WEF, 2016). However, small parties might perceive it as a risk that reduces their market and may be hindered by the costs required to invest in new technologies (Bavassano et al., 2020). Larger players, on the other hand, are keen on exploiting the benefits of adopting such technologies and are driving the adoption. The digitalization of the shipping processes enables these parties to make significant savings in the resources usually required to gather and exchange shipping data (Bavassano et al., 2020). It can improve the efficiency of their processes, which leads to better customer service. This is a major requirement for LSPs of all sizes to sustain in the market (e.g., TradeLens use case, 2021b). However, having such a high level of digitalization and visibility accessible to the entire shipping ecosystem puts more pressure on LSPs to leverage their value-adding services beyond the market average to create competitive advantage. Freight forwarders and LSPs can capitalize on the provided rich data environment to develop new services and products that can generate new revenue streams. With the use of TradeLens, for example, different solutions can be deployed in TradeLens marketplace layer and can be accessed by the growing TradeLens ecosystem (TradeLens Documentation, 2019).

(4) Customs Authority and Customs Broker: Digitalization of trade documents has a significant impact on the shipping processes including the work of custom brokers and authorities (Okazaki, 2018; Segers et al., 2019). This has been identified as one of the key potential application areas for blockchain in the maritime industry (Lambrou et al., 2019; Segers et al., 2019; Yaren, 2020). One of the key challenges in the customs procedure is fighting customs fraud. Fraud in customs includes reducing the transaction value of the imported goods to reduce customs duties (Segers et al., 2019). Customs authorities use different trade documents to cross-validate the information provided in the shipping documents to fight fraud. These processes are manual, expensive, and time-consuming and can result in shipment delays and great financial losses when dealing with falsified documents (Segers et al., 2019). Blockchain has the potential to transform customs procedures to become more data-driven and more embedded within the shipping processes by providing a secure and immutable record of shipment transactions and documents that are shared in real time between all the parties involved in the shipment (Okazaki, 2018; Yaren, 2020). The enabled automation and digitalization of document retrieval and validation can significantly help in reducing errors and administrative work (Segers et al., 2019; Yang, 2019). The impact of digitalization on the customs processes depends on the level of digitalization adopted by the customs authorities and the regulations related to the use of digital documents (e.g., usage and approval of electronic BOL), which differ significantly between countries (Okazaki, 2018; Yang, 2019).

(5) Ports and Terminals: Ports and terminals are key players in integrating logistics (Bichou & Gray, 2007; Tsiulin & Reinau, 2021). In Ports and Terminals, despite the level of digitalization in place, there is still a significant amount of paperwork and a large variety of discrete administrative systems that lead to many inefficiencies in port management (Port of Rotterdam, 2019). The digitalization of workflow and use of blockchain for documents exchange enable timely and efficient access to required information, which is a major success factor in ports and terminals (Tsiulin & Reinau, 2021). The use of an industry-wide platform enables greater visibility for port and terminal operators across multiple carriers, providing rich data for better yard planning and management (TradeLens, 2020). This results in greater benefits for the industry as a whole such as streamlining vessels arrival and departure, and cargo loading and release. Therefore, ports and terminals are crucial players in any industry-wide digital solution to realize its full benefits.

(6) Financial Services: The involvement of financial services in the shipping processes can differ depending on the Incoterms (Incoterms 2020, 2021) of the shipping contract. Incoterms identify the allocations of costs and risks between buyers and sellers (Irannezhad & Faroqi, 2021). When letters of credit are required, banks undergo a lengthy verification process before issuing them (Tsiulin et al., 2020). Since the banks are not directly connected with ports and terminals, they lack visibility about cargo status and hence might not be notified about the cargo arrival and/or not receive the necessary documentation in a timely manner (Tsiulin et al., 2020). All of these can cause delays in cargo release that can lead to demurrage and detention costs. In the case of TradeLens, for example, banks can verify the identity of the shipper and access all the required documents directly from the platform, in a timely manner that expedites the verification process (TradeLens Use Cases, 2021e). Different countries have different regulations regarding the use of electronic documents such as the use of electronic BOL which might impact their use by banks as well (Irannezhad & Faroqi, 2021).

Table 18.2 provides a summary of the impact of digitalization on the shipping processes from the perspective of each of the main actors in the shipping ecosystem.

TABLE 18.2 Impact of digitalization on the shipping processes of the main shipping actors.

Shipping entity role	Impact of digitalization on shipping processes opportunities	Impact of digitalization on shipping processes Challenges
(1) Ocean carriers	• Optimize shipping documents creation and submission processes. • Improve containers management processes. • Better vessel route and transportation planning. • Better customer services.	• Need to disrupt internal processes. • Integration with legacy systems.
(2) Shippers and BCOs	• Better supply chain planning and management. • Reduced costs and lead times. • Better supply chain visibility and traceability (i.e., helping to guarantee product provenance, and enhancing sustainability). • Better response to supply chain risks and disruptions.	• Integration to existing solutions. • Costs of digitalization (required investments, maintenance, resources, etc.). • It might require modification to existing business processes. • Change management.
(3) Freight forwarders and LSPs	• Timely response to customers' enquiries. • Reduce administrative costs (e.g., fetching information from different carrier websites) and improve efficiencies. • Utilize available data for better customers' services. • Avail of resources to improve customers' experience. • New revenue pools with products and services to be developed leveraging TradeLens enriched end-to-end data.	• Raises competition to the development of more value-adding service offerings. • Jeopardizes the value of certain logistics services (e.g., provision of shipment tracking information becomes automatically available).
(4) Customs brokers and customs authorities	• Faster access to trade documents required for cargo clearance. • Reduced errors and fraud by getting the documents directly from the source. • Use of blockchain to ensure documents authenticity and documents versioning tracking.	• The custom clearance processes differ across countries, which might require different solutions. • High dependence on the level of digitalization of the customs authorities and the regulations of the country regarding the use of digital trade documents. • Integration with existing systems. • Costs of integration and impact on existing processes.
(5) Ports and terminals	• Near real-time visibility to vessel and container schedules, which lead to better yard and operations planning.	• High dependence on the level of digitalization in place in the Ports and Terminals, which can differ between countries. • Integration with existing systems. • Costs of integration and impact on existing processes.
(6) Financial services	• Reduce document validation and processing times by getting direct sourcing from a secure medium. • Faster access to all required documentation, which may help prevent fraud.	• Development of regulations that support the use of digital documents (e.g., eBL).

6. Discussion and conclusion

This chapter has investigated the impact of digitalization enabled by blockchain technology on the shipping ecosystem based on a study of one of the most prominent shipping industry-wide solutions, TradeLens. Learning from pioneers in technologies like blockchain can help in better understanding the technology and its implication, similar to the way Toyota was studied to better understand, adopt, and implement lean practices (Ferdows, 2018).

Having a solution like TradeLens that extends beyond the ocean carrier is essential to overcome the existing challenges in this industry. In addition to its capability to securely handle and manage shipment documents with the use of blockchain, TradeLens provides end-to-end visibility and accessibility to over 134 shipping data events that include data for shippers, freight forwarders, authorities, ports and terminals, ocean carriers, and banks (TradeLens Documentation, 2019). Hence, TradeLens is a critical case study to understand and analyze the impact of digitalization on the shipping industry (refer to TradeLens use cases—Table 18.1). TradeLens provides a very rich data environment that serves different parties. These data can be analyzed using different analytics tools including Business Processes Modeling, Six Sigma, Total Quality Management (TQM), and Cause−Effect Analysis to derive valuable insights and establish continuous feedback to improve shipping and logistics business operations (Feibert et al., 2017).

The shipping industry has longed for a reliable solution that improves visibility and efficiencies, especially in the handling of trade documents, which has been a critical bottleneck responsible for the majority of delays and costs in the shipping processes. The multiple cyber-attacks that hit many of the top ocean carriers have raised concerns about the security of digital solutions (Cimpanu, 2020), potentially hindering the digitalization of trade documents. The emergence of blockchain as a technology that provides a secure medium for information sharing while ensuring data immutability, privacy, and traceability has made it a very attractive solution to underpin and leverage the digitalization of shipping processes. Blockchain applications for handling shipment documentation are expected to result in a 65% reduction in shipment processing time (Cargo Smart, 2018). Blockchain also promotes transparency and leverages trust between partners in the shipping industry by enabling the verification of the different entities and their assets (Li & Zhou, 2020, pp. 1−19). The potential benefits from deploying blockchain have encouraged the development of many blockchain-based solutions in the shipping industry.

As with TradeLens, most of the identified elements in the SWOT analysis (Section 18.3) will be relevant to other blockchain-based solutions in the industry (e.g., Smart Cargo (2018)). The availability of more than one industry-wide platform raises additional concerns including the use of several platforms, the interoperability between the different platforms and potential implications of platforms competition (Rietveld & Schilling, 2021). These are all important areas that are recommended for future research. The implications discussed in Section 18 provide valuable insights to practitioners on the potential impact of the digitalization of shipping processes on shipping operations.

The use of a single case study is a research limitation of this study. However, considering the emergence of blockchain in digitalizing the shipping processes, TradeLens has by far been a pioneer in providing an operational blockchain-enabled digital solution in terms of its scope (it extends beyond the ocean carriers), size (there is an increasing number of participants), and operations (there is an increasing number of shipments processed through the platform). All of these make the analysis valuable and informative, albeit based on a sole case study. Many of the research findings and analysis are also supported by the existing conceptual literature and secondary data sources that have enabled triangulation and generalization of the findings presented here. Nonetheless, further study involving multiple case studies and applications will provide additional insights into this emerging and challenging area of research, which is vital for global commerce.

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Chapter 19

How can SMEs participate successfully in Industry 4.0 ecosystems?

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Abstract

Small- and medium-sized enterprises (SMEs) may find it challenging to acquire the technologies and capabilities associated with Industry 4.0. This chapter investigates the role of collaboration within supply chains for the development of technologies and solutions in Industry 4.0, with a specific focus on SMEs. We explore collaboration in the digital era through three lenses: (i) Open Innovation; (ii) Social Exchange Theory; and (iii) Boundary-Spanning. We show how horizontal and vertical collaboration in supply chains support Industry 4.0 technology development and explain how these relationships can create innovation ecosystems for Industry 4.0 solution development. We base our findings on a longitudinal study of a Brazilian ecosystem. We mapped the relationships and technologies offered by 87 SMEs and interviewed 37 stakeholders of this ecosystem. We also followed a testbed project for 2.5 years to collect observational data and interviewed 40 enterprises. We discuss how relationships evolve in an innovation ecosystem oriented to Industry 4.0 technology solution provision and how technology platforms emerge within the ecosystem. The findings show how collaboration in such ecosystems can support technology development for SMEs in the Industry 4.0 context. Based on the findings we present a three-stage collaboration model to support SME engagement in Industry 4.0.

Keywords: Collaboration; Industry 4.0; Innovation ecosystems; Platforms; SMEs; Supply chain; Technology provision.

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1. Introduction

Industry 4.0—also called the "Fourth Industrial Revolution"—represents a new industrial scenario in which both production systems and business models are transformed by the advent of digital technologies (Schumacher et al., 2016; Weking et al., 2020). According to Rüßmann et al. (2015), Industry 4.0 comprises nine main elements: Internet of Things, cybersecurity, cloud computing, horizontal and vertical integration systems, additive manufacturing, Augmented and Virtual reality, Big Data and Business Analytics, autonomous robots, and simulation. With the connectivity offered by technologies such as the Industrial Internet of Things (IIoT), companies face a digital era in which equipment, devices, and products are interconnected to improve processes and develop new technologies (Frank, Mendes, et al., 2019; Kahle et al., 2020). From an operational perspective, these elements reduce setup time, material handling, and processing time, among other aspects that help improve shop floor productivity (Brettel et al., 2014; Jeschke et al., 2017). From a market perspective, these elements allow companies to offer new solutions to customers, such as services offered through Cloud computing and Data Analytics (Ardolino et al., 2018; dos Santos et al., 2020).

This new industrial age brings changes in competition rules, industrial structures, and customer demands (Dalenogare et al., 2018; Jeschke et al., 2017). As a result, there is a need for twofold digital innovation addressing both internal and external processes for product and service provision. Managing these two sides simultaneously is complex for companies, especially for small- and medium-sized enterprises (SMEs) (Moeuf et al., 2018). SMEs generally lack the resources, competencies, skills, and capabilities to invest and to develop more disruptive solutions with an uncertain return on

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investment using cutting-edge technologies (e.g., AI, IoT, cloud, to mention but a few) (Ghobakhloo & Iranmanesh, 2021). In addition, they face limitations in Industry 4.0 when acting in business-to-business (B2B) relationships, i.e., they struggle to offer 4.0 solutions and understand their customers' needs (Kahle et al., 2020; Masood & Sonntag, 2020). From the technology providers' perspective in the Industry 4.0 context, a single firm hardly has sufficient capabilities and knowledge to offer a complete set of solutions that meet customer needs (Kahle et al., 2020; Nara et al., 2021).

SMEs acting as "technology providers" in supply chains are companies with automation and IT expertise to provide technologies, components, and services associated with software and hardware (e.g., sensors, Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP) systems, robots, system integration) (Benitez et al., 2021). On the other hand, "technology adopters" are enterprises that adopt these IT and automation solutions and technologies in their manufacturing systems, configuring a B2B relationship in the supply chain (Frank, Dalenogare et al., 2019). From the technology adopters' perspective, companies demanding solutions often do not have a sufficient understanding of their digital needs (Frank, Dalenogare et al., 2019; Kiel et al., 2016). Therefore, there is a crucial need to collaborate with supply chain partners to understand and meet these demands.

In this regard, some developed countries have created strategic programs to shape business scenarios capable of supporting digital transformations from Industry 4.0. Among these, it is worth mentioning the "Plattform Industrie 4.0" from Germany, the "Advanced Manufacturing Partnership" from the United States, and the "Made in China 2025" initiative from China (Liao et al., 2017). These programs consider industrial development policies that focus on Digital Champions—companies that have taken digitalization to the highest degree (Geissbauer et al., 2018)—working as central players for technology solution provision in their supply chains and contributing to the industry's digital transformation.

These programs support technology development at a country level in advanced economies. However, most studies are focused on the firm level and Industry 4.0 technology adopters' side (e.g., Dalenogare et al., 2018; Frank, Dalenogare et al., 2019). This opens an avenue for studies that look at the technology providers' side. Taking this view, it is possible to discover how to leverage technology development through Supply Chain Management (SCM). To do this, some approaches stimulating industrial clusters' collaboration have been analyzed in the literature (Benitez et al., 2020; Kahle et al., 2020). However, there is little research (e.g., Benitez et al., 2021) that deals with how domestic industries can strategically integrate Industry 4.0 concepts and collaborate with supply chain partners for technology solution provision. Most studies related to supply chain and Industry 4.0 are literature reviews (e.g., Chauhan & Singh, 2019; Frederico et al., 2019; Schniederjans et al., 2020) that seek to understand the potential impacts of Industry 4.0 technologies to develop digital supply chains.

Following the perspective of supply chain collaboration (Barratt, 2004), this chapter discusses how SMEs can collaborate with their supply chain partners to establish a technological ecosystem capable of coping with the Industry 4.0 demands (Rong et al., 2015). As demonstrated by Reynolds and Uygun (2018), in the Massachusetts ecosystem, despite SMEs traditionally having the weakest linkages, they can benefit from industry-university applied research. For instance, the Fraunhofer Institute, which acts as a bridge between research institutes and industry, provides examples of successful engagement of SMEs in ecosystems for technology development and provision in Germany (Dassisti et al., 2019). With this perspective, we investigate ecosystem characteristics in the Industry 4.0 context and show how innovation ecosystems can create industry platforms for SMEs to compete (Benitez et al., 2020). In this chapter, we first summarize our findings reported previously in Benitez et al. (2020, 2021) and then provide a systemic and integrative view of such findings and expand the discussions on the practical implications provided by them in the following sections. Section 2 presents a contextualization about supply chain technology provision in Industry 4.0, while Section 3 describes the research methodology. Sections 4–6 explain how supply chain actors can start to collaborate for technology provision, reshape the traditional supply chain configuration as an innovation ecosystem, and expand relationships within these ecosystems, respectively. Section 7 debates how supply chains can evolve from a linear relationship to a platform-driven ecosystem. Section 8 shows how Industry 4.0 technologies can mature and become platforms that connect with their surroundings for technology development. Our discussion ends with a collaboration-oriented conceptual model for Industry 4.0 technology solution provision in Section 9, while Section 10 concludes the debate.

2. Supply chain technology solution provision in Industry 4.0

In recent years, academic scholars and practitioners have debated with great interest the potential of Industry 4.0 technologies to digitalize supply chains. Hence, many studies, especially literature reviews (e.g., Ben-Daya et al., 2019; Chehbi-Gamoura et al., 2020; Frederico et al., 2019; Novais et al., 2019), were published debating the potential of digital technologies like big data, IoT, and the Cloud to enable digital supply chains. Overall, these studies tend to focus on the potential of such technologies to digitalize supply chain processes. Despite the great potential from digitalization in supply chains, there is a clear gap of empirical evidence in how digital technologies can integrate and improve supply chain performance. This is more evident when the object of study is related to technology development and provision through supply chain collaboration in the SCM literature (e.g., Frederico et al., 2019). Few studies (e.g., Benitez et al., 2020; da Silva et al., 2019) address this topic, and the lack of studies is even more evident when empirical evidence is considered (e.g., Benitez et al., 2021). Another concerning factor is related to the firms' size when studies related to digital supply chains are considered. Most of the studies focus on large companies and their supply chains, neglecting the SME context. Therefore, this reinforces a wrong idea—that Industry 4.0 is solely for large enterprises with the necessary skills, capabilities, and financial resources to invest in it.

When we look to SMEs, Industry 4.0 certainly is a major challenge because of their limited financial resources to acquire the interdisciplinary knowledge and limited capabilities to develop complex solutions independently (Benitez et al., 2020). The Industry 4.0 literature does analyze the challenges, barriers, critical factors of success, and opportunities for SMEs (Ghobakhloo & Iranmanesh, 2021; Horváth & Szabó, 2019; Mittal et al., 2018; Moeuf et al., 2020; Müller et al., 2018), but frequently it lacks empirical evidence for these analyses. However, we also see a potential for SMEs, especially as technology providers, because they master one specific IT, automation, software, and/or hardware system in their supply chains. This is even clearer in the electro/electronic and automation sector, where SMEs normally work as technology providers for other companies, supporting supply chain connectivity and integration (Benitez et al., 2021). Their potential to develop Industry 4.0 solutions resides in their likelihood to collaborate with supply chain partners for technology exploration and exploitation and value co-creation practices. Thus, in this chapter, we explore this potential, giving insights into how SMEs can collaborate in their supply chains for Industry 4.0 technology solution provision. Moreover, we also discuss how these alliances can generate innovation ecosystems and, consequently, technological platforms for Industry 4.0 solution provision.

3. Methodology

Fig. 19.1 summarizes our methodological approaches utilized for the studies reported in this chapter. Several methodological approaches were adopted, which we reported previously in Benitez et al. (2020, 2021). The study involved three research stages. In the first stage, we analyzed 11 years of a Brazilian ecosystem by mapping the relationships and technologies offered by 87 SMEs in their supply chains. We also ran a focus group with 39 SMEs from this survey to

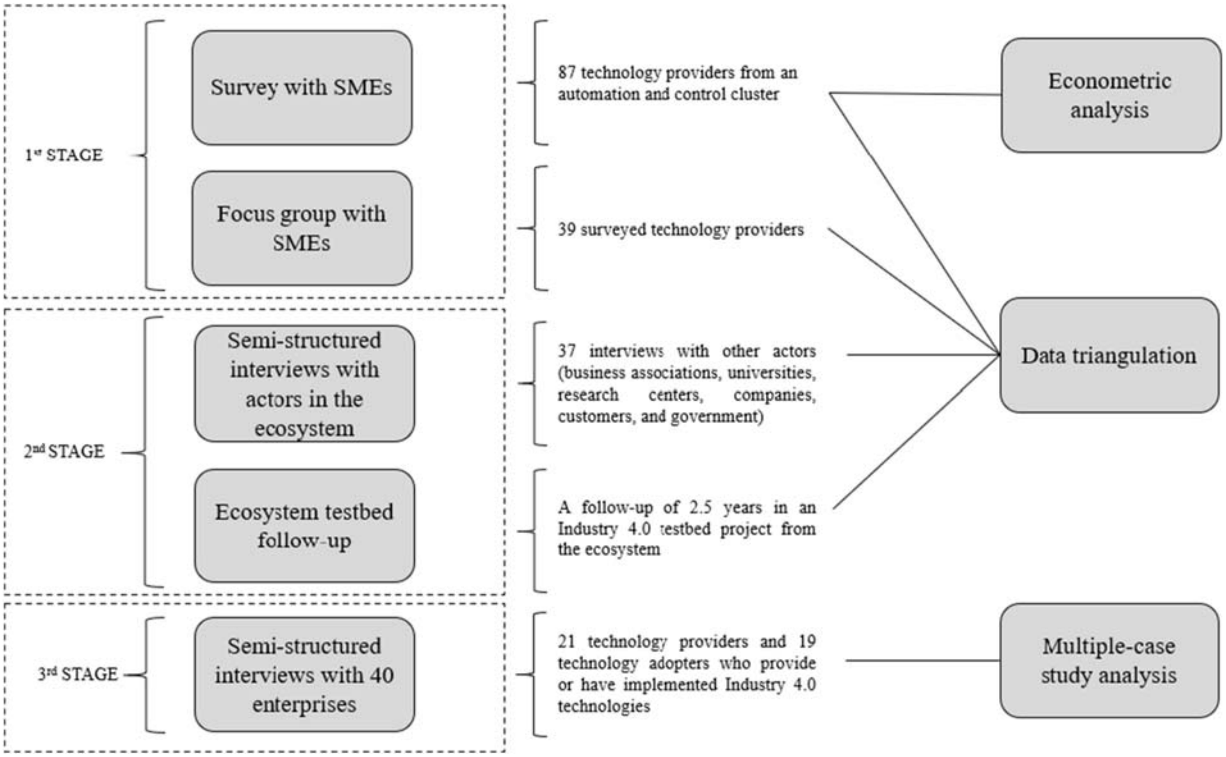

FIGURE 19.1 Methodological approaches utilized for the studies reported in this chapter.

discuss the results. We employed a quantitative approach through a survey method (Baierle et al., 2020; Nara et al., 2019) using an econometric procedure (see Benitez et al., 2021) to understand how supply chain partners' involvement can moderate the effects on Industry 4.0 technology development contributions. In the second stage, we interviewed 37 stakeholders and followed an Industry 4.0 testbed project from this ecosystem for 2.5 years. Alongside this analysis, we also performed qualitative research through data triangulation to analyze such an ecosystem and understand its shifts during the evolution of different actors' relationships (see Benitez et al., 2020). In the third stage, we employed a multiple-case study analysis by selecting 40 enterprises to shed light on potential platform cases (i.e., which Industry 4.0 technologies can be configured as platforms to provide products and services). For this, we considered two surveys[1] employed in our previous works (Benitez et al., 2020; Frank, Dalenogare et al., 2019). The first survey was performed with 87 SMEs characterized as technology providers that comprise a major industrial cluster in automation and control in Brazil. The other survey involved 92 manufacturing companies as technology adopters from Brazil's machinery and equipment industry (Frank, Dalenogare et al., 2019). In the case of technology providers, since the survey only involved SMEs, we also selected and contacted large and multinational technology providers to complement our sample. These companies were chosen using the following four criteria: (i) be a leading global technology provider; (ii) have a Brazilian branch (where the survey was conducted); (iii) be committed to Industry 4.0 trends (according to websites, reports, and news); and (iv) be a provider of one or more Industry 4.0-related technologies. Thus, we selected 40 enterprises strongly related to Industry 4.0 technology provision or adoption. Twenty-one were technology providers from these companies, and 19 were technology adopters, which related to at least one of the Industry 4.0 technologies.

4. Starting collaboration—an Open Innovation approach for Industry 4.0 technology solution provision in supply chains

Theoretical lenses regarding collaboration in supply chains follow two main lines: upstream (suppliers) and downstream (customer) relationships. Many SCM studies have investigated the effects of suppliers' and/or customers' involvement in firm performance (e.g., Asare et al., 2013; He et al., 2017; Yu et al., 2013, to mention but a few), while some studies (e.g., Chen et al., 2019; Pathak et al., 2014; Siluk et al., 2017) focus on other relationships for innovation generation and technology development. As demonstrated by Frank et al. (2021), diversity in collaborative relationships can help firms acquire external knowledge for product development. Barratt (2004) argued that collaboration in a supply chain context when related to other non-conventional partners tends to be embryonic, especially because of their distinct nature and business vision (e.g., a university partner has a main goal of education). The author states that collaboration in supply chains follows two main directions: vertical collaboration and horizontal collaboration. Vertical collaboration refers to the traditional supply chain partners (suppliers and customers). In contrast, horizontal collaboration is related to competitors and other organizations (i.e., any other actor with the potential to contribute to the supply chain). Thus, some horizontal actors like R&D centers, universities, competitors, and government agencies emerge as important potential contributors for technology development in SCM (Benitez et al., 2021; Kahle et al., 2020).

In the context of Industry 4.0, SMEs can take advantage of the distinct features of other organizations (e.g., knowledge obtained from universities and research centers) and engage in coopetition strategies with their competitors to leverage technology development over their supply chain structure to reach new market segments (Müller et al., 2018). Both vertical and horizontal collaboration can be paramount for technology solution provision in Industry 4.0. An Open Innovation (OI) strategy can be a lever for technology development over a supply chain configuration. OI can help SMEs pursue external sources of knowledge and technologies to develop their own complementary solutions (Mubarak & Petraite, 2020). It can open paths to collaborate with different actors and encourage and influence them to integrate resources, knowledge, skills, and efforts for technology development. Benitez et al. (2020) and Kahle et al. (2020) argue that different types and sources of collaboration are desired and pursued for Industry 4.0 in traditional linear supply chains to support innovation and solution provision. Thus, following Benitez et al. (2021), a supply chain stream or ecosystem for Industry 4.0 can be configured with supplier and customer partnerships (vertical collaboration) and competitors and other organizations (e.g., R&D centers) partnerships (horizontal collaboration), as shown in Fig. 19.2.

As previously demonstrated in Benitez et al. (2021), SMEs can use inbound OI activities (e.g., technology sourcing and scouting) as levers for advancing Industry 4.0 technology solution provision. *Technology scouting* is the identification, observation, and information acquisition about new technological trends for the decision on whether to acquire a technology (Van Wyk, 1997). OI activities can be the keystone to engage other actors in supply chains for the development of

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[1] The resulting industrial reports can be consulted in https://www.ufrgs.br/neo/.

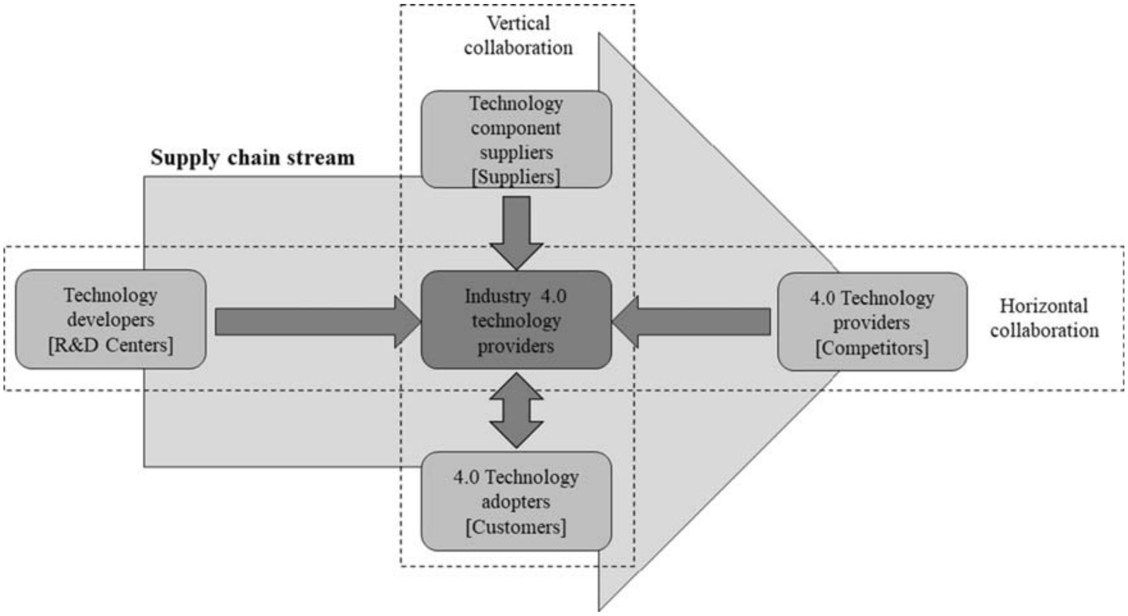

FIGURE 19.2 Example of Industry 4.0 supply chain stream (collaboration partners). *Adapted from Benitez, G. B., Ferreira Lima, M. J. do R., Ayala, N. F., & Frank, A. G. (2021). Industry 4.0 technology provision: The moderating role of supply chain partners to support technology providers.* Supply Chain Management: An International Journal*. (in press), ahead-of-print.*

technological solutions (Baierle et al., 2020; Nara et al., 2019). For instance, technology scouting with customers can help SMEs explore and prospect future technology application trends. Collaborating with customers through a technology scouting activity can allow an SME to better understand their customer's needs and new market trends (Wang et al., 2015). For example, with smart devices, SMEs can monitor and improve their products use by having access to customer feedback (Kahle et al., 2020).

Technology sourcing is the activity of buying or using external technology through intellectual property agreements (Van de Vrande et al., 2009). Technology sourcing can be supported by collaboration with R&D centers and universities that work in the initial stages of Technology Readiness Level (TRL) to develop concepts and technologies (Phaal et al., 2011), while technology providers can implement them to their portfolio in the final stages of TRL for the market. Since the initial stages of TRL refer to research and development through proofs-of-concept and the last stages are related to the market launch of the product or technology, this activity can help SMEs to concentrate R&D efforts for technology development. Moreover, outbound activities (i.e., purposive commercialization and capture of internally developed ideas in the organization's external environment) can also be enablers for SMEs, collaborating with other competitors to commercialize their specific Industry 4.0 skills and technologies integrated as a solution for technology adopters (Benitez et al., 2020; Frank, Dalenogare et al., 2019). Thus, these activities show a clear synergy between providers and adopters (Fig. 19.2) for technology solution development toward Industry 4.0. However, to achieve this degree of synergy, many SMEs need to reconfigure their way of thinking and expand horizons from their supply chain structure to the entire ecosystem that surrounds them.

5. Reshaping linear supply chains to become innovation ecosystems

Our research[2] results showed a high potential from horizontal collaboration in supply chains, suggesting the need for a reconfiguration from linear supply chains to innovation ecosystems. In a traditional supply chain with a transactional approach,[3] SMEs cannot leverage all their potential in Industry 4.0. To innovate and develop technology solutions, SMEs need to exploit interdependencies, synergy, and co-creation approaches. Innovation ecosystems that have value creation as the main goal provide a more effective approach. Ritala and Almpanopoulou (2017) note that innovation ecosystems are

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[2] For more information see Benitez et al. (2020, 2021).

[3] Transaction costs have been mainly used to understand and evaluate Supply Chain Management by scholars and practitioners, being essentially a theory of efficient governance of transactions in particular and exchange relationships in general (Ketokivi & Mahoney, 2020).

environments that require interdependency among different actors to develop and create new knowledge and inventions (e.g., products and services) and bring them to the market. Collaborations with competitors and other actors integrating different sources of knowledge and technologies for Industry 4.0 solution provision is empowered by an ecosystem's approach.

According to Adner (2006), innovation ecosystems start to be constituted when the relationships between actors have a functional goal enabling technology development and innovation. When regional actors start to collaborate, having value creation and innovativeness as a general strategic goal (Ritala & Almpanopoulou, 2017), innovation ecosystems emerge as a configuration to attend to these expectations. Because Industry 4.0 requires an extremely innovative environment, many players (e.g., government, industry, and academy) have started to create initiatives, policies, and strategic planning, supporting innovation ecosystems creation worldwide (Jeschke et al., 2017; Reynolds & Uygun, 2018).

Innovation ecosystems and Industry 4.0 is a theme that has evolved only slowly in the literature. It has just a few studies discussing the topic (see Benitez et al., 2020; Kahle et al., 2020; Reynolds & Uygun, 2018; Rong et al., 2015), showing that it needs further investigation and empirical evidence. Most Industry 4.0 studies concentrate on industrial performance, technology benefits, and digitalization in SCM. In addition, because of the difficulty of agreement about the relationships and governance mechanisms in ecosystems, something that is less complex in transactional exchanges, scholars have tended to focus on operations management at the supply chain level. The opportunities and difficulties for SMEs to have a protagonist role in Industry 4.0 technology ecosystem need to be better explored.

Ecosystems studies (Adner & Kapoor, 2010; Autio & Thomas, 2014; Adner, 2017; Dedehayir et al., 2018) have tended to focus on governance systems managed by large companies where SMEs and other players (e.g., universities or startups) have a supportive or secondary role. Some examples are the ecosystems and platforms managed by big players like Microsoft, Cisco, and Intel identified by Cusumano and Gawer (2002) and Gawer and Cusumano (2002), and more recently, ecosystems and platforms managed by Amazon and Apple (Cusumano et al., 2020). Reynolds and Uygun (2018) identify SMEs' limited knowledge and access to frontier technologies that result in weak ties with ecosystems' partners. Because of this, SME collaboration has been frequently analyzed in a more conceptual manner, with discussions centered on the benefits and barriers in supply chain relationships. However, a traditional transactional approach at the supply chain level may not be sufficient for SMEs to be competitive and successfully catch and ride the fourth Industrial Revolution wave. We believe an innovation ecosystem perspective led by SMEs with a focus on value co-creation between actors that interact to exchange value and rewards can be a suitable configuration to reap benefits from Industry 4.0 (Benitez et al., 2020). Next, we discuss how a Social Exchange perspective can enable SMEs to evolve their relationships in their supply chains and consequently find value in new collaborative practices inside an ecosystem for technology solutions provision.

6. Expanding relationships—a Social Exchange view in innovation ecosystems for Industry 4.0 technology solution provision

Social Exchange Theory (SET) was defined by Blau (1964) and Emerson (1976) as an action—reaction system of exchange based on reward mechanisms for value exchange. SET considers direct social interactions between actors through four elements: trust, commitment, reciprocity, and power. Trust is defined as an actor's expectation about other actors that they will perform correctly and justly in their activities for mutual benefit without the need for monitoring. Commitment implies that actors are committed to the cause to perform their duties for the perpetuity of the relationship. Reciprocity means that the relationship is bidirectional. Power refers to the relative dependence between actors to execute the main project and how this may influence decisions and behaviors. Considering these four elements, interactions between actors consist of voluntary exchanges of value that rely on trust and reciprocity over time (Tanskanen, 2015) and generate high-quality relationships (Cropanzano & Mitchell, 2005). For companies, especially SMEs, that seek and pursue strong partners to co-develop Industry 4.0 solutions, a SET approach relying on the four elements provides an alternative solution to expand horizons and relationships.

We discuss the structural view of innovation ecosystems with the SET from a previous case study in one of our studies from an Industry 4.0—oriented ecosystem during its 11 years of evolution (Benitez et al., 2020). The enterprises that compose such an ecosystem work in the electro/electronic and automation sector providing software and hardware technologies like sensors, actuators, MES and ERP systems, industrial automation, and system integration for other enterprises. Their supply chain is mainly composed of technology component suppliers for assembly and manufacturing companies (customers) like the ones from the Brazilian Machinery and Equipment Builders' Association (ABIMAQ). Traditionally, these enterprises were labeled as OEMs (Original Equipment Manufacturers) because the supply chain is

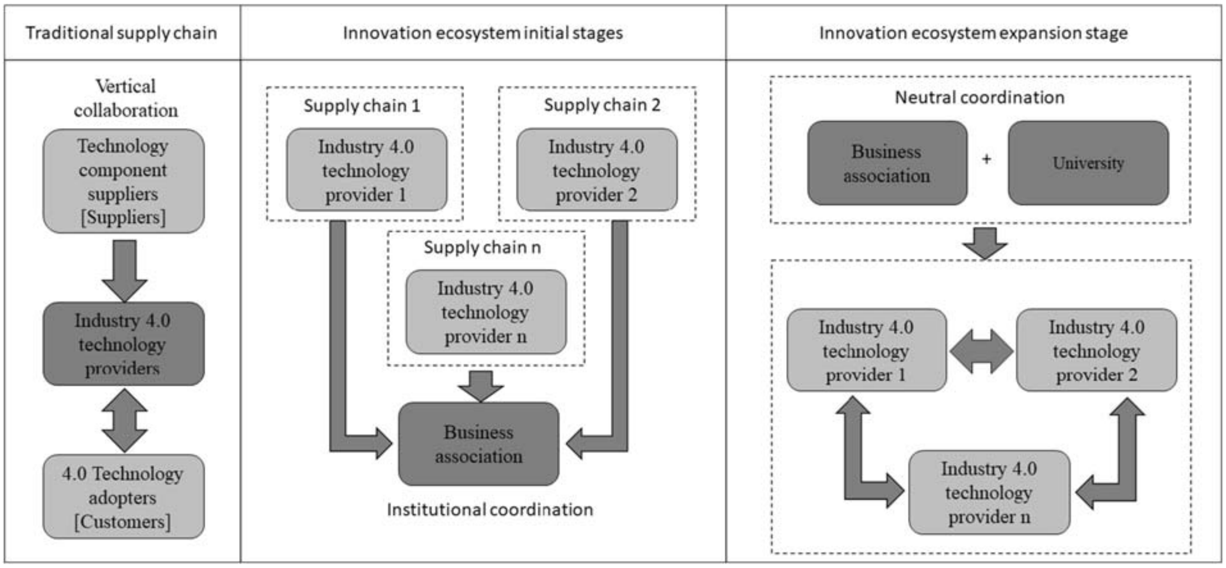

FIGURE 19.3 From linear supply chain to ecosystem structure (case study). *Adapted from Benitez, G. B., Ayala, N. F., & Frank, A. G. (2020). Industry 4.0 innovation ecosystems: An evolutionary perspective on value cocreation.* International Journal of Production Economics, 228*, 107735.*

based on B2B relationships, and they provide products and subsystems for other enterprises. We characterize these enterprises as technology providers since they started to collaborate to develop Industry 4.0 solutions with automation and digital technologies in the last years (Benitez et al., 2020). Our results show that the four SET elements—trust, commitment, reciprocity, and power—support interdependency in the ecosystem's structure along with its evolution. In other words, the relationships have evolved in the ecosystem through the four SET elements, helping the SMEs to mature and co-develop solutions oriented to Industry 4.0. Fig. 19.3 shows the governance structure and shifts from a linear supply chain model to an expansion stage innovation ecosystem.

Before the beginning of the ecosystem approach, the enterprises' relationships were through contracts that were transactional in nature between suppliers and customers. They also participated in a regional cluster of electro/electronics organizations, coordinated by a Business Association. When Industry 4.0 started to gain strength in the international scenario, this regional cluster began to reshape its strategy to generate a large innovation ecosystem composed of all SMEs and their respective supply chains. The initial link and governance structure between the SMEs was the Business Association that had the *power* to start the initiative and gather potential partners. The *reciprocity* initially was based on common access to resources coming from business alliances. In the case of *commitment*, the firms only participated if they saw an opportunity to reduce costs in their business, while *trust* was based on the presence of the Business Association assuring equality. Thus, in the first stages of this ecosystem, it was clear that many features and traces from a traditional linear supply chain remained since the SMEs did not have strong ties.

Concerning the lack of engagement and low commitment, the Business Association looked for a partnership with a University to help the governance structure of this ecosystem. During the expansion stage of the ecosystem, the governance *power* leads to neutral coordination (i.e., players that are not competitors in the market and that have fair purposes for the whole ecosystem) between the University and Business Association. The University played a key role in helping companies to define their capabilities for each of the projects developed in this stage. Moreover, while the University created and coordinated testbed projects with some selected companies from the ecosystem, the Business Association assumed the policy and political role for the ecosystem. From this orchestration perspective, it was possible to leverage more *commitment* and *trust* from the SMEs to engage in Industry 4.0 initiatives. *Commitment* was possible through strategic alliances for complex projects for Industry 4.0 technology solution development. *Trust* was obtained through joint experiences in these strategic alliances, where firms shared their competencies and expertise. Finally, *reciprocity* was established by the synergy effects resulting from combining capabilities in order to reach new market segments. In this stage, we can notice a total shift to an ecosystem approach and mindset with few traces from a transactional relationship in the supply chain.

When the first testbed project ended, we noticed a gradual shift to a *platform-driven ecosystem structure*, where key technologies emerged as drivers of relationships among the companies, resulting in value co-creation. We verified that SET elements started to be configured around internal platforms developed in the ecosystem.

7. From supply chains to a platform-driven ecosystem structure

Platforms have been receiving attention in Industry 4.0 literature due to their potential to generate "network effects" where more complex and disruptive solutions are developed through technology addition (dos Santos et al., 2020; Sturgeon, 2019). The platform concept has been developed by scholars in three overlapping waves of research, focused on product development, technological systems, and economic transactions (Gawer, 2011), respectively. The concept was first coined in the 1990s by Wheelwright and Clark (1992) in the product development wave, introducing the term "product platform," described as new products that "meet the needs of a core group of customers" being of easy modification into derivatives through the addition, substitution, or removal of features. In the second wave, technology strategists identified platforms as valuable points of control for innovation at the industry level (Bresnahan & Greenstein, 1999; Cusumano & Selby, 1995). In the third wave, industrial economists adopted the term "platform" to characterize products, services, firms, or institutions that mediate transactions between two or more groups of agents (two-sided or multisided markets) digitally (Gawer, 2011; Rochet & Tirole, 2003).

From the evolution of the governance mechanisms in the innovation ecosystem approach, we noticed that when SMEs reached a certain degree of maturity and trust in relationships, they started to configure their businesses in a platform-driven structure. In other words, SMEs started to develop their own platforms embedded with testbed projects with their partners for Industry 4.0 technology solution provision. We also observed that, depending on the business solution required, other platforms started to emerge. Thus, SMEs who initially only relied on their traditional supply chain partners (upstream and downstream) started to configure platforms (i.e., a foundation led by a technology connected with its surroundings) with other players to reach new markets, as shown in Fig. 19.4.

Alongside the evolution of the subject in literature, Gawer and Cusumano (2014) suggested two predominant types of platforms: internal or product platforms and external or industry platforms. Product platforms are assets organized in a common structure from which a company can efficiently develop and produce a stream of derivative products (Muffatto, 1999). Industry platforms, in turn, are products, services, or technologies organized as a business ecosystem to drive innovations (Gawer, 2011). We follow the industry platform nomenclature, as it encompasses the open environments of technological architectures pursuing complementary innovations. In an Industry 4.0 context, where new products and technologies are pursued, companies and ecosystems can define technological architectures through industry platforms to develop new digital solutions (Benitez et al., 2020). Thus, the structure of innovation ecosystems can be self-organized or managerially designed with multilayer networks of actors with different attributes to provide a system of innovative products and services (Tsujimoto et al., 2018).

In the next section, we discuss how some technologies can become platforms for the ecosystem, meaning that they become central technologies for the solutions, connecting other technologies as complementors and add-ons pursuing complementary innovations. We use a Boundary-Spanning (BS) perspective because it allows the degree to which a specific technology connects with its surroundings to be assessed, defining whether it is a platform or not.

8. Maturing technologies—a Boundary-Spanning perspective for Industry 4.0 platforms

Studies in Industry 4.0 platforms usually investigate the potential for data sharing on technological platforms based on IoT and Cloud technologies without showing details about collaborative development for technologies and solutions in Industry 4.0 (e.g., Cusumano et al., 2019; Fahmideh & Zowghi, 2020; Fan et al., 2019). We show another perspective by explaining when a given technology matures and starts to connect with other devices to develop new Industry 4.0 solutions. For instance, a 3D printer, which normally is used as a single technology for service provision in the production process, can operate as a platform when connected with other technologies in a new product development process. For this, we explain that such platforms can coordinate and communicate through boundary activities in organizations. BS is defined as the creation of linkages that integrate and coordinate communication across organizational boundaries (Aldrich & Herker, 1977). In this sense, BS can help understand how companies connect through technologies working as platforms to obtain valuable information and create more complex solutions (Aldrich & Herker, 1977; Piercy, 2009). BS

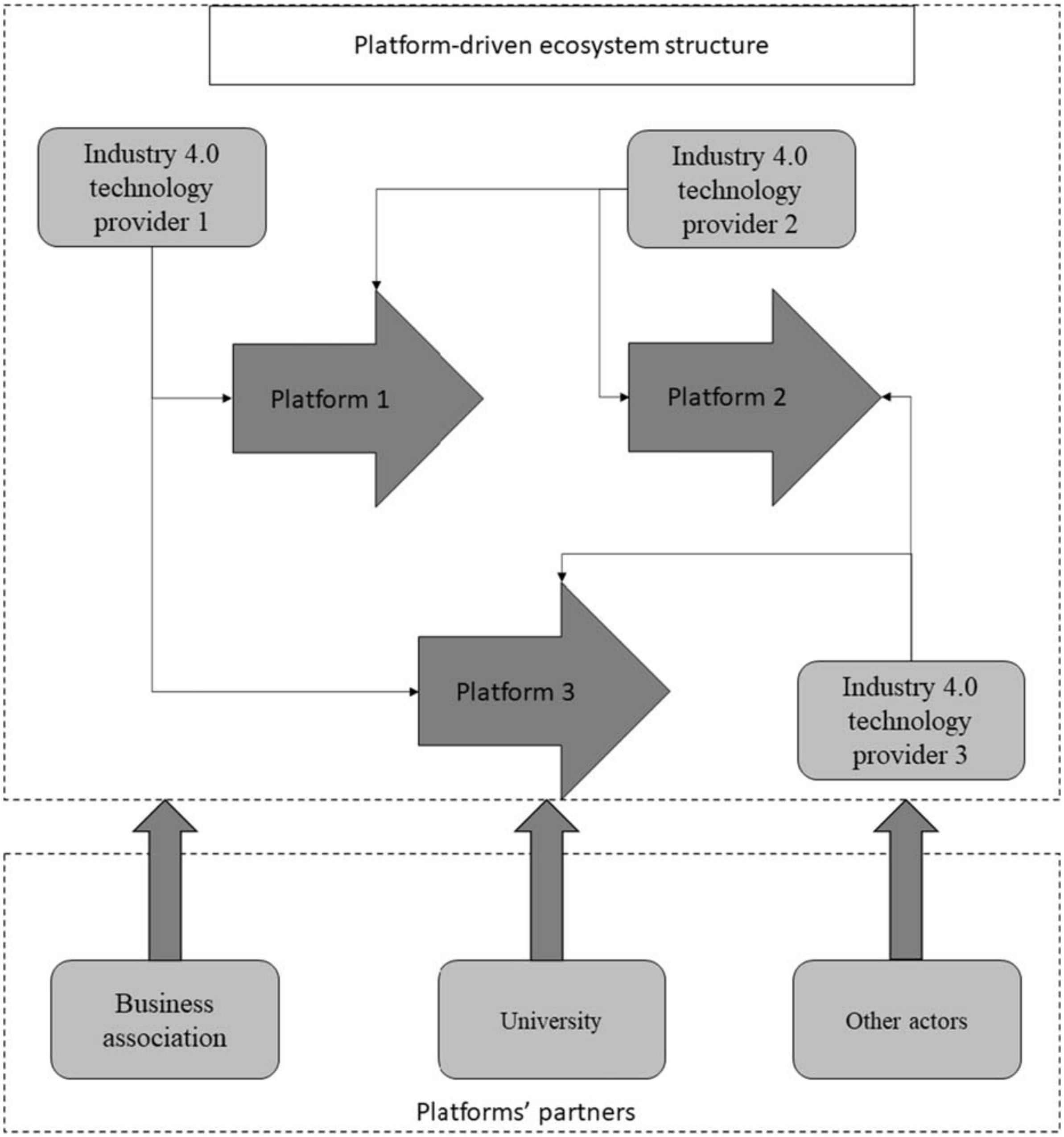

FIGURE 19.4 Platform structure. *Adapted from Benitez, G. B., Ayala, N. F., & Frank, A. G. (2020). Industry 4.0 innovation ecosystems: An evolutionary perspective on value cocreation.* International Journal of Production Economics, 228, *107735.*

encompasses four main activities: *information collection and processing*, *external representation*, *task coordination*, and *knowledge transformation* (Aldrich & Herker, 1977; Ancona & Caldwell, 1992; Tippmann et al., 2017).

Information collection and processing is the interpretation and transmission of information around the organization. *External representation* is the action to convince other actors to engage in the cause and collaborate on it. *Task coordination* is the alignment of activities in the group. *Knowledge transformation* is the capability to transform knowledge across organizations' boundaries into outcomes that generate value for the group. These concepts help shows how platforms operate in the Industry 4.0 context.[4] First, *information collection and processing* explain how connected technologies allow interoperability in systems. *External representation* activity explains how collaboration is made through

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[4] More details will be presented in our working paper (Benitez et al., 2022).

actions that persuade other parties by creating favorable impressions about the product or organization to obtain resources, high levels of commitment, and financial support. *Task coordination* explains how technologies are integrated to work organically to develop more complex solutions. Finally, *knowledge transformation* explains how value is generated through the platform for solution provision.

From the 40 enterprises interviewed, our analysis confirms that Industry 4.0 platform configurations are not only composed of general-purpose technologies such as Cloud and IoT as the key platforms but other technologies such as MES, which operate as platforms at different business levels. However, our findings indicate that these technologies can work as platforms only in certain circumstances, which are linked to the BS activities they perform. These explain how the technologies may connect with their surroundings to work as a platform. For instance, MES systems work as platforms mainly focused on data collection and management inside enterprises, which is the strongest BS activity of this platform configuration. Thus, it works as a platform because it manages all technologies in the production system, configurating and responding in real time to any demand variations inside the factory. Moreover, in accordance with our previous study in Benitez et al. (2020), we draw attention to the importance of "add-ons" for platforms in the Industry 4.0 context. We point to the need to integrate other complementary technologies as "add-ons" with these core technologies, for instance, prototypes from 3D printers with RFID sensing for the batches in workstations equipped with collaborative robots, all providing traceability and real-time data for the MES system. A further example is an ERP system managing a smart grid system in a supply chain to provide data transparency and energy efficiency across all tiers. This system is supported by traditional automation technologies (industrial robots, mechanical and electrical equipment), IoT, and AI algorithms for optimization in manufacturing. Thus, these core technologies can perform BS activities as a platform by orchestrating the add-ons to work organically.

Most of the time, Industry 4.0 technologies are operating for other purposes, normally related to industrial automation or Smart Manufacturing, as suggested by Dalenogare et al. (2018) and Frank, Dalenogare et al. (2019), but not as platforms. For instance, we found cases in which the MES system is performing only simple dashboard commands in computer software and is not connected to other technologies. We also noticed that IoT technology is present in several cases but simply connecting systems through a Wi-Fi connection. The results show that these technologies operate as platforms when the business vision and business strategy are tightly related to technology management (Bharadwaj et al., 2013). The platform's concept in technology systems should guide technology structuring for the establishment of technology-as-platform in the Industry 4.0 roadmap (Mittal et al., 2018; Schumacher et al., 2016).

By using BS activities, we identified technologies-as-platforms by measuring the degree of connection that certain technology has with its surroundings, allowing us to gather evidence on how supply chain collaboration evolves to a platform-driven ecosystem structure where SMEs and other players engage in platforms to co-develop Industry 4.0 technology solutions. Consequently, firms' willingness, especially SMEs, to collaborate and co-develop solutions is the determinant factor in this new industrial age. Next, we combine all discussions previously presented in a conceptual model explaining collaboration for Industry 4.0 technology solution provision.

9. A conceptual model for Industry 4.0 technology solution provision

We have discussed how three different lenses, OI, SET, and BS, help to explain how effective innovation ecosystems can be developed for SMEs in supply chains. We now present a conceptual model in Fig. 19.5 with different collaborative approaches for the development of solutions and technologies in the context of Industry 4.0. Three studies (Benitez et al., 2020, 2021, 2022)[5] were developed to define this model.

The conceptual model explains that approaches based on OI (Chesbrough, 2003) can pave the way for companies to collaborate in their supply chains for the development of solutions in the Industry 4.0 context, which is known to be difficult (CNI, 2016; Dalenogare et al., 2018). Kahle et al. (2020) point out that the main barriers associated with SMEs in the Brazilian context are related to costs and uncertainties regarding investment. The OI strategy, where companies bring resources and knowledge from external sources of collaboration, has been proven to be an alternative to help companies engage in technology development for SMEs in their supply chains. OI can be classified as the starting point for SMEs to engage in an Industry 4.0 roadmap. This can be done through the participation of local institutions like universities, business associations, or regional government acting as "neutral coordinators" to stimulate SMEs engagement for Industry 4.0 dissemination and adoption. Some works have been done in recent years presenting policies and OI actions for SMEs engagement toward the Industry 4.0 roadmap (De Marco et al., 2020; Kahle et al., 2020).

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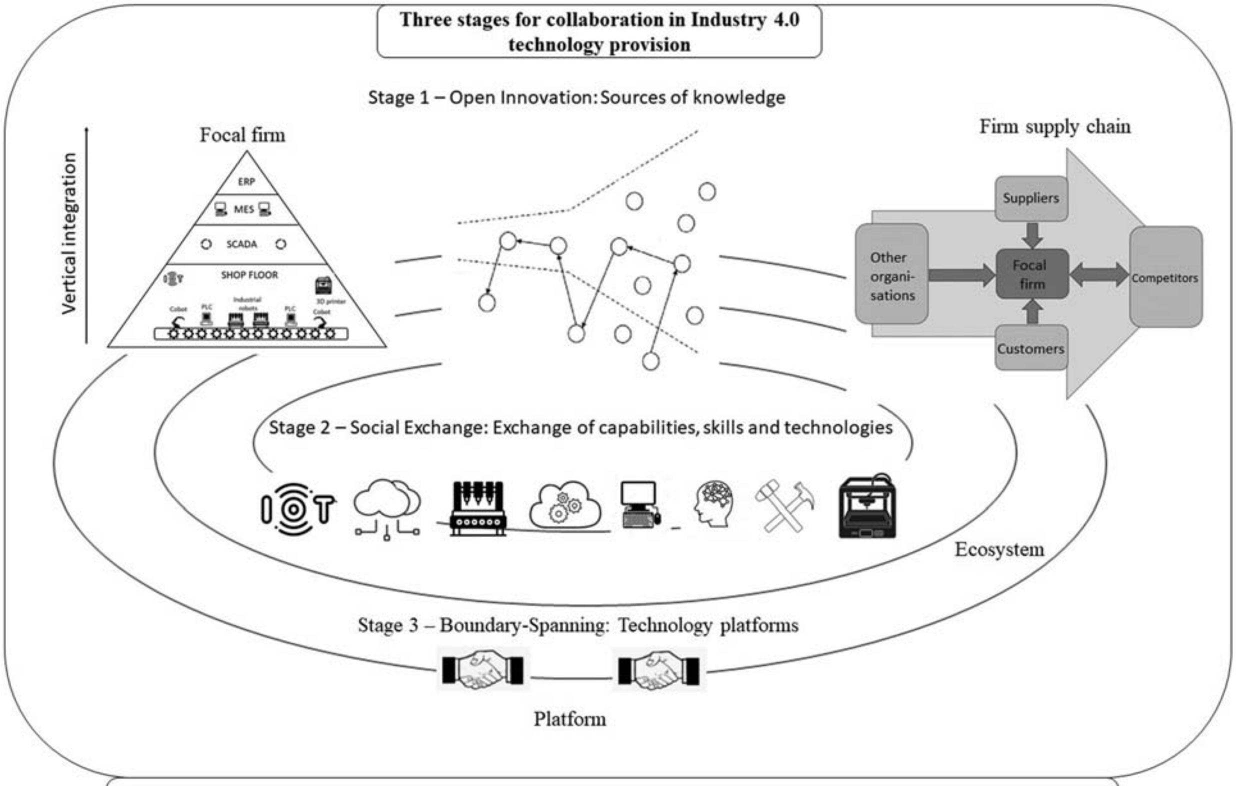
[5] Benitez et al. (2022) is under review process.



Maturing technologies – Boundary-Spanning: different technologies turns into platforms to develop new solutions

Expanding relationships – Social Exchange: only through trust, reciprocity, commitment and power to maintain interdependency relationships it is possible to achieve rewards and value exchange through collaboration

Starting point – Open Innovation: a way for companies to engage and collaborate in initiatives in Industry 4.0

FIGURE 19.5 Industry 4.0 collaboration conceptual model.

For relationships to be established and have a healthy long-term run, adopting and demonstrating SET principles can facilitate productive ecosystem engagement. Through commitment and trust, companies collaborating with third parties can achieve their strategic objectives and reach new markets (Wu et al., 2014). However, companies need to understand that there are higher goals beyond their own individual goals within these collaborations, especially in the Industry 4.0 context. By understanding this, reciprocity is shaped for the exchange of values and eventual rewards within these relationships. Finally, the power of a bargain to maintain all actors engaged in the cause (i.e., collaboration for product development) is essential for the SMEs to keep a healthy evolutionary exchange of capabilities and skills for Industry 4.0 provision.

After the first stages (starting point and horizon expansion) are achieved, the model also explains how to broaden borders and achieve different business level engagements (firm, supply chain, or ecosystems). Therefore, when SMEs mature their relationships, they can start a model oriented to platforms, where matured technologies disseminate and transform information for Industry 4.0 solution provision. This stage reflects technologies operating as boundary objects in the most connected degree where SMEs collaborate and develop their own solutions inside a platform to remain competitive in Industry 4.0.

In summary, the findings presented show three stages for SMEs engagement and collaboration in Industry 4.0: (i) how to start collaborating through OI; (ii) how to expand relationships in collaboration through SET; and (iii) how technologies mature and turn into platforms through BS.

10. Conclusions

Further empirical evidence is needed regarding Industry 4.0 technology acquisition and development across supply chains. Moreover, when we look at SME contexts, the subject is even cloudier on how SMEs can engage effectively in Industry 4.0 scenarios. We provide a compilation of the results from our previous research (Benitez et al. 2020, 2021) to show how these different concepts connect in the creation of Industry 4.0 ecosystems. SMEs facing technological turbulence in an environment like Industry 4.0 should start by looking for coopetition (i.e., competitive and cooperative) strategies to remain competitive. Moreover, we recommend that SMEs not look only for immediate rewards through transactional relationships in their supply chains. We recommend they search for long-run relationships based on trust, commitment, reciprocity, and power. These elements can support firms, especially SMEs, to engage in Industry 4.0 ecosystems and develop new solutions through value co-creation practices.

Although our chapter promotes a debate on how SMEs can engage and keep relationships for solution provision, starting collaboration is always a critical stage for these enterprises. We believe these limitations should be overcome in initiatives where other players can perform a key role as orchestrators for local and regional SMEs to engage in Industry 4.0. Our results can be useful for business associations, government agencies, and universities to create mechanisms to engage SMEs in Industry 4.0. We show that the governance structure is a flexible and critical factor of success for SMEs in Industry 4.0 since many shifts of leadership may occur during the evolutionary lifecycle of an ecosystem. We call for more studies to explain the governance structure of supply chains and ecosystems mostly composed by SMEs. Analyzing the governance behavior alongside the evolution of SMEs engagement may pave the way for stronger SME engagement in Industry 4.0. Our theoretical lenses can help researchers to initiate more studies in (i) partner selection to acquire or strengthen ties in the supply chain for the development of products and technologies; (ii) understand how to acquire new partners and collaborate at different levels of the business to develop technologies; (iii) understand how to strengthen relationships and maintain them in the long term within their businesses; and (iv) manage and operate different Industry 4.0 technologies as platforms.

One limitation is that our case study was conducted in Brazil, an emerging economy with its own features that differ in some respects from developed countries like the United States and Germany. Some countries like Germany already have strong policies for Industry 4.0 initiatives (Plattform Industrie 4.0) for SMEs competitiveness, while Brazil still struggles to find a suitable industrial policy to promote this debate. This is concerning since, as suggested by Frank et al. (2016), the main innovation strategy adopted by Brazilian companies is based on technology acquisition rather than R&D investment. However, as shown in that study, such strategies did not show the expected innovation outputs and one explanation is that companies do not invest in cutting-edge technologies, but only in upgrading existing technologies (Frank et al., 2016). We can notice this in Dalenogare's et al. (2018) work, which showed that most Brazilian entrepreneurs do not have high expectation in cutting-edge technologies such as Cloud and big data for operations and product development, respectively. Thus, the lack of vision of some of the most cutting-edge technologies from Industry 4.0 reflects a misalignment with global trends toward digitalization. In a scenario like this, SMEs are the most impacted since if they do not perceive value in digital technologies, they will face several difficulties in the following years. We call for studies to support Brazilian policies for Industry 4.0 dissemination. Testbeds projects, as the one studied in Benitez et al. (2020), can help in understanding how SMEs could engage in the Industry 4.0 dissemination over the country. Some initiatives from the Brazilian Industry 4.0 Chamber[6]—a multistakeholder chamber—to outline policies for advanced manufacturing and intelligent industries toward the Industry 4.0 journey have been made and can be a paramount for SMEs to become competitive in the Industry 4.0 field in the country.

As concluding remarks, future studies need to analyze the relationship of collaboration within different environments and Industry 4.0 technologies verifying their effects on different business strategies. Future research can check how different collaboration types can develop business models or support a particular model used by a company. These propositions of studies could help companies, especially SMEs, to move toward Industry 4.0 with different strategies for their businesses. Finally, future studies could consider other operations in the supply chain, such as the ones related to purchasing and logistics. With more empirical evidence, it may be possible to draw a roadmap for companies that do not have enough resources or skills to buy or develop technologies individually. Developing a roadmap that focuses on collaboration in Industry 4.0 and not on adopting technologies like most of the proposed studies in the literature (Ghobakhloo, 2018; Mittal et al., 2018; Schumacher et al., 2016) can be an alternative way for SMEs to remain competitive in Industry 4.0 era.

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[6] The complete Action Plan and its participants you can see at: https://antigo.mctic.gov.br/mctic/export/sites/institucional/tecnologia/tecnologiasSetoriais/Camara_I40__Plano_de_Acao_Camara_brasileira.pdf.

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Part V

Research frontiers in the Digital Supply Chain

Chapter 20

Network science for the supply chain: theory, methods, and empirical results

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Abstract
Supply chain management is notable among management disciplines with its core focus on relationships and interactions between organizations. Yet, the unit of analysis in supply chain management research is typically a buyer–supplier dyad or a short chain of interfirm connections, neglecting the impacts of the broader network in which these connections are embedded. To address this major gap, several studies have analyzed supply chains from a network science perspective, which models a system as a set of nodes and links. It employs analytical and computational methods to examine both network structure and dynamics, highlighting the importance of the broader network structure on firms' capabilities and performance. In this chapter, we provide a concise review of the theory, methods, and empirical results from this growing stream of literature. We discuss the interpretations of different network concepts and measures in a supply chain management context. We present key results from computational modeling and empirical studies on the structure and dynamics of supply networks and their effects on operational and financial performance, innovation, network stability and resilience. In doing so, we provide mathematical definitions of key network concepts, methods, and measures for supply chain practitioners and researchers new to this area of research.

Keywords: Network analysis; Supply chain management; Supply networks.

1. Introduction

Supply networks have repeatedly come under the spotlight during various crises. After the 2011 earthquake in Japan, automotive manufacturers suffered shortages as the sole Xirallic pigment factory in the world had to stop production due to its proximity to the Fukushima nuclear power station (Reuters, 2011). In 2013 a major food adulteration scandal occurred in the UK, where DNA tests revealed that various meat products sold by major retailers were contaminated with horse meat, in some cases up to 85% (Guardian, 2013). The weaknesses were attributed to the complexity of the contractual supply networks involved and the difficulty of surveillance thereof. In 2021 the automotive industry experienced a large-scale shortage of semiconductor chips, this time due to the pandemic (Wired, 2021). As is clear in these high-profile incidents, prime entities can be extremely vulnerable to disruptions and bottlenecks deep in their supply networks, without even being aware of these dependencies. It is not only the shocks originating from direct and indirect suppliers that makes supply networks strategically important. Extended supply networks are being leveraged by many companies as a source of competitive advantage (Basole et al., 2018). For instance, Toyota has historically established their supply chain management strategy on *keiretsu*, a closely working network of suppliers that are essential in product development, cost reduction, and innovation (Liker & Choi, 2004). Similarly, industrial clusters achieve enhanced production capability through an interdependent network of different types of links within the cluster (Lomi & Pattison, 2006).

The importance of interdependencies and interactions between firms is being more and more recognized as a part of the theory of firm (Borgatti & Li, 2009). From its inception, supply chain management has focused on interfirm connections, but the unit of analysis has mostly been restricted to buyer–supplier dyads and short linear chains (Borgatti & Li, 2009; Hearnshaw & Wilson, 2013). However, dyads and chains do not exist in isolation as they connect to form extended supply networks. Firms not directly connected can still affect each other indirectly via multiple paths on the network, through

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which local dynamics and risk in one part of the network can propagate to other parts (Demirel et al., 2019; Kim et al., 2015; Wang et al., 2021).

Supply chain networks have traditionally been designed by prime entities that have power over and visibility of their networks in a quest to achieve desired operational and strategic objectives. However, this design ability does not extend to distant tiers. Supply chain networks for multiple prime entities intertwine with each other, limiting the control ability of any individual agent in these extended networks (Brintrup et al., 2016; Demirel et al., 2019; Osadchiy et al., 2021b; Perera et al., 2017; Wiedmer and Griffis, 2021). Hence, supply networks have been conceptualized in several studies as complex systems that exhibit emergence, interdependence between actors, self-organization, and adaptation (Brintrup et al., 2017; Perera et al., 2017; Zhao et al., 2019). Individual firms act autonomously with their local goals, while the system level properties and performances are determined by the interdependencies between the firms. Hence, a network perspective is required to understand the strategy and the behavior of firm.

The network science approach, which involves modeling a system as a set of nodes and connections between them, has been developed in the past three decades in different fields, including physics, biology, sociology, and economics (Newman, 2018). The prominence and potential of network analysis has been boosted by digitalization and availability of data about supply networks. A major premise of network science is that the structure affects function, hence the pattern of interfirm connections influences behavior and performance in supply chains (Brintrup et al., 2017; Wiedmer and Griffis, 2021). In particular, the extant literature has shown that the structure of the supply network affects financial performance (Lu & Shang, 2017), operational performance (Kim et al., 2011; Osadchiy et al., 2021a), innovation (Bellamy et al., 2014; Gao et al., 2015; Potter and Wilhelm, 2020), risk contagion (Wang et al., 2021), stability (Demirel et al., 2019), and resilience (Brintrup et al., 2016; Kim et al., 2015; Zhao et al., 2019).

In this chapter, we provide a brief state-of-the-art review of the theoretical and empirical literature on the network analysis of supply chains.[1] While covering key concepts, results, and discussions in the literature, we also adopt a tutorial-like approach for those who are new to this area. To do this, we provide mathematical definitions of the network concepts and measures introduced.

We first outline the steps of supply network analysis in Section 2 and then in the remaining sections we provide details on each of the steps. In Section 3, we identify commonly used data sources. In Section 4, we introduce the fundamental network concepts, required for the remainder of the chapter. In Section 5, we present the key network measures, defined at both node and network levels, their interpretation, and results from the empirical literature. In Section 6, we review the emerging empirical and modeling literature on the effects of network structure on supply chain performance, behavior, and dynamics. In Section 7, we conclude with identifying gaps in the literature and recommending areas for further research.

2. An outline of supply network analysis

As for other analysis approaches, supply network analysis starts by asking relevant research questions, which concern the structural properties of a supply network, their dynamic evolution, and their impact on the behavior and the performance of firms in the network. Once the research topic and questions are determined, the next step is to identify and utilize an adequate dataset(s). After loading and preprocessing the data for network analysis, the local and global network metrics and statistics are computed and interpreted. Finally, we look to answer the research questions, which is typically done by analyzing the effect of certain network statistics on firm-level or network-level performance measures. Below, we outline these steps, while the details are provided in the subsequent sections.[2]

2.1 Data selection or generation

In Section 3, we discuss the various sources of supply network data commonly used in the academic literature. Secondary data sources typically capture only structural information, i.e., which firm is connected to which others, while primary data may provide more details on transactions and relationships, but typically at a smaller scale. The choice of the data set will depend on the sector and the geographical region of interest, the level of detail sought, the coverage of different types of firms (publicly listed, multinationals, joint ventures, etc.), and also the researcher's access to the data. An alternative to using real-world supply network data is to generate synthetic networks, which resemble real networks in terms of certain

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[1] In the remaining, we use the terms *supply chain* and *supply network* interchangeably, since we argue that individual supply chains cannot be generally understood and analyzed in isolation from the extended networks in which they are embedded.

[2] It is worth noting that this is a simplified view of the process, since, for instance, the supply network data chosen or the simulation model might have to be revised later in the analysis or access to data might restrict the set of research questions that can be answered.

aspects, based on theoretical models. Although a comprehensive review of these network generation methods is beyond the scope of this chapter, we discuss the fundamental models in Section 5.2, which have been proposed in the network science literature to characterize the structure of systems from various domains and have also been adopted as models of supply networks in some studies. We refer the interested reader to Perera et al. (2017) and Wiedmer and Griffis (2021) for a fuller account of network generation methods and the assessment of their validity for reproducing real-world supply network characteristics.

2.2 Network analysis software and data preprocessing

Once the supply network data are obtained, or generated, this should be inputted to a network analysis software tool. There are several software tools and packages for network analysis. *Gephi* and *UCINET 6* provide graphical user interfaces to compute a rich set of network metrics, to run algorithms, for instance for community detection, in which the network is partitioned into a set of internally closely linked clusters of firms, and to visualize networks with different layout options. For those wishing to implement new network measures and/or link the network analysis with other types of analysis, such as regression analysis or network simulations, general-purpose programming languages provide more flexibility. *Python* has *NetworkX* and *Igraph* packages for network analysis, while *R* has the *Igraph* package. These packages provide the required functionality to work with networks, while the possibility of writing customized code for a specific model or a metric gives the desired flexibility. One can of course combine different software products, i.e., load and analyze the network data in *Python* and then plot it in *Gephi*, which may produce better visuals due to the many visualization options available and the ease of click and edit feature of *Gephi* objects.

Once the network data are inputted to the software of choice, it is important to first inspect the data and preprocess it for network analysis. Depending on the focus of the analysis, one needs to decide on the boundary of the network and exclude nodes and links that do not fall within this boundary. For instance, if the focus is on the supply network between an automanufacturer and its parts suppliers, other types of suppliers, such as finance and insurance providers, need to be dropped from the network, together with their links. One can merge different supply network data sets for cross-validation, as different data providers use different methods and sources for inferring links between firms. In the analysis, it is common to drop nodes that do not belong to the largest network component (see Section 4 for the definition). Finally, the network data can contain firm and link features, such as company size and transaction value. If there are missing values and/or anomalies, these should be handled by either dropping these observations or using imputation methods, in which missing values are replaced by plausible values according to a certain criterion, such as the most frequent value, median, or predicted value based on other attributes, as in standard empirical research.

2.3 Descriptive network analysis

Once the network data are loaded and preprocessed, the network is explored and analyzed in a descriptive way, similar to the Exploratory Data Analysis (EDA) stage of common empirical research. There is a set of standard concepts and statistics used to describe and characterize networks. In Table 20.1, we list the typical questions asked to describe the properties of

TABLE 20.1 Describing networks: Questions and network concepts.

Level	Question	Network concept
Node	Which firms are most important/critical in the supply network?	Node centrality
Node	How redundant are the connections of a focal firm? How likely are the suppliers and customers of a firm to interact directly with each other?	Clustering
Link	Which connections of a firm are more important?	Link weight, Hub-authority scores
Network	How much do firms differ from each other with respect to their number of connections?	Degree distribution
Network	How efficiently can information and materials be transmitted on the supply network? How quickly can you reach other nodes on a network?	Geodesic distance
Network	Do firms self-organize into closely knit groups with shared interests and/or latent characteristics?	Community detection

the network. The questions and concepts covered in Table 20.1 are the most common descriptive questions asked in the literature and constitute the focus of Sections 4 and 5.[3] The technical concepts and their interpretation in a supply chain management context are discussed in the next sections.

2.4 Mathematical, simulation, and statistical analysis

Once we develop a general understanding of the structure of the network, the final step is to analyze how the supply network's structure, e.g., node level centrality metrics and network level attributes such as the average network distance between firms, affects its function; hence firm and network level outcomes. The outcome measures of interest can be computed from mathematical/simulation models of processes on the supply network or can be obtained from firm-level empirical data sets, if the relevant data are being measured and stored for the firms in the supply network. Such analysis allows answering questions such as "How does the network position of a firm affect its operational, financial, and innovation performance?" and "How do the structural properties of the network affect system characteristics such as stability and resilience?" We discuss several of these questions and corresponding empirical strategies in Section 6.

3. Data sources for supply network analysis

Early studies on supply networks used primary data collection via industry surveys as the main source of data for network analysis, as suggested by Borgatti and Li (2009). Some studies have followed this survey approach since then (Bode & Wagner, 2015; Gao et al., 2015), while others have collected firm-level data through close collaborations with a smaller number of prime entities to map their extended supply networks in order to identify critical suppliers (Choi & Hong, 2002; Demirel et al., 2019). This approach equips the researcher with detailed contextual information and product level data, such as Bill-of-Materials structure and supplier part assignments. However, such detailed network mapping at the product level is a laborious and costly activity, which inhibits scaling up the approach to larger networks.

Recent empirical studies have sought to use secondary data sets curated by data providers, mainly as a service offered to investors and other stakeholders. The Securities and Exchange Commission (SEC) requires US companies to report their key customers that exceed 10% of their revenues in their 10-K and 10-Q filings, and also key suppliers that might constitute risk in their 8-K filings. These documents constitute an important source of supply network information for publicly listed companies in the US. The Mergent Online Supply Chain and Compustat Supply Chain Suite databases extract supply relationships from SEC filings. For instance, Mergent Online has been used in Lu and Shang (2017), Zhao et al. (2019), Wiedmer and Griffis (2021). These data sets are prone to sampling bias as only major supply relationships are covered and only for public companies in the US. Factset Revere Supply Chain Relationships and Bloomberg SPLC (previously Connexiti) databases enrich the SEC filings with other sources of information, including investor presentations, company documents, analyst reports, and press releases, to form a global data set of supply, competition, and partnership relationships. Factset Revere Supply Chain has been used by Chae et al. (2020), Osadchiy et al. (2021a,b), Piraveenan et al. (2020) while Bloomberg SPLC has been used by Basole et al. (2018), Bellamy et al. (2014, 2020), Brintrup et al. (2017), Wang et al. (2021).

These secondary data sets specify which firms supply to which other. However, they either completely lack data on which products are supplied or contain data on only general categories of products sold by a supplier, but not to a specific buyer. The automotive industry is an exception, where finer detail data are available. Marklines automotive database captures more detailed product information, which has for instance been used in Brintrup et al. (2016), Potter and Wilhelm (2020). However, even with this data set, one cannot precisely map the extended supply network of a chosen automotive manufacturer. It is not possible to validate whether a supplier of a supplier is selling the part to be used in the manufacturing of a system purchased eventually by the focal firm or one of its competitors. This constitutes a major data challenge for empirical supply network analysis.

4. Network basics

A supply network can be defined as the network of firms involved in the manufacturing and delivery of a certain group of products and/or services (Kim et al., 2011; Wiedmer and Griffis, 2021). Mathematically speaking, a *network* (or a *graph*) is

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[3] The answers to the same questions can be captured by using network concepts different from Table 20.1. For instance, Demirel et al. (2019) use the influence measure to quantify the importance of links for the propagation of inventory dynamics on a supply network rather than an externally provided link weight parameter. Such concepts are beyond the scope of this illustrative set of questions and answers.

an ordered pair $\mathbb{G} = (\mathbb{V}, \mathbb{E})$ of the set of *nodes* (*vertices*) $\mathbb{V}$ and the multiset $\mathbb{E}$ of *links* (or *edges*). Without loss of generality, we label the nodes by integers 1, …, n, where n is the number of nodes in the network (*network size*). A link $e = (i,j)$ in $\mathbb{E}$ connects the node $i \in \mathbb{V}$ to node $j \in \mathbb{V}$. For supply networks, nodes are generally taken to represent firms, while links can correspond to different types of relationships between them, e.g., material flows, information flows, and contractual relationships.

Typically, only a single link is assumed from one node to another, in which case $\mathbb{E}$ reduces to a set and the network structure can be represented by the binary *adjacency matrix* $\mathbf{A} = [A_{ij}]_{i,j \in \mathbb{V}}$. The matrix element $A_{ij} = 1$ if there is a link from node i to node j, i.e., $(i, j) \in \mathbb{E}$, and $A_{ij} = 0$ otherwise. The adjacency matrix can also be used to represent the count of connections between two nodes in *multigraphs*, where multiple edges are allowed between two nodes, and the weights of links in *weighted networks*, e.g., monetary values of financial flows, but we here consider unweighted networks without multiedges. The link e_{ij} in $\mathbb{E}$ is said to be *undirected* (or *bidirected*), if e_{ji} is also in $\mathbb{E}$. A network that consists of only undirected links is called an *undirected network*, while it is called a *directed network* (or a *digraph*) otherwise. For instance, a network representing material flow on a network would be directed, while a network representing competition between firms may be undirected.

For an undirected network, we define the *degree* (or *valence*) of a node as the number of links it has with other nodes, or equally the number of direct neighbors $\mathbb{N}_i$ (node j is a neighbor of i, $j \in \mathbb{N}_i$, if $A_{ij} = 1$). The degree of node i is $k_i = |\mathbb{N}_i| = \sum_{j=1}^{n} A_{ij}$. The total number of links m in an undirected network is obtained from $2m = \sum_{i=1}^{n} k_i = \Sigma_{i,j} A_{ij}$. The mean degree in an undirected network is $<k> = \frac{2m}{n}$, while the density d is the fraction of existing links to all possible links, i.e., $d = \frac{2m}{n(n-1)} \approx \frac{<k>}{n}$.

In directed networks, we distinguish between *in-neighbors* and *out-neighbors*. *In-neighbors* of node i, $\mathbb{N}_i^{in}$, are those nodes j from which there are in-coming links to node i, i.e., $A_{ji} = 1$. *Out-neighbors* are defined analogously: $j \in \mathbb{N}_i^{out} \Leftrightarrow A_{ij} = 1$. In-degree and out-degree are defined accordingly as the number of in-neighbors, $k_i^{in} = \left|\mathbb{N}_i^{in}\right| = \Sigma_j A_{ji}$ and out-neighbors, $k_i^{out} = \left|\mathbb{N}_i^{out}\right| = \Sigma_j A_{ij}$. The total numbers of incoming and outgoing links are always the same, i.e., $m = \Sigma_i k_i^{in} = \Sigma_i k_i^{out} = \Sigma_{i,j} A_{ij}$ so are the average in-degree and out-degree: $<k> = <k^{in}> = <k^{out}> = \frac{m}{n}$. The density of a directed network is $d = \frac{m}{n(n-1)} \approx \frac{<k>}{n}$.

Moving from direct neighbors to indirect neighbors, a *walk* of length l is a sequence of nodes $\{v_{(1)}, v_{(2)}, \ldots, v_{(l)}\}$ that are consecutively visited via links. Hence, nodes $v_{(k)}$ and $v_{(k+1)}$ must be linked, i.e., $A_{v_{(k)}v_{(k+1)}} = 1$ for all $k = 1,\ldots,l-1$. If no nodes are visited twice in a *walk*, that is when the walk does not intersect with itself, the walk is called a *path*. Multiple walks and paths can exist between two nodes. If one considers all walks from node i to node j, the shortest of these, which is necessarily a path, is called a *shortest path* (or *geodesic path*). The *shortest path length* from node i to node j provides the *network distance* (*geodesic distance*) between these two nodes. The maximum of the shortest path lengths between all pairs of nodes in a network is called the *diameter* of the network, which characterizes the maximum distance on a network.

In a network, it may not be possible to reach each node from every other node. A *component* is a maximal subset of the nodes in which each node can be reached from any other by a walk. It is maximal in the sense that if a node is not contained in a component, it cannot be reached from the nodes in that component. The largest of the components of a network is called the *largest connected component* (*LCC*). In directed networks, if we ignore link directions, the obtained components are called *weakly connected components*. If walks obey links' directions, the resulting components are called *strongly connected components*.

The network properties described mathematically above are summarized in Inset 20.1.

5. Structure of supply networks: theory, methods, and empirical results

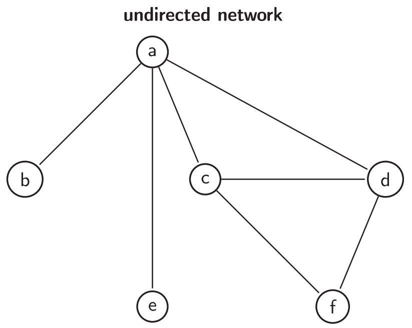
In Section 5.1, we first discuss node-level measures and their interpretation in the supply chain context. In Section 5.2, we review the key network-level statistics and discuss the structure of supply networks.

5.1 Node-level network measures

We shall call a firm of particular interest and importance, e.g., a prime manufacturer, the focal firm. Node level measures are essential for characterizing such a focal firm's role and importance based on its position within the supply network in which it is embedded. Yan et al. (2015) introduce the concept of a nexus supplier to describe suppliers that are particularly

INSET 20.1 Key definitions for directed and undirected networks relevant for supply networks

A supply network is formed of firms (nodes) and their connections (links). Contractual relationships between firms in a supply chain are mutual, forming an undirected network between firms. In contrast, products flow in a certain direction, that is downstream in a supply chain, forming a directed network.



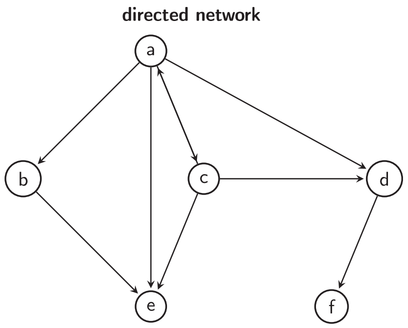
Adjacency matrix **A** denotes who is linked to whom. An entry has a value of 1 if there is a link between two nodes, and 0 otherwise.

$$\mathbf{A} = \begin{array}{cc} \begin{matrix} a & b & c & d & e & f \end{matrix} & \\ \begin{pmatrix} 0 & 1 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 \end{pmatrix} & \begin{matrix} a \\ b \\ c \\ d \\ e \\ f \end{matrix} \end{array}$$

The degree k_i of node i is the number of its connections. *Mean degree* $<k>$ is the average of the individual node degrees. *Density* d is the fraction of the number of links to maximum number of links. $k_a = 4$, $k_b = 1$, $k_c = 3$, $k_d = 3$, $k_e = 1$, $k_f = 2$, $<k> = 7/3$, $d = 7/15$.

One can walk from one node to another node on the edges of the network. The shortest of these between two nodes is called *shortest* (*geodesic*) *path*, the length of which is the network (geodesic) *distance*, contained in the *distance matrix* **D**. The maximum distance on a given network is called the diameter.

$$\mathbf{D} = \begin{array}{cc} \begin{matrix} a & b & c & d & e & f \end{matrix} & \\ \begin{pmatrix} 0 & 1 & 1 & 1 & 1 & 2 \\ 1 & 0 & 2 & 2 & 2 & 3 \\ 1 & 2 & 0 & 1 & 2 & 1 \\ 1 & 2 & 1 & 0 & 2 & 1 \\ 1 & 2 & 2 & 2 & 0 & 3 \\ 2 & 3 & 1 & 1 & 3 & 0 \end{pmatrix} & \begin{matrix} a \\ b \\ c \\ d \\ e \\ f \end{matrix} \end{array}$$



Adjacency matrix A is not symmetric in directed networks.

$$\mathbf{A} = \begin{array}{cc} \begin{matrix} a & b & c & d & e & f \end{matrix} & \\ \begin{pmatrix} 0 & 1 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} & \begin{matrix} a \\ b \\ c \\ d \\ e \\ f \end{matrix} \end{array}$$

The *in-degree* k_i^{in} is the number of incoming links, while *out-degree* k_i^{out} is the number of outgoing links. In-degree corresponds to the number of direct suppliers of a firm, while out-degree is the number of direct customers.

$k_a^{in} = 1,\ k_b^{in} = 1,\ k_c^{in} = 1,\ k_d^{in} = 2, k_e^{in} = 3,\ k_f^{in} = 1,$

$k_a^{out} = 4,\ k_b^{out} = 1,\ k_c^{out} = 3,\ k_d^{out} = 1,\ k_e^{out} = 0,\ k_f^{out} = 0,$

$<k^{in}>=<k^{out}>= 3/2,\ d = 3/10$

A *network component* is a part of the network in which you can reach each node from one another by a *walk* and it should not be possible to reach any of the nodes not contained in a component. If the walks must obey the directions, it is called *strongly connected components*. In this example, the network partitions into (*a*, *c*), *b*, *d*, *e*, *f* as only *a* and *c* are reachable from each other. If you do not enforce the directions, you obtain *weakly connected components*. Here, there is only one: (*a*, *b*, *c*, *d*, *e*, *f*), which is equivalent to the original network. The largest of the components is called the *largest connected component* (*LCC*).

important due to their network position. In contrast to strategic suppliers, which belong to the visible and manageable part of the supply network, nexus suppliers can be positioned deep in the extended network, for which the focal company may often have only limited visibility (Wiedmer and Griffis, 2021). The focus is moving from building strong cooperative relationships with strategic suppliers to managing complex supply networks (Lu & Shang, 2017) and improving visibility, facilitated by digitalization (Wang et al., 2021). The centrality of a firm changes with the extent of the network considered.

For instance, Piraveenan et al. (2020) compare the structure of production networks at the national and global levels, showing that local SMEs are more central locally than globally and countries with origin in a different country are more central globally.

Borgatti and Li (2009) propose three different mechanisms through which the network position can affect performance. The most fundamental mechanism is that of transmission, which concerns the flow of information, material, and financial resources. Having a central position in the network provides a firm with easier access to and control over information and resources (Lu & Shang, 2017). The second mechanism concerns the interdependencies between decisions and the coordination of actions. The stronger the connections between the firms, the more correlated their performance becomes (Borgatti & Li, 2009). As a consequence of the correlations between firms, risks can no longer be assumed to be idiosyncratic and the risks spread on the network (Wang et al., 2021). The third mechanism is adaptation, where the dynamic environment contains the network of relationships around a firm (Hearnshaw & Wilson, 2013). Borgatti and Li (2009) postulate that nodes with similar network positions develop similar capabilities and strategies in a drive to adapt to their environment. Suppliers that occupy similar network positions are more likely to share information with, and affect each other (Chae et al., 2020).

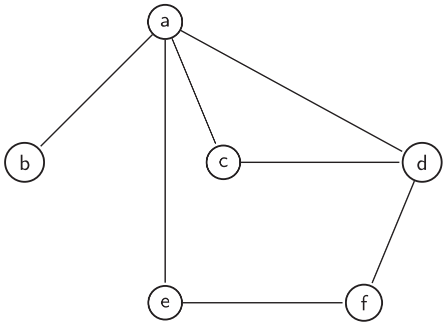
The importance of a node can be defined with respect to several centrality measures. *In-degree* (*out-degree*) *centrality* (see Section 4) is related to the supply (demand) load in material flow networks, as managing each link, incoming or outgoing, requires managerial resources and creates a load on the focal firm (Brintrup et al., 2017; Kim et al., 2011). Nodes with high in-degree centrality tend to act as systems integrators, which are pivotal in managing and coordinating product architecture changes (Brintrup et al., 2017; Kim et al., 2011; Yan et al., 2015). High out-degree requires that the firm acts as a supplier for many firms in the downstream, which enables it to benefit from economies of scale and diversification against idiosyncratic demand shocks. Firms with high out-degree have to maintain balance between multiple demand streams, hence they may strongly impact cost and quality (Yan et al., 2015). In undirected contractual networks, the *degree centrality* is related to the influential scope of a firm as this is the number of partners with which it has direct contractual relationships (Brintrup et al., 2017; Kim et al., 2011). Hence, firms with high degree centrality in contractual networks act as coordinators.

Higher *degree centrality* ensures direct access to more sources of information; however, the information obtained from different suppliers can be redundant and of limited value. Furthermore, processing information is costly and demanding; hence not only the number of connections but also to whom a firm is connected matters. Being connected to other important nodes facilitates access to key resources. For undirected networks, this is captured by the *eigenvector centrality*, x_i, that defines centrality in terms of the centrality scores of its neighbors: $x_i = \frac{1}{\kappa}\Sigma_{j=1}^{n} A_{ij}x_j$. This is equivalent to the eigenvalue-eigenvector equation $\mathbf{Ax} = \kappa\mathbf{x}$, where κ is the leading (largest) eigenvalue and $\mathbf{x} = (x_1, x_2, \ldots, x_n)$ is the corresponding eigenvector, containing nonnegative centrality scores. In directed networks, *eigenvector centrality* may suffer from many nodes scoring zero. This can be fixed by the closely related *Katz centrality* that assigns constant importance β to nodes with zero out-degree. *Katz centrality* of node i satisfies $x_i = \alpha\sum_{j=1}^{n} A_{ij}x_j + \beta$, where it is common practice to take $\beta = 1$. Yan et al. (2015) suggest eigenvector centrality is related to operational importance as nodes with high eigenvector centrality are connected to other central firms; hence disruptions in these nodes are likely to propagate to other parts of the network. Basole et al. (2018) associate eigenvector centrality with the ability to access, manage, control, and coordinate supply chain activities. The most important node centrality measures for supply network analysis are summarized in Inset 20.2.

For directed networks, centrality can be defined with respect to being an *authority*; i.e., a node referenced by other important nodes, or a *hub*, which provides links to other important nodes. *Authority centrality* (x_i) and *hub centrality* (y_i) are defined in terms of each other: an *authority* is referred to by many *hubs* and a *hub* refers to many *authorities*, which is expressed mathematically as $x_i = \gamma_1\sum_{j=1}^{n} A_{ji}y_j$ and $y_i = \gamma_2\sum_{j=1}^{n} A_{ij}x_j$. Then, the vectors of *authority* and *hub centrality*, $\mathbf{x} = (x_1, x_2, \ldots, x_{\boldsymbol{n}})$ and $\mathbf{y} = (y_1, y_2, \ldots, \mathrm{y}_{\boldsymbol{n}})$, satisfy $\mathbf{A}^{\mathrm{T}}\mathbf{Ax} = \gamma\mathbf{x}$ and $\mathbf{AA}^{\mathrm{T}}\mathbf{y} = \gamma\mathbf{y}$, where $\gamma = 1/\gamma_1\gamma_2$ is the leading eigenvalue of the matrix $\mathbf{A}^{\mathrm{T}}\mathbf{A}$. Hence, the authority and hub centrality scores are the eigenvectors of $\mathbf{A}^{\mathrm{T}}\mathbf{A}$ and $\mathbf{AA}^{\mathrm{T}}$, respectively, both corresponding to the leading eigenvalue of both matrices. When compared with the eigenvector centrality, which is the eigenvector of the leading eigenvalue of the symmetric adjacency matrix $\mathbf{A}$ in undirected networks, we use the eigenvectors of $\mathbf{AA}^{\mathrm{T}}$ and $\mathbf{A}^{\mathrm{T}}\mathbf{A}$ for hub and authority scores in directed network, since the adjacency matrix $\mathbf{A}$ is no more symmetric. Borgatti and Li (2009) argue that when both hub and authority centrality scores are high, it characterizes a firm operating in a competitive market, in which agility is essential. If the hub score is high, but the authority score is low, it corresponds to a sales-oriented firm, while the opposite corresponds to a procurement-oriented firm. Considerations for centrality in directed supply networks are outlined in Inset 20.3.

INSET 20.2 Network centrality measures for supply networks

Network centrality measures concern how important different nodes are with respect to their position in the network. The centrality measures should be interpreted relatively, providing a ranking between nodes in the network.



$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 & 0 \end{bmatrix} \quad \mathbf{D} = \begin{bmatrix} 0 & 1 & 1 & 1 & 1 & 2 \\ 1 & 0 & 2 & 2 & 2 & 3 \\ 1 & 2 & 0 & 1 & 2 & 2 \\ 1 & 2 & 1 & 0 & 2 & 1 \\ 1 & 2 & 2 & 2 & 0 & 1 \\ 2 & 3 & 2 & 1 & 1 & 0 \end{bmatrix}$$

The *degree centrality* is simply the degree of the node; hence captures only the local neighborhood. The more business connections a firm has, the more important it is within the whole network. In this example, node *a* is the most important with degree 4, followed by *d* with degree 3, then by *c*, *e*, and *f* with identical degrees of 2, and finally *b* with degree 1.

Degree centrality assumes all connections have equal value. However, being connected to more important nodes would generally matter more. There are two ways of becoming more central: connect to many and/or connect to other central nodes. One such measure is the *eigenvector centrality*, which calculates the node centrality from the centralities of its direct neighbors in an iteration. The eigenvector centrality is obtained from the eigenvector of the adjacency matrix **A** corresponding to the largest eigenvalue. For the example, this evaluates to $x_a = 0.5634$, $x_b = 0.21678431$, $x_c = 0.40845488$, $x_d = 0.49816569$, $x_e = 0.34101159$, $x_f = 0.32287568$. The node *a* is the most central because it has both highest degree and is connected to other central nodes (*c* and *d*). Nodes *a*, *c*, and *d* form a *clique* together. Eigenvector centrality differentiates between *c*, *e*, and *f*, which have the same degree 2. Node *c* has the highest eigenvector centrality because it is connected to two central nodes, *a* and *d*. Node *e* has a higher score than *f* because its neighbor *a* has higher centrality than *d*.

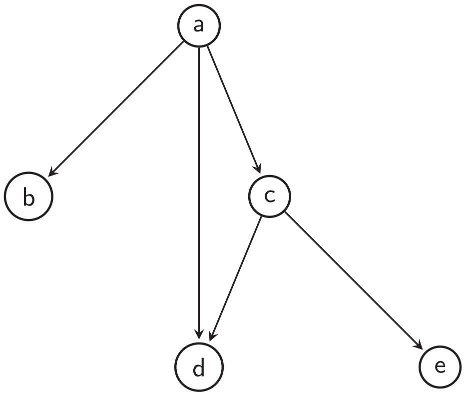
Being close to other firms on a network makes a focal firm central. A firm or an individual who can reach others by using one intermediary is in a more advantageous position than one that has to use two intermediaries. This is captured by *closeness centrality* c_i, which is the harmonic average of the node's geodesic distances to other nodes. For the example, we use the distance matrix **D** above to obtain $c_a = (1/1 + 1/1 + 1/1 + 1/1 + 1/2)/5 = 27/30$, $c_b = 17/30$, $c_c = 21/30$, $c_d = 24/30$, $c_e = 21/30$, $c_f = 20/30$. Node *a* does not only have many connections and to other central nodes, but it is also close to other nodes (only *f* in distance 2). Observe that *c* and *e* have the same closeness centrality because their all shortest paths other than to nodes *d* and *f* must go through *a*, which is one step away from both.

While closeness centrality captures how quickly a node can access information and resources in other parts of the network, *betweenness centrality* captures the extent to which other nodes rely on a focal node to reach other parts of the network. Betweenness centrality is used in quantifying the gatekeeper role. A firm might not be important on its own and might not have many links, but it is still central if it constitutes the only link between two *communities*, a cluster of densely connected nodes. Betweenness centrality is obtained by calculating the ratio of shortest paths on which a focal node sits. For the example, all shortest paths from *b* to *c*, *d*, *e*, and *f* should pass through *a*. Similarly, node *a* sits on the unique shortest path between *c* and *e*. These altogether contribute 5. Node a is not on the shortest paths for *c&d*, *d&f*, *c&f*, and *e&f*. These contribute 0. There are two shortest paths for *d&e*: *d—a—e* and *d—f—e*. Since *a* is contained in one of the two, it contributes 1/2. Hence, the *betweenness centrality* $b_a = 0.55$. The others can be calculated analogously, returning $b_b = 0$, $b_c = 0$, $b_d = 0.2$, $b_e = 0.1$, $b_f = 0.1$.

According to the transmission mechanism, quick access to different sources of information and other resources is essential. This is measured by *closeness centrality*, the harmonic average of geodesic distance to other nodes on the network: $c_i = \frac{1}{n-1}\Sigma_{j\neq i}\frac{1}{d_{ij}}$, where d_{ij} is the shortest path length from node i to j. Firms that are only a few hops away from other nodes do not depend on other powerful entities to reach information and resources hosted elsewhere in the network (Kim et al., 2011). Therefore, closeness centrality is associated with informational independence and fast access to novel information (Bellamy, Ghosh, & Hora, 2014). Firms with high closeness centrality act as navigators that can navigate for

INSET 20.3 Considering centrality in directed networks

Katz centrality and *hub-authority centralities* address problems encountered with calculating *eigenvector centrality* for directed networks. First, one should decide whether the left or right eigenvector should be used. Using the left eigenvector corresponds to treating firms with central customers as central, while the right eigenvector focuses in contrast on the suppliers. Here, we use the left eigenvector, but changing to the right eigenvector is straightforward.



$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The main problem with using eigenvector centrality in directed networks is the existence of many nodes with zero centrality. The *eigenvector centrality* recursive equation for node *a* calculates the score from the centralities of its customers, that is $x_a = (x_b + x_c + x_d)/\kappa$. If we apply the same rule to the node *b*, its score x_b must be zero because it does not have any customers, likewise nodes *d* and *e*. Hence, all firms at the bottom (downstream) will be wrongly assigned centrality zero. *Katz centrality* solves this problem by allowing an importance β (commonly taken to be 1) to nodes with zero out-degree.

More importantly for supply networks, *hub-authority scores* enable differentiating between customer and supplier roles. An *authority* is a customer of important suppliers, while a *hub* is a supplier supplying to important customers. *Authority centrality* and *hub centrality* calculate the centrality in terms of each other, that is a node with high hub centrality has many customers with high authority score and vice versa. These are calculated from the eigenvectors, but not of the adjacency matrix $\mathbf{A}$, but of $\mathbf{A}^\mathbf{T}\mathbf{A}$ and $\mathbf{A}\mathbf{A}^\mathbf{T}$ for authority and hub scores, respectively. Authority scores are $x_a = 0$, $x_b = 0.447$, $x_c = 0.447$, $x_d = 0.724$, $x_e = 0.276$, while hub scores are $y_a = 0.851$, $y_b = 0$, $y_c = 0.526$, $y_d = 0$, $y_e = 0$. The authority score of node *a* is zero, because it does not have any suppliers; but it has the highest hub score because all firms, except node *e*, buy from them. Node *c* is the only node with both positive hub and authority scores, since it has both customers and suppliers.

information quickly, i.e., with smaller number of hops on the network, and can access reliable information easily (Brintrup et al., 2017; Kim et al., 2011).

Another centrality measure defined in terms of shortest paths is that of *betweenness centrality*, which quantifies how much other nodes rely on a focal node to reach other parts of the network. Closeness centrality is conceptually more relevant if the focal node is involved in generating information, while betweenness centrality concerns the function of information and relational mediation, hence a brokerage role (Brintrup et al., 2017; Kim et al., 2011; Perera, Bell, & Bliemer, 2017). The *betweenness centrality* is defined as $b_i = \frac{2}{(n-1)(n-2)}\sum_{j\neq k}\frac{M_{jk}^{(i)}}{M_{jk}}$, where the summation is over all node combinations j, k. M_{jk} is the total number of shortest paths from node j to node k, out of which $M_{jk}^{(i)}$ shortest paths go through the focal node i.[4] Betweenness centrality, when interpreted in a material flow network, is associated with operational criticality in terms of the impact of quality, delivery, and cost performance. Nodes with high betweenness centrality are crucial for smooth downstream material flows and can become bottlenecks, if not properly managed (Borgatti & Li, 2009; Kim et al., 2011; Yan et al., 2015).

Combining different centrality measures for supply networks, Shao et al. (2018) develop the *nexus supplier index* (*NSI*), which is an aggregate index of node criticality computed from *degree centrality*, *betweenness centrality*, *closeness*

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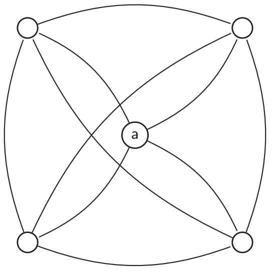
[4] This equation is normalized by the total number of node pairs $(n-1)$ $(n-2)/2$ for an undirected network. In directed networks, paths in both directions should be considered and the sum should be normalized by $(n-1)$ $(n-2)$.

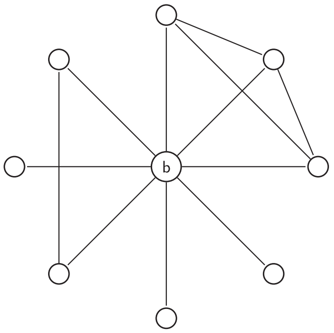
centrality, and *eigenvector centrality*. The weights of each type of centrality in the index are optimized by data envelopment analysis. Once the nexus suppliers are identified as the firms with top-k *NSI* scores, Shao et al. (2018) classify them as *operational nexus supplier* and *monopolistic nexus supplier* according to the individual centrality measure components. Operational nexus suppliers are taken to be those with high degree, eigenvector, and betweenness scores, while monopolistic nexus suppliers are the ones with high betweenness centrality, consistent with the initial heuristic proposed by Yan et al. (2015).

Similar to the betweenness centrality, the *local clustering coefficient* captures the importance of a node in acting as a mediator between its direct neighbors. *Clustering* concerns *transitivity*: If two nodes have a common neighbor, how likely is it that they are themselves neighbors? Defined for a focal node *i*, *local clustering coefficient* is the ratio of number of links between the neighbors of node *i* to the maximum number of links, that is $cc_i = \frac{\sum_{j,k\in \mathrm{N}_i,\ j\neq k} A_{jk}}{k_i(k_i-1)/2}$. Low local clustering refers to a *structural hole* position (Burt, 2009), which is typically measured by the *effective size* that reduces to $s_i = k_i - (k_i - 1)\, cc_i$ in undirected and unweighted networks (Latora et al., 2013). Another related measure is *redundancy*, which can be computed from the local clustering coefficient and degree by $r_i = cc_i(k_i - 1)$; leading to $r_i + s_i = k_i$, where k_i is the node degree. Hence, *effective size*, the typical measure of the structural hole position, is the number of nonredundant connections of a node. The neighbors of a node that occupies a structural hole position are reliant on that node to communicate with and access information from each other. A structural hole position enables efficient access to nonredundant and independent information, hence a strongly relevant network property for coordination and innovation (Borgatti & Li, 2009; Gao et al., 2015; Lu & Shang, 2017). Introducing direct links from suppliers to buyers, hence disintermediation of the focal firm, may weaken the brokerage role of the focal firm that fills the structural hole position. Introducing links between suppliers may reduce supply base uncertainty, improve reliability of information, and create opportunities for information exchange, and hence innovation, but may also lead to information redundancy and collusion of suppliers (Basole et al., 2018; Lu & Shang, 2017). Transitivity and structural hole positions in supply networks are summarized in Inset 20.4.

INSET 20.4 Transitivity and structural hole positions in supply networks

Local clustering coefficient captures *transitivity* by quantifying how likely the two neighbors of a focal node are themselves connected by a direct link. This enables answering to what extent the direct customers and suppliers are making business with each other without the intermediation of the focal firm.





Node *a* has four neighbors. The maximum number of links between the neighbors is 4 × 3/2 = 6 and all of these are attained. Hence, the local clustering coefficient $cc_a = 1$. Node *b* has eight neighbors. Out of the possible 8 × 7/2 = 28 links only 4 are realized, which leads to $cc_b = 1/7$. *Global clustering coefficient* is the mean of local clustering coefficients over the network. This means more redundancy, for instance, as a cushion against disruptions in some of the links, but also reduced efficiency.

Nodes that occupy *structural hole positions* constitute a nonredundant information channel between their neighbors. The suppliers of a firm occupying a structural hole position would be less likely to interact with each other; hence the risk of information leakage on costs is low. However, it also means that suppliers will not be collaborating with each other on product development. A structural hole position is characterized by low local clustering, and equivalently low *redundancy,* which is defined as $r_i = cc_i\,(k_i - 1)$.

5.2 Structural properties of supply networks

Several studies in the literature have evaluated common network topologies established in other fields as potential models to capture supply network structure (Hearnshaw & Wilson, 2013; Wiedmer and Griffis, 2021). In particular, supply networks were suggested to exhibit *small-world* and *scale-free* properties as well as a *community structure*.

Many real-world networks from different domains that have been studied empirically display very small *mean geodesic distance* $<d> = \frac{1}{n(n-1)}\sum_{i\neq j} d_{ij}$ despite containing thousands to millions of nodes. The mean geodesic distance is typically less than 10 and scales logarithmically with network size in many models (Newman, 2018). This is known as the *small-world* property, when combined with high network clustering $cc = \frac{6\times number\_of\_triangles}{number\_of\_paths\_of\_length\_two}$ The canonical model of small-world networks is the Watts-Strogatz model (Watts and Strogatz, 1998), which we illustrate computationally in Fig. 20.1, where for intermediate values of p networks benefit from both high clustering and short path lengths. Shorter characteristic path length is associated with efficiency and global connectivity since there are fewer sources of bottlenecks and information distortion (Hearnshaw & Wilson, 2013; Wiedmer and Griffis, 2021). Hence, the addition of links between nonconsecutive tiers in supply networks, particularly by disintermediation, can be expected to increase efficiency due to shorter path lengths. Hearnshaw and Wilson (2013) argue that high clustering contributes to efficiency because they enable cross-validation of information, facilitate coordination, and reduce opportunism.

The *scale-free* property is characterized by the type of the *degree distribution*, p_k, which denotes the fraction of nodes with degree k. In homogeneous networks, such as the Erdős-Rényi random graph model, the degree distribution is concentrated around a typical degree and decreases fast, typically exponentially, in the tail (large k). We illustrate the degree distribution of a random graph computationally in the right hand-side plot of Fig. 20.2. In contrast, heterogeneous networks, many examples of which have been reported in various domains, are found to lack such a typical value and have power-law degree distribution, at least in the tail, i.e., $p_k \propto k^{-\alpha}$ (Barabási & Albert, 1999). The power law exponent α is typically in the range $2 \leq \alpha \leq 3$, where the mean degree is finite but the degree variance is infinite. We show a power-law degree distribution with $\alpha = 3$ in the left hand-side plot of Fig. 20.2. In these *scale-free* networks, most nodes have small degree but there are a few nodes with arbitrarily high degree, i.e., they are *hubs*. The canonical model of scale-free network structure is the Barabási-Albert (BA) model, which considers a growing network where each new node connects to the

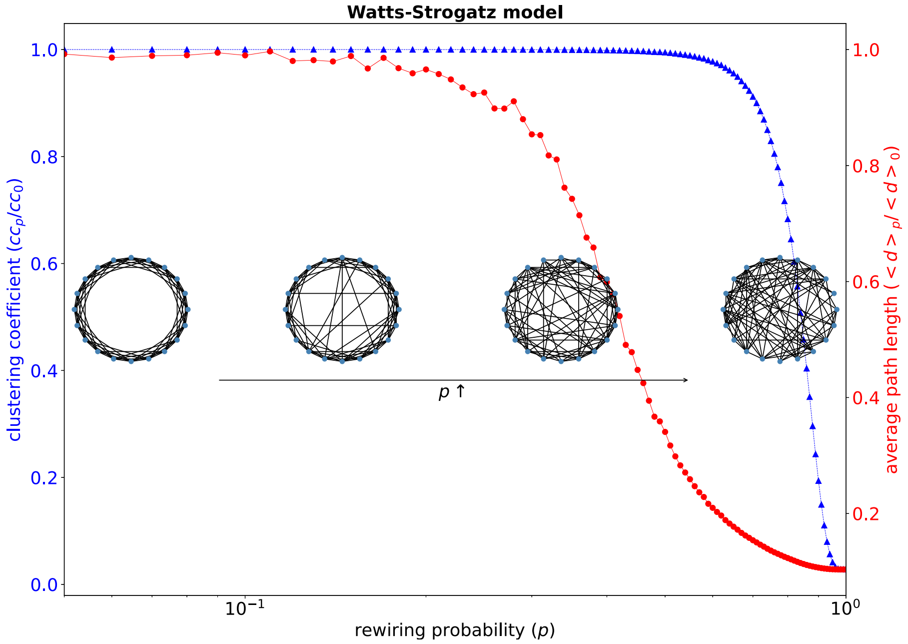


FIGURE 20.1 Watts-Strogatz model with varying rewiring rate p. Clustering coefficient cc (blue [black in print version]—triangles) and average path length $\langle d \rangle$ (red[gray in print version]—circles) are computed for different p values. We use the parameters in Watts and Strogatz (1998), i.e., 1000 nodes and degree of 10. For each p, we compute the network statistics for 100 random network realizations and average them. For $p = 0$, we start from a ring network (network visualization—first from left), where each node is connected to all nodes within some distance (five to the left and five to the right). The network has high clustering due to local connections but a high average path length because it requires many steps to reach other nodes on the opposite side of the ring. As p is increased, some links are rewired, creating short cuts between otherwise distant nodes (network visualization—second from left). This leads to a decrease in the average path length $\langle d \rangle$, while the clustering coefficient persists at high values as most connections are still local. For intermediate p, there is an ideal balance between local connections and random connections, which provides high clustering and low average path length, respectively (third network). If the rewiring rate is high, it converges to a random graph (fourth network), for which the clustering drops as well.

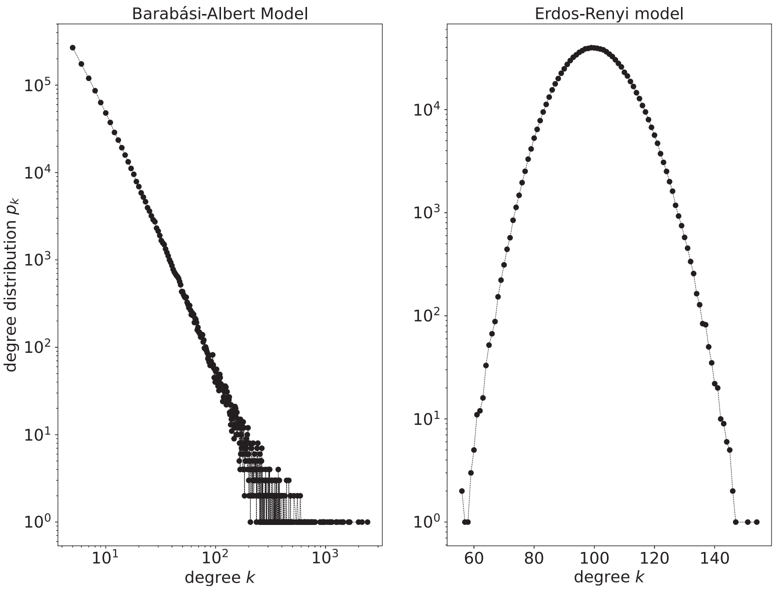


FIGURE 20.2 Degree distributions in the Barabási-Albert model (left - $N = 10^6$, $m = 5$) versus the Erdős-Rényi random graph model (right - $N = 10^6$, $p = 10^{-4}$). In the Barabási-Albert model, the simulation starts from a small network. At each time step, the network grows by the addition of a new node. The new node establishes m links with the existing nodes with probability proportional to their degree, i.e., a link is formed with the existing node i of degree k_i with probability $k_i / \sum_j k_j$, where the summation is over all existing nodes at that step. This is called the *preferential attachment* mechanism, according to which nodes with higher degree get more and more links as the network grows. This leads to the power-law degree distribution with exponent 3, i.e., $p_k \propto k^{-3}$. Therefore, there are some nodes in the tail that can have arbitrarily large degrees, hence the name scale-free network. This is in contrast to the Erdős-Rényi random graph, where pairs of nodes are connected with a uniform probability p. This leads to a homogeneous network with approximately Poisson degree distribution centered around the mean degree, i.e., $(n - 1)p$.

existing nodes with a probability proportional to their degree, known as the *preferential attachment* mechanism (Barabási & Albert, 1999). In the BA model, nodes that join earlier have higher expected degree (early mover advantage) and the clustering coefficient decreases as the network grows. The scale-free structure has been seen as representative of the typical hub-and-spoke supply network structure (Wiedmer & Griffis, 2021) and a consequence of the increased efficiency through the coordination of the hubs (Hearnshaw & Wilson, 2013). However, there are also several opposing mechanisms. Power laws are truncated due to finite size effects, limited supplier management resources of firms, and the reluctance of firms to connect with powerful hubs (Hearnshaw & Wilson, 2013). Characteristics of firms, such as financial and operational performance and size, are known to affect the choice of partners, which can be captured by models that use preferential attachment with respect to a fitness score, not purely degree (Hearnshaw & Wilson, 2013; Perera et al., 2017).

Hearnshaw and Wilson (2013), Wiedmer and Griffis (2021), and Osadchiy et al. (2021b) claim extended supply networks exhibit *community structure,* according to which different groups of firms with common interests, latent characteristics, and functions form densely connected clusters. There are many ways in which community can be defined mathematically and detected algorithmically. Here, we restrict our interest to the most commonly used method of *modularity maximization* and refer the reader to Fortunato and Hric (2016) and Newman (2018) for other approaches and details. *Modularity* is a quality score for a given partitioning of the network into communities and the *community detection* seeks to find the partition that maximizes this quality score. *Modularity* is high if there are many links within the communities and few between the communities, which is mathematically expressed as $Q = \frac{1}{2m}\sum_{ij}\left(A_{ij} - \frac{k_i k_j}{2m}\right)\sigma_{g_i g_j}$. The variable g_i denotes the community of node i, while $\sigma_{g_i g_j}$ is the Kronecker delta function, i.e., if nodes i and j are in the same community then $\sigma_{g_i g_j} = 1$, otherwise it is zero. Since the problem is NP-Hard, heuristic methods are used. The most popular is the *Louvain algorithm* (Blondel et al., 2008), which is an agglomerative algorithm that starts with assigning each node to a community on its own and then iteratively merges communities until the modularity does not increase further. In Fig. 20.3, we show the community membership for the industry network of US-based publicly listed companies, computed from the Louvain algorithm.

Several studies have empirically tested the existence of these network properties and structures in real-world supply networks. Brintrup et al. (2016) report that the supply network of the automotive industry has low mean geodesic distance, and modularity and clustering scores higher than the random graph model, but the network is not scale-free (exponential degree distribution). Brintrup et al. (2017) show that the degree distribution of Airbus's extended supply network follows a power-law with an exponential cut-off. They identify a community structure where the hubs connect different communities that demonstrate some concentration with respect to geographical location, supply chain tier, and products/parts supplied. Wiedmer and Griffis (2021) present a comprehensive analysis of extended networks between publicly listed US-based companies. They find evidence for scale-free topologies, with power law exponents in the interval $2 \leq \alpha \leq 3$ in most cases; low mean geodesic distance but clustering coefficient lower than random graphs; significant community structure with high modularity; and a hierarchical network structure, which combines community structure with scale-free

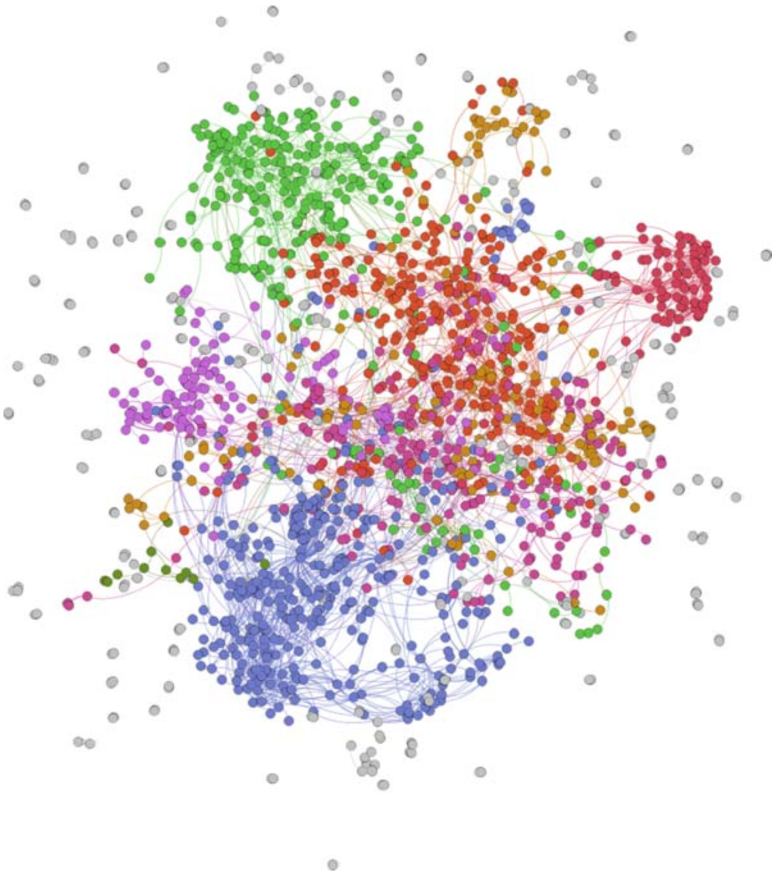


FIGURE 20.3 Network visualization by community membership for the industry network of US-based publicly listed companies. The buyer–supplier relationships between all firms in year 2019 are based on the Compustat Supply Chain Suite dataset. The graph visualization is made in Gephi with the force atlas layout. The network is partitioned into communities by the Louvain algorithm. Different colors highlight distinct industrial communities, which include firms along supply chains as well as the same industries.

topology where hubs connect communities and the local clustering coefficient decreases with the node degree. Hence, there are mixed results in the literature, but as a general observation, the more "extended" the supply network is, i.e., including more tiers as well as indirect suppliers and customers from different industries, the more support for scale-free and community structure is found.

The studies above consider single snapshots of supply networks. Osadchiy et al. (2021b) analyze the time evolution of global supply networks. Consistent with the trends of increasing outsourcing and product complexity, they find that the mean degree has increased over time. They identify stable communities that feature companies from related industries (groups of firms along the supply chain, instead of concentrated in a single tier and industry). Communities have become more fragmented over time, that is no large communities managed to overhaul and integrate the network. Instead the concentration decreased and the number of communities increased over time. Consequently, some firms with abnormally high betweenness centrality that constitute bridges between the fragmented communities have emerged.

6. Effects of network structure on performance

Several recent studies in the literature have analyzed the impact of local and global network structure on the performance and the dynamics of firms, using empirical methods as well as simulation models. Here, we briefly review the findings in three areas that have received particular attention: (i) impact of network structure on operational and financial performance, (ii) impact of network structure on resilience, and (iii) impact of supply network structure on innovation.

6.1 Network structure and operational and financial performance

Lu and Shang (2017) and Bode and Wagner (2015) empirically analyze the impact of structural complexity of the supply base, the visible and manageable part of the supply network, on financial and operational performance. Among the direct buyers and suppliers of a focal firm, Lu and Shang (2017) distinguish between the "visible" part of the network and the "invisible" part (links in which the focal firm is involved vs. not involved) and analyze their impact on financial performance. They show that the visible network's horizontal complexity (number of first tier suppliers) has an inverted U-shape effect on financial performance, while the vertical complexity (depth of the supply base) does not have a significant effect. The spatial complexity (number of countries in the supply base) has a U-shaped effect, where only truly global firms with a diverse global supplier portfolio benefit from global sourcing financially. Bode and Wagner (2015) show that the number of disruptions increases with the horizontal, vertical, and spatial dimensions of complexity, while the different dimensions amplify the effects of each other. The not-so-visible network includes (i) links from suppliers of the focal firm to its customers, which introduces a disintermediation risk and has a negative but diminishing effect on the financial performance, and (ii) links between the suppliers of the focal firm, which increases cooperation opportunities and has a positive and diminishing effect (Lu & Shang, 2017).

A key aspect of operational performance is the bullwhip effect, which corresponds to the distortion of demand information by firms, i.e., higher variability of a firm's orders than its demand, and the upstream amplification of demand variance. Osadchiy et al., 2021a empirically analyze the bullwhip effect in supply networks and show that firms benefit from adding customers, removing customers, and rewiring their existing connections by reduced aggregate demand variability, beyond the law of large numbers, which acts in the opposite direction to demand distortion. Hence, firms can leverage and restructure their local network to improve their operational performance. Demirel et al. (2019) analyze material flow networks using generalized modeling, a dynamical systems method from ecology, to identify nodes of high importance and sources of network-induced instabilities beyond the bullwhip effect. They show that cyclic motifs, caused by not-so-visible links, and competition between different prime entities for limited products at upper tiers destabilize the flows. Bidirectional links in product flow networks are shown to be influential on network dynamics. Demirel et al. (2019) demonstrate contrasting effects with changing network complexity: limited supply availability stabilizes supply networks for individual prime entities, while they destabilize industry-level supply networks.

6.2 Network structure and resilience

Supply networks have grown and been shaped by drives mainly to decrease costs and increase efficiencies and production capabilities through globalization, elongation, specialization, and removal of redundancies according to lean principles (Perera, Bell, & Bliemer, 2017). However, these trends and the overall increased complexity of supply networks tend to increase vulnerability (Bode & Wagner, 2015; Zhao et al., 2019). In particular, due to interdependencies between suppliers, risks propagate on the supply network (Wang et al., 2021). Wang et al. (2021) show empirically that the risk of a focal firm increases with the risk of its second tier suppliers and the sharing of the second tier suppliers by first tier suppliers, which leads to correlations in the risks of first tier suppliers.

Supply network resilience, that is the ability of supply networks to remain connected, maintain their function, and sustain their performance despite disturbances and disruptions, has attracted particular attention in the supply chain management literature (Ivanov & Sokolov, 2013; Kim et al., 2015). Several studies have assessed the impact of supply network structure on resilience (Brintrup et al., 2016; Kim et al., 2015; Perera, Bell, & Bliemer, 2017). In particular, scale-free networks are known to be resilient against random failures, but fragile against attacks that target highly connected nodes (Albert, Jeong, & Barabási, 2000). This finding has been echoed in several supply chain management studies that applied these theoretical results to a supply chain context (Kim et al., 2015; Perera, Bell, & Bliemer, 2017). For instance, based on simulations with random removal of nodes (firms), Kim et al. (2015) show that scale-free networks are more resilient than block-diagonal networks, which are characterized by high modularity. Perera et al. (2017) review the metrics that have been used to measure the resilience of supply networks. The most common metric used in different disciplines is the size of the LCC of the nondisrupted part of the network. Network diameter and mean geodesic distance of the LCC characterize the ease of accessibility. To add more supply chain realism, the *largest functional subnetwork* concept is introduced that corresponds to the LCC with at least one supply node (Perera, Bell, & Bliemer, 2017). Brintrup et al. (2016) combine supply networks with product networks and measure the resilience in terms of *assembly completeness*, that is the availability of the number of parts/systems required for assembly after the disruption. Sokolov et al. (2016) show how to quantify the ripple effect in supply chains using network connectivity, complexity, reachability, and centralisation analysis.

The studies reviewed above do not capture the adaptive nature of supply networks, that is firms redistribute the load and rewire their links in response to experienced and/or perceived network failures or significant changes in the supplies and/or demands on the network. Based on simulations parametrized from secondary network data, Zhao et al. (2019) show that reactive strategies, where firms rewire their links once their first tier suppliers are disrupted, greatly reduce the impact of disruptions, essentially showing that the effect is overestimated in models in which this adaptive nature of the network is not captured. They further show that the resilience of a supply network under a proactive strategy, which involves arranging in advance backup suppliers for those specific first tier suppliers that are most likely to be hit by distant disruptions, improves the resilience further.

6.3 Supply network structure and innovation

Supply networks act as incubators of innovation through providing access to novel information and other resources, mediating long-term cooperations, facilitating valuable and tacit knowledge sharing between firms, early supplier involvement in design, and supplier integration (Basole et al., 2018; Bellamy, Ghosh, & Hora, 2014; Gao et al., 2015; Potter and Wilhelm, 2020). Recent empirical literature provides insights about the impact of the strength and abundance of supplier relationships and the uniqueness of information, characterized by different network measures. Bellamy, Ghosh, and Hora (2014) show that the innovation output of a firm increases with network accessibility, measured by *information centrality*, while its effect is positively moderated by the interconnectedness of the suppliers, measured by density of the ego network or local clustering coefficient in the extended network. Similarly, Basole et al. (2018) show that the innovation output increases with access to information, measured by eigenvector centrality, and interconnectedness, while the two variables interact positively. Gao et al. (2015) find that technological diversity among suppliers promotes innovation, which is positively moderated by the strength of the relationships between suppliers but negatively moderated by the local clustering coefficient. Hence, firms occupying a structural hole position with low local clustering benefit more from technological diversity between suppliers due to their access to unique information and their gate-keeping role. Chae et al. (2020) differentiate between general innovations and the innovations that matter for an original equipment manufacturer (OEM) and show that innovations valuable for the OEM are more likely when prolonged relationships are established with culturally similar suppliers. Suppliers that have higher *structural equivalence* with their OEMs, measured by the fraction of the number of common neighbors between an OEM and a supplier to the number of all neighbors, are more likely to contribute valuable innovations.

Potter and Wilhelm (2020) analyze co-patenting by suppliers in Toyota's supplier network, showing that the in-degree centrality of the supplier promotes the number of its co-inventions with other suppliers through absorbing knowledge from a larger supply base. The effect is found to be negatively moderated by both the local clustering coefficient, hence positively by the structural hole position, and also the closeness centrality of the supplier. Therefore, suppliers in the periphery of the network tend to engage more in co-inventions. Mazzola et al. (2018) contrast structural hole positions, which enable exploring nonredundant and novel information in the concept development phase of new product development, and network central positions, which enable the reliable exploitation of inputs from more information sources in the commercialization of the concept. They show that firms effectively switch between these positions in supply networks, which enables them to benefit from both exploration and exploitation. Bellamy et al. (2020) show that administrative environmental innovations positively affect environmental disclosures by enabling systems that track, standardize, and share data about environmental impact of firms' and their supply chains' activities. They show that network accessibility, measured by closeness centrality, and control over information flows, measured by betweenness centrality, have positive moderating effects on this relationship, while interconnectedness has an inverted U-shape moderating effect.

7. Conclusions

In this chapter, we have introduced the fundamentals of network analysis. In addition to establishing definitions of key network concepts and methods, we provided a discussion of their meaning in a supply chain context. We briefly reviewed theoretical models proposed for describing and analyzing the topology of supply networks and the characteristics of large-scale real-world supply networks. We presented contemporary results on the effects of supply network structure on operational and financial performance, stability, risk, resilience, and innovation. We close by identifying four major gaps in the literature and recommending related directions for further research.

First, empirical research on supply networks has proliferated in the past five years with the availability of secondary data sets. However, these data sets do not provide precise information about the products that flow on these networks (see Section 3). More granular and closer to real-time data are needed for more accurate empirical analysis of supply networks. We can expect the digitalization trend in general, and digital twins (Liu et al., 2021) and blockchains, in particular, to generate new sources of network data. The availability of such data, together with the application of anonymization and network reconstruction algorithms, will provide a better understanding of the structure of supply networks and more extensive empirical and computational investigations.

Second, as outlined in Section 6, different metrics measuring distinct aspects of network position, e.g., degree centrality, betweenness centrality, closeness centrality, and effective network size, have been shown to be associated with differing aspects of firm performance. However, these different measures tend to be highly correlated with each other. Hence, more research is needed to understand the mechanisms through which the structure affects the function in supply networks. We anticipate more theoretical and empirical research on the modeling and the analysis of the impact of the supply network structure on firm performance.

Third, studies in the extant literature have mostly considered static network measures and their relationships with firm performance. Recent studies show that dynamic processes on supply networks and the adaptive network restructuring affect and help determine network stability (Demirel et al., 2019), resilience (Zhao et al., 2019), and product development (Mazzola et al., 2018). Dolgui et al. (2020) introduce the concept of X-network and argue that dynamic restructuring of supply networks is crucial for contemporary businesses. Similarly, Osadchiy et al. (2021a) find that firms manage their customer base by adding/removing supplier links, effectively mitigating the extent of the bullwhip effect along supply networks. Despite the importance of establishing and estimating the causal effects of the managerial and policy decisions that impact firm performance through supply network restructuring, there is limited theoretical, mathematical, and empirical research on the dynamics of supply networks, which we anticipate to become a major research direction. We expect the application of related network science methods and modeling frameworks, such as adaptive networks, temporal networks, and nonlinear time series analysis, to help in addressing this gap in the literature.

Fourth, the supply network analysis literature has predominantly analyzed different types of connections in isolation from each other. However, different types of interactions occur simultaneously and in an interdependent way. Such systems can be modeled as multilayer networks (Boccaletti et al., 2014) with for instance supply, competition, and partnership layers. Future research in this direction can be envisaged to explain the co-evolution of these different dimensions of interfirm relationships and their impact on firm and network performance.

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Chapter 21

Deployment considerations for implementing blockchain technology in the pharmaceutical industry

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Abstract

Blockchain is a technology that has found promise in the supply chain and logistics sector, offering an approach to establishing distributed ledger (DL) functions to centrally processed transactions in a decentralized manner. This feature may enhance regulatory compliance and product fulfillment in pharmaceutical supply chains. This chapter reviews primary applications in processing pharmaceuticals, including tracking and tracing of product necessary to assure integrity and safety, inventory management, and clinical trial efficacy. Based on industry reference models, issues emerge regarding how a DL effectively scales with transaction volume. An illustrative example demonstrates how a DL consolidates transaction volume and stabilizes variability, focusing on transactions related to exceptional situations such as those related to returns, commissioning issues, delivery disturbances, and recalls. While a DL can consolidate pairwise communication between trading partners, the net effect of this replacement diminishes as transaction rates and variability grows throughout the network. Furthermore, we demonstrate how capacity savings grow with network size, but gradually approach a maximum level. While a DL can stabilize transaction variability as transaction rates increase, the capacity savings gradually decrease. Future research areas include studies to corroborate results, explore data management, permission and access methods, partner collaboration, and implementation costs.

Keywords: Blockchain; Blockchain scaling; Distributed ledger technology; Pharmaceutical distributed ledger.

1. Introduction

Blockchain is a technology concept that can find general purpose applications across many vertical industries, providing benefits by building upon existing business and operational models. Blockchain was first introduced in a seminal work (Nakamoto, 2008). Blockchain is based on a social source of truth versus, a lone source, through a shared decentralized database model instead of a single centralized database system. It is a trust protocol built on elements of networking and cryptology that can be used to ensure trust without necessarily using an intermediary or central authority. In this respect, it can be used to create a reliable distributed ledger (DL) of record describing who owns what, and who transacts with whom. It is predicated on the simple idea that if everyone witnesses, believes, and agrees to something, then it is authentic and irrefutable. These features could generate enormous opportunities for innovating supply chain operations. While there are protocols, such as IOTA (Popov, 2019) and Hedera Hashgraph (Baird et al., 2018), that are known to support DL implementation, blockchain has emerged as a frontrunner for adaptation in supply chain operations.

2. Blockchain overview

Blockchains are implemented on a distributed network of computers, called nodes, with each node representing a participant in the blockchain. The size of the network is indicative of trust among the parties. Blockchain is basically a bookkeeping method that chains together ledger entries so that they are very difficult to modify later. This enables groups

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of unrelated parties to jointly keep a secure and reliable ledger of transactions that record a transfer of custody of information between two parties. Instead of a central system, a shared protocol is utilized employing consensus algorithms so that all nodes agree upon what data comprise the legitimate blockchain.

Each new transaction takes all the information from the previous transaction, including a unique key, and creates a new key, or cryptographic hash, which in essence is a digital fingerprint that is irreversible. Update or deletes (read/writes) of a transaction are denied and are locked using private keys. Transactions are collected in blocks and organized in a tree structure known as a Merkle tree (Lamport, 1979). Prior to adding a transaction to a block, the identity of the party publishing the transaction is validated by other parties on the network and may also require the event or transaction itself to be validated by the others. The rules governing the consensus process can vary with the type of blockchain implementation, such as Bitcoin, Ethereum, Hyperledger, and others (Lashkari & Musilek, 2021).

Implementing blockchain requires special application software to establish governance of the blockchain. This includes enabling organizations to select the desired open blockchain standard (such as Bitcoin, Hyperledger, or other), establish and trigger transactions, choose the appropriate communication protocols, size the peer network, select the cryptographic methods, and define the flooding and consensus algorithms, among other things. To minimize upfront capital investments and provide an easy low risk adoption of blockchain technology, cloud-based blockchain-as-a-service offerings are appearing (Sankar et al., 2017).

Fully private or permissioned blockchains are used in situations where all participants on a blockchain already have a degree of trust among them. They are more efficient since they do not involve any reliance on miners (designated nodes charged with adding blocks) and assume that all network nodes are trusted, thereby reducing verification costs. The identity of those nodes adding blocks is known and assigned by the organization. This also has the advantage of more compatibility with preexisting privacy and compliance requirements. Currently, there are numerous alternative blockchains, DLs, and/or blockchain-related software products being developed and marketed (TechnoDuet, 2021).

Blockchain is an enabler for maintaining symmetric information across a network. It can provide an alternative to realizing a consistent view of the same information distributed across many nodes using the principal of "once and done." Simply put, once a transaction is completed, it cannot be repudiated. Embedded within the hash value is transaction history information which cannot be easily altered or compromised, thereby making the information immutable. This proof of provenance renders the information as trustworthy when viewed by different participants at different nodes. The distributed nature of blockchains is somewhat counter to the concept of large centralized databases. This feature eliminates the need for an intermediary system to house a centralized image of a piece of information, leading to cost savings in transaction verification and auditing (a concept known as costless verification). It also discourages transaction validation costs from outpacing transaction benefits, which is characteristic of information asymmetry (Catalini & Gans, 2016).

3. Supply chain benefits of blockchain

Fundamental to blockchain is its ability to solve issues of trust. These include digitally recording a software-based transaction execution that has occurred between two entities and rendering the record irrefutable. When one considers the numerous kinds and volume of business transactions that occur on a daily basis, this fundamental capability can have profound impacts. Transactions such as land titles, loans, sales, intellectual property, procurement, identities, quality certification, votes, contract fulfillment, document verification, and so on lend themselves to this kind of capability. In addition, these features have lent themselves to adaptation for supply chain operations.

At the heart of a blockchain's appeal for use in the supply chain is the smart contract, which in essence is a self-executing contract (Min, 2019). It is a set of logic based on rules that govern business transactions that are embodied within computer software and distributed across a blockchain network whose nodes represent supply chain participants. When executed, the logic determines if and how a transaction is posted to the blockchain. For example, smart contract logic might check to see if an invoice from a registered agent has been reconciled with purchase orders and then send payment to a supplier when a shipment is received, signaled via the blockchain fabric, which is the software system running the core blockchain functions.

The smart contract process begins by determining what items get recorded in the DL. The ledger would serve as an audit trail for the material. A key question is what variables are needed to characterize the transactions, how is the asset to be digitized, and what variables are required by both parties to assure proof of provenance. This has to be agreed up front by all parties. Those variables that are agreed upon are then included in the ledger.

If one of the parties breeches the ledger and tries to alter the chained information, this would prevent the next transaction from being chained or added to a block due to a nonconsensus situation (exception handling for these scenarios would need to be further defined). Moreover, if one of the parties breeches the ledger and tries to alter the nonchained

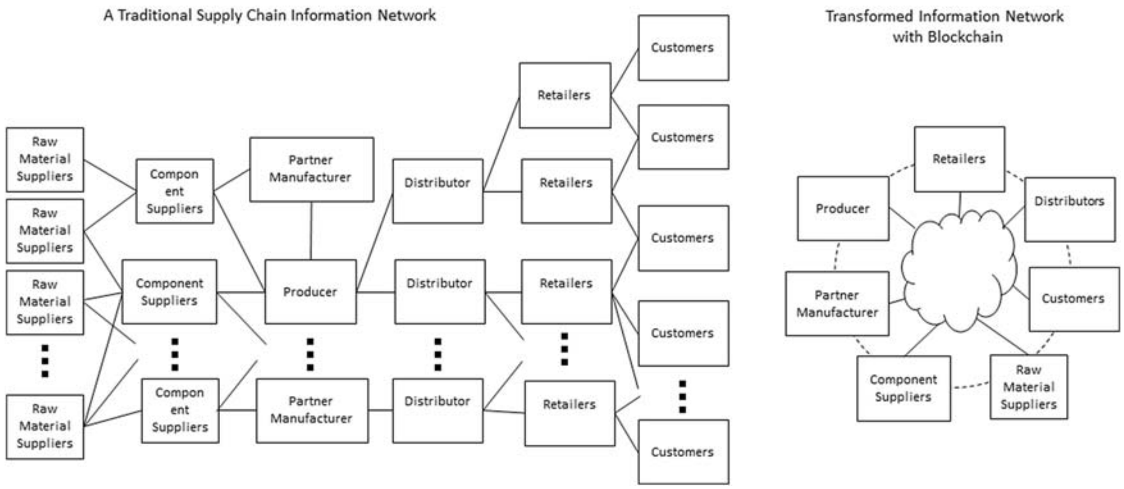


FIGURE 21.1 Transformation of a traditional supply chain information network with blockchain.

information, then the system must determine how to handle this situation. For example, perhaps the chain is recomputed when this occurs and it is determined that it has been altered, leading to another nonconsensus situation. The chain fabric in use would have to determine how such circumstances are handled.

Blockchain's potential extends far beyond cryptocurrency applications and is already viewed as an underlying mechanism that can improve supply chain efficiency and efficacy (Min, 2019). Logistics requires complex international regulations that govern the movement of goods across the globe, tying up inventory and creating the overhead costs of managing the movement. The information involved is voluminous and is prone to error or corruption between the intermediaries involved, due to the information asymmetries that are present.

Fig. 21.1 shows the transformation of a traditional supply chain network into a blockchain DL network. In the traditional multitier supply chain network, the movement of data through the network often mimics the flow of goods. In a DL environment using blockchain, all data and information can be shared in a decentralized fashion, with all parties seeing the same data. This eliminates the need for each supply chain partner acting as an intermediary between adjacent partners in sharing information. In the strictest sense, permissioned nodes must be able to view transactions to be able to approve or reject them, but this depends on the nature of the supply chain application.

The ability to bestow instant trust within recorded transactions can lend itself to improving efficiencies within the many functions that are characteristic of supply chain operations, including monetary exchanges, operational transactions, contracting and sourcing, among others, without the exclusive need of a centralized system. The fact that it serves as a DL enables end-to-end documentation to track and trace where and how materials are sourced, purchased, allocated, and used. Transparency and accountability can thus be improved, and materials can be more easily authenticated with regard to their source and quality. This can accelerate the flow of goods, help control product recalls, and provide additional transparency into logistics activities. More vertical integration would be motivated since the costs associated with moving information between partners would be reduced with the improved transparency provided by the DL (Pan, 2016).

4. Pharmaceutical industry applications

The pharmaceutical supply chain network is typically complex, as was shown in Fig. 21.1. Relationships with contract manufacturers and distributors further compound this complexity, which often blurs the manufacturers' multitier end-to-end visibility (Ellis, 2020). It has also limited the agility of supply chain players to adopt new practices and technologies, often leading to inconsistent adoption, with a tendency toward functional local or siloed, versus end-to-end, solutions. The underlying complexity poses collaboration challenges between players, often inhibiting realization of nonholistic solutions. The pharmaceutical industry was significantly affected by the COVID-19 pandemic, with widespread shortages, degradation of on-time in full delivery performance, and cost increases. Applications of blockchain in the supply chain of pharmaceutical products thus emphasize hardening of transaction data to enhance visibility into some of the critical areas of need: tracking and tracing, supply integrity, inventory and product safety. While doing so could avoid the challenges experienced during the pandemic, visibility into these areas is only as good as the quality of the data foundation, as with all information technology.

4.1 Track and trace

Information asymmetry and inconsistency is ever present between supply chain participants, creating obstacles to tracking specific transactions and goods. Tracking is the ability to identify and locate the movement of a product through the supply chain. While tracking capabilities have advanced over the years, strides in tracking information technology can provide the foundation for tracing. The International Organization for Standardization defines tracing as the ability to trace the history, application or location of an entity using recorded identifications (Stranieri et al., 2017). Traceability requirements for food and drugs are increasingly becoming mandatory in many countries. There are thousands of third-party companies that are paid to provide research on the movement of pharmaceuticals, posing a financial burden in the manufacturing supply chain (Bhardwaj, 2018). Such expense could be offset with a blockchain based DL.

Downstream participants will often require recorded identifications regarding a product, including its assembly process, material lists, and precautionary warnings. Quite often, the integrity of a product's transaction history requires extensive processes and controls which are not easily achievable. Used in conjunction with a DL, the transfer of goods between two parties, identified as two addresses in the blockchain, can be recorded. The transaction would include additional information such as location, date, price, and quantity. A blockchain can render each transaction record as irrefutable, enabling all parties who access the ledger the ability to trace ingredients or components to their legitimate place of origin (Lohr & Popper, 2017). While this presents an enormous opportunity for blockchain, it is not without challenges.

Serialization is the assignment of unique traceable numbers to individual items. Products need to be serialized to follow the product and conduct verification at certain points as it moves through the supply chain to ensure its legitimacy. Many countries require that such information is reported to a responsible government agency and/or other supply chain partners. In the pharmaceutical industry, this information is often required to be retained for about 12 years. The GS1 standard, established by the Internet Corporation for Assigned Names and Numbers (ICANN), is used by much of the world to establish a standardized method of serialization. It employs a two-dimensional (2D) barcode which contains a variety of information, including the company's Global Trade Identification Number (GTIN), a product identifier, expiration date, and additional data (Tracelink, 2015). Work is underway to associate barcodes with blockchain hash values, such that a product's transaction history can be traced. A pharmaceutical industry level initiative is underway to address this need relative to compliance with federal regulations. This is discussed later in this chapter.

4.2 Supply integrity and safety

Drug safety in the pharmaceutical supply chain focuses on how drugs are manufactured. The traceability of active pharmaceutical ingredients during the manufacturing process can be challenging. Thus, detecting drugs that do not contain the intended active ingredients can ultimately avoid patient harm. The number of deaths related to these issues has been increasing in recent years. The issue of supply provenance has already been ongoing within the food industry, with about 10% of people falling ill or dying from contaminated food each year (Diaz, 2017). In addition, counterfeit or illegitimate food products cost consumers millions of dollars. However, the problem of provenance of supply is not only restricted to food and drugs but includes a wide variety of goods including clothing, diamonds, automotive and electronics, among others. The complexity of today's supply chains makes it difficult for retailers, producers, and consumers to verify the authenticity of a product's ingredients and components, nor uncover any wrong-doings with regard to ethical sourcing, child labor, counterfeiting, and other unscrupulous and/or illegal methods used in creating the product.

Blockchain's traceability features, as discussed above, enable the traceability of drugs from manufacturer to patient, and the ability to identify where breaks occur during the processing of the medication in the supply chain. So, for example, a transaction record of a shipment of a particular product arriving at a factory could be chained and stored in a DL, together with information about the product, factory, and other pertinent details, to remain available for verification when needed. Such details could include quality control data, temperature, shipment and delivery dates, safety certifications, and even the credentials of the employees carrying out specific tasks. These applications can also leverage sensor technology that can measure characteristics such as shock, temperature, and humidity and record this information within the ledger. Depending on the nature or value of the product, such information could be used to detect potential product damage. Key conversion steps occurring along the way from supply to customer, such as sterilization and disinfection, could be recorded and coded in the ledger. This not only can improve product safety but it can also reduce trace times from days to seconds, which can consequently lead to operational cost savings.

In addition, blockchain integrated within a DL can enhance the recall management process of informing players within the supply chain, as well as the public, of pharmaceuticals that have been retracted from commerce. Up to one million people are killed each year worldwide as a result of recall errors (Bhardwaj, 2018), thus the better tracking of product through the supply chain would have a significant effect. Furthermore, the data stored in the ledger can be used for descriptive analytics to identify production bottlenecks, and more cost-effectively support product safety audits. Consumers may be able to detect the integrity of a product by simply scanning the product's code.

4.3 Inventory management

As previously discussed, managing inventories based on demand requires proper visibility into the supply chain. Furthermore, due to the COVID-19 pandemic, the perceived integrity of demand forecasts has deteriorated. While inventory is usually a popular means of safeguarding against forecast uncertainty, timely visibility into inventories of finished goods is required to aid against drug shortages. The vast number of incompatible systems across the entire supply chain, from the ingredient supplier to pharmacies, further obfuscates real-time access to data and visibility. When forecasting accuracy becomes questionable, a countermeasure is to perform more frequent and granular planning at the transaction data level. Blockchain technology could improve transaction data integrity, and when integrated within a DL, and can overcome the incompatibilities across systems. This could potentially improve visibility into the inventory of wholesalers, and allowing manufacturers to manage their inventory levels with shorter lead times, and be better prepared for spikes in demand (Bhardwaj, 2018).

4.4 Clinical trial management

Many use cases for integrating blockchain into the clinical trials have been entertained (Bhardwaj, 2018). Those that have the most significant potential is the supply chain of large molecules and clinical kit management. As more biotech companies develop large molecule medicines from a variety of sources, there is a need to identify and validate molecules along the various points on the supply chain of the final product. These medicines are sophisticated biopharmaceuticals of molecular sizes far greater than typical chemically synthesized drugs, thus requiring very specific storage and processing requirements. The aforementioned track and trace capabilities afforded by blockchain can serve this need. Another use case involves providing patients with proper clinical kit management practices, whereby patients must be monitored and tracked for compliance with prescribed medication regimens. Doing so would provide more accurate results from clinical patient studies. Thus overall, a blockchain decentralized ledger can enhance the management of clinical studies as well as improve the integrity of the study results.

5. Pharmaceutical blockchain reference model

Blockchain has been viewed as a technology to underpin the cautionary actions for the production and distribution of pharmaceuticals. While tracking and tracing is necessary due to the increased use of counterfeit drugs (Scott et al., 2018), tracing an exception or nonconformity upstream through the supply chain can be quite challenging due to limited information exchange between tiers, special sharing agreements between trading partners and regulatory restrictions. Yet, traceability is necessary to guarantee product authenticity and integrity, and to reduce the risks associated with counterfeiting and product contamination.

One major opportunity for blockchain has arisen from regulations enacted in 2013 by the United States Food and Drug Administration (FDA) as part of The Drug Quality and Security Act (DQSA). In particular, Title II of the DQSA is the "Drug Supply Chain Security Act" (DSCSA) which was enacted by the US Congress to outline steps to build an interoperable system to identify and trace certain prescription drugs as they are distributed (Scott et al., 2018). The main purpose of this legislation is to protect consumers from drugs that may be counterfeit, stolen, contaminated or harmful. Counterfeit medications in the pharmaceutical supply chain pose a major financial and humanitarian threat for all parties involved. More than 100,000 annual deaths related to counterfeit medications have been reported by the World Health Organization with total estimates as high as one million (Scott et al., 2018). Counterfeit medications cost the pharmaceutical industry $40 billion annually and the market continues to grow as indicated by a record 25 million illegitimate medicines apprehended by Interpol in 2017 (Scott et al., 2018).

In light of this, the DCSCA addresses licensing and registration requirements for all members of the supply chain and a consistent traceability requirement for pharmaceutical products from manufacturers to dispensers in the US Members of the pharmaceutical supply chain are expected to confirm the chain of ownership, identify and address suspicious activities, and respond quickly to information requests made by enforcement officials. The DSCSA requires wholesale distributors and third-party logistics providers to report licensure and tracing information annually to the FDA. By 2023, Title II is expected to produce a digital, interoperable traceability framework for pharmaceutical products allowing for faster and more efficient identification of illegitimate drugs before they can cause harm to patients.

The GS1 standards group, as previously mentioned, has issued a standard called the GS1 Electronic Product Code Information Services (EPCIS), for DSCSA lot-level management, serialization, and item-level traceability. This involves sharing data between manufacturers, wholesalers, repackagers, and pharmacies (both hospitals and retail) in the form of transaction information, transaction history, and transaction statements at the lot (or batch) level of identification. Transaction information includes, among other information, the product name, number, lot information, and information relating the transfer of ownership. Transaction statements certify the integrity of the party transferring ownership. Item serialization requires manufacturer and repackagers to serialize packages of drug products using a product identifier, either a GTIN or National Drug Code, and serial number, lot number, and expiration date. Serialized item-level traceability requires making available information that would allow supply chain partners to trace the ownership back to the original manufacturer or repackager.

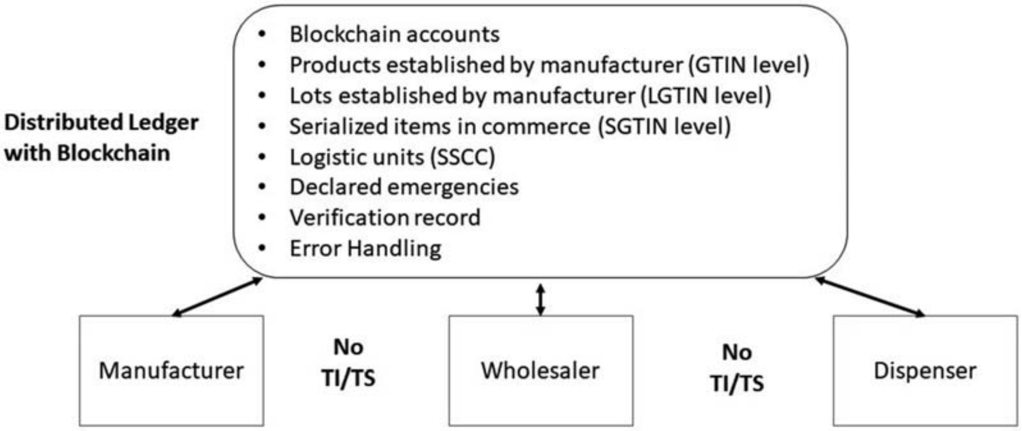
The Center for Supply Chain Studies organized an initiative involving many pharmaceutical industry players to develop a standard reference model to identify the extraction of information from EPCIS transactions involving a pharmaceutical to a shared blockchain to comply with DSCSA requirements (Center for Supply Chain Studies, 2018). The issues with developing such a model centered around the determination of what information should be chained (on-chain) versus kept off the chain (off-chain). Several issues became apparent:

- It was found that it was infeasible and impractical to store all serialized EPCIS transactions (e.g., commissioning, packing, shipping, receiving) between trading partners, due to the volumes of information that would have to be processed and stored.
- Such information could be appended so that it can be used for operational purposes as well as by trading partners. It would be necessary to identify which information would satisfy the common needs of trading partners.
- While the DSCSA requires sharing transaction information with a focus on chain of custody between trading partners, it is not necessary that all detailed transaction information must be ledgered and accessed by everyone. In fact, many times partners will be reluctant to share data that they do not wish to disclose.
- The transaction information or transaction statements to be on-chained should be such that the exchange of the same information outside the blockchain would not be necessary.
- An additional identifier called the serial shipping container code could be useful in identifying logistic units (i.e., containers) for traceability.

The greater the complexity of traceability standards, the greater the number of transactions that will be required to be efficiently managed by an overarching system, fostering the need for greater capacity (Stranieri et al., 2017). For this reason, and for the reason that the information need not necessarily be shared across all trading partners, an alternative approach was examined. Instead of on-chaining all transactions, the resulting reference model was formulated and is illustrated in Fig. 21.2. It is based on the strategy of transforming and condensing transaction data off-chain into agreed upon transactional state tables that can be efficiently on-chained. States can be defined, such as fit for commerce, in-commerce, provenance, or whether the item is DSCSA exempt. Transactions can be referenced, if needed, using pointers or addresses versus storing all the transaction's information within the blockchain DL down to the pallet, case, or package level. Thus, the blockchain serves as an extension of localized transaction data to augment centralized information.

Enacting the reference model within the EPCIS framework also revealed some additional issues. These include error and exception processing (e.g., replacing an erroneous on-chain transaction with a new one); creating additional transactions for chaining (e.g., documenting the verification check of a drug); the handling of different GLN identifiers for the same transaction partner due to state law requirements; and the ability to verify transaction partners in the case of a saleable return. This last scenario involves how a manufacturer can verify whether a received return originated from an authorized nonadjacent downstream trading partner. This would require an implicit indication accompanying the product that it was originally placed into commerce by the manufacturer and is not counterfeit.

In the case of a temperature-sensitive drug there are also cold chain requirements which necessitate that a drug be placed in a temperature-controlled environment to maintain the efficacy of the drug. While sensor and/or smart product label technology can be used to produce indications as to when a product undergoes a temperature excursion during its movement through the supply chain, sharing of such information with pertinent trading partners can be challenging. The above DSCSA reference model served as a foundation on which cold chain exception handling can be supported.



GTIN	Global Trade Identification Number
SGTIN	Serial Global Trade Identification Number
LGTIN	Lot Global Trade Identification Number
TI	Transaction Information
TH	Transaction History
TS	Transaction Statements
SSCC	Serial Shipping Container Code

FIGURE 21.2 DSCSA proposed blockchain reference model.

5.1 Implementation issues

Despite the implementation costs associated with blockchain, the DSCSA mandates are motivating the pharmaceutical industry to innovate and absorb blockchain solutions within their traditional supply chains. The more immediate reasons driving this effort is to enhance the traceability of pharmaceuticals, ensure verification and safety of returned products with the intent to resell, and ultimately minimize the distribution of counterfeit drugs. These objectives warrant the need to classify transactions that characterize these exceptional situations during the course of processing, controlling, and distributing pharmaceuticals. While there are numerous other possible disturbances that could arise (Huq et al., 2016), only transactional events resulting from the exceptional situations of major concern would be stored on the DL.

The concerns center around retrieving transaction information data back to the manufacturer, which could require vast amounts of transaction between unconnected or unfamiliar supply chain participants. Blockchain's inefficiencies in distributing data at scale and limited existing real-world solutions beyond proof-of-concepts (Center for Supply Chain Studies, 2018) have raised concerns about its ability to handle the huge volumes of EPCIS transactions associated with processing the multitudes of pharmaceuticals transacted on a regular basis. Studies have shown that blockchain has low-moderate setup costs, moderate-high costs for adding transactions versus traditional systems (Babich & Hilary, 2018). Nevertheless, blockchain, implemented as a DL system, could better fill the need to enable track and trace of exceptional transactions, versus all transactions, among participants who are not directly connected (Center for Supply Chain Studies, 2018).

The following are general categories of exceptional transactions that might be suitable for tracking using a blockchain DL.

5.2 Authenticity nonverification

Verification requirements are mandated by the DSCSA requiring wholesalers to verify authenticity of prescription medications, particularly those that have been returned and intended for resale. (In the United States over 50 million units are returned each year with an intent to resell.) This requires confirmations that the product was purchased directly from the manufacturer, exclusive distributor of the manufacturer, or repackager that purchased the product directly from the manufacturer. The inability to meet the verification requirements could lead to substantial loss for wholesalers and possibly the entire supply chain.

5.3 Nonsaleable returns

The DSCSA requires wholesalers to verify, for any returned product that they determine is saleable, the identity of the manufacturer who originally placed that product in commerce. If a party returns product to the sending party who finds that the items are not saleable (expired, recalled, damaged, etc.), that party must either return the items to the party they received them from (manufacturer or another wholesaler) or transfer them to a party designated to process returns. This party destroys the product and provides information of the destruction to the manufacturer.

5.4 Improper commissioning

A party that receives product must verify that the product received placed into commerce, or commissioned, by the manufacturer. Receipt of a noncommissioned product, or other information indicating that the product should not be treated as saleable, would require noting.

5.5 Information flow interruption

Interruptions in information flow that disrupt the processing throughout the supply network might require transactions with alerts to the effect. Such disturbances could arise from information technology mismatch issues, and could result in incomplete transactional information and inhibit the ability to track and trace exceptions. The proliferation of non-standardized systems could result in communication problems between trading partners causing incomplete or delayed information. For example, the DSCSA requires that a trading partner cannot receive product without also receiving proper DSCSA mandated information. One party might batch process their information causing the transaction information to be available several hours after the product is delivered. The receiving party indicates that the transaction information is not available and must process the product only up to the point of shipment. Prior to use, that party must verify that the Transaction Information (TI) from the sending party is available and that the item was commissioned by the manufacturer.

5.6 Delivery disturbances

Of concern are disruptions due to numerous causes, such as quality, environmental, health, safety, transportation, or other issues leading to the untimely delivery of transactions or mismatched transactions. Mismatches between demand and supplier responsiveness can easily be transferred from one player to another, since pharmaceutical manufacturing could involve multiple players each providing active pharmaceutical ingredients, product formulation, packaging, and distribution across different countries. The opportunities for delay are thus quite real and may require exception handling if product efficacy is threatened.

5.7 Unfit for commerce

There are many events that would indicate that a product was not fit for commerce (such as recall, damage, expired product, temperature excursion, determination of illegitimacy, etc.). Quality defects typically arise from unforeseen and random interruptions arising from process disturbances in manufacturing, such as machine break downs or defective raw materials. In addition, temperature-sensitive drugs must be placed in temperature-controlled environments, as was earlier described. Any cold chain excursions could destroy the efficacy of a drug (Huq et al., 2016). Such disturbances would thus need to be recorded.

5.8 Error processing

EPCIS contains an error declaration element to indicate that an EPCIS event was in error. Such errors arise when logistics units are sometimes packed incorrectly, shipments arrive at the wrong destination, etc. Logging such errors would help resolve discrepancies between what happened and what was recorded as happening.

5.9 Security and confidentiality

In general, a trading partner should be permissioned to post information to a DL. Standards may need to be developed for compliance of trading partners to post and access data in a DL. Ensuring that transaction information data are accessible to only those that have, or have had, ownership of a product might require handling of digital signature exchanges or other authentication methods. For example, situations might arise where a party may need to access the DL for a product in question. That party may need to calculate a hash value of their local view of the related data and match it against the blockchain version of the hash value to identify the appropriate transaction. Confidential data from prior transactions would have to be redacted or removed if it was not intended to be shared with those who were not party to a transaction.

5.10 Recall

A recall should alert a trading partner whether anyone in the supply chain had posted an exception that would render a product unusable (recall, damage, expired, etc.). This would cause them to not sell, transfer, dispense, or administer the product. Recalls are typically made at the lot level. The exception would advise of the lot in question and provide a means of obtaining more information.

5.11 Declared emergency

The DSCSA contains provisions where transaction information and transaction statement sharing can be suspended in the event of a declared emergency. This kind of exception would be noted, and which product was part of the emergency so as to not render that product illegitimate after the emergency.

5.12 Counterfeits

Each legitimately commissioned item should have one and only one EPCIS entry. If a duplicate occurred, this exception would need to be noted in the DL if another transaction for the same product was created.

6. Scaling issue analysis

Keeping information centralized across multiple participants in a supply chain should be weighed against the benefits of decentralization. Centralized databases are often used to support multipoint versus pairwise (or bilateral) information exchange. If the operational and storage costs of centralizing data with shared write access is excessive, then this could present an opportunity for replacing the centralized database with a blockchain-based DL. A blockchain protocol could provide the mechanisms to receive and distribute information across a network and keep that information synchronized so that everyone sees the same thing, thus serving as an internal reflection of trust. In turn, this would eliminate the costs of using intermediaries to provide a centralized data service.

In a supply chain, which typically involves creating, reselling, and moving items between various parties and locations, transaction history regarding exceptional situations can be extremely valuable. Transactions generated from different parties who depend on each other will require a specific sequence or timing of events. If a significant number records must be maintained but without being changed, reordered, or deleted, as in the case of exceptions, a blockchain-based DL can provide a cost-effective alternative to centrally maintaining transaction records. Depending on the nature of the ledger, information can be made to be both transparent and publicly accessible. It is for this reason that a blockchain-based DL could be well suited to handle exception-based transactions. The merits of doing so lie in the ability to pool transactions by buffering multiple sources of variability that would not necessarily occur simultaneously across pairs of trading partners in a supply chain. This overall reduces the likelihood of extreme values of capacity needed to handle the transaction volume (Hopp, 2011). While this concept is not new, it is fundamental to understanding the benefits of blockchain as a more cost-effective means of establishing DLs versus conventional technology.

In the context of this analysis, we define exceptions as transactions that pertain to abnormal circumstance regarding the product whether mandated by the DSCSA, special agreements or for operational reasons. As described above, exceptions may include whether the product was improperly made, unfit for commerce, recalled, returned, expired, or required inspection or investigation, or had its provenance compromised in some way, perhaps through a temperature excursion. Additional assertions might include whether the product is under DSCSA compliance or required for a declared emergency. Relative to the massive volume of pharmaceuticals that are exchanged each day, exception volumes can represent at least 2%−3% of sales (Morris, 2018), amounting to about $6 billion annually (Irish, 2010). Additionally, counterfeit drugs can amount to $200 billion in annual cost (Irish, 2010). Thus, any ability to improve exception handling can yield huge savings for the industry.

6.1 Illustrative example

To illustrate the above point, we use a simple network comprised of the pharmaceutical trading partners of a specific product or product class, as shown in Fig. 21.3. Shown are six trading partners sharing information via a DL which is synchronized using a blockchain protocol. The mechanism would be deployed as a smart contract, which is a set of logic based on rules that govern business transactions. The rules are embodied within computer software that is distributed across a blockchain network whose nodes represent supply chain participants. When executed, the logic determines if and how a transaction is curated and posted to the blockchain. The software is deployed as a distributed application (Dapp) which is accessed by each trading partner. Dapps serve as agents that interact with the blockchain fabric on behalf of a party. They can be activated on a platform of choice, such as a computer or networked appliance or reside on a cloud, based on the type of use of the contract. Dapps view the blockchain and update it based on events and conditions that they continuously monitor per those defined by the smart contract. For reasons previously stated, the network is designed to handle transactions related to exceptions. Not shown are off-chain databases that are individually owned and operated by the trading partners, which might interface with a Dapp to exchange exception-related information with the DL.

We assume that exceptions occur at random and have a relatively low rate of occurrence, and thus employ a Poisson discrete probability distribution for modeling the number of transaction exceptions produced between trading partners in a fixed unit of time which in this case is 1 day:

$$P(x,\lambda) = \begin{cases} e^{-\lambda}\displaystyle\sum_{i=0}^{x}\frac{\lambda^i}{i!} & ; x \geq 0 \\ 0 & ; \text{otherwise} \end{cases} \tag{21.1}$$

where $P(x,\lambda)$ is the cumulative probability (or percent of transactions) served by x units of transaction capacity and λ is the mean rate of transactions per day. For a Poisson distribution, it follows that λ also equals the variance of the distribution,

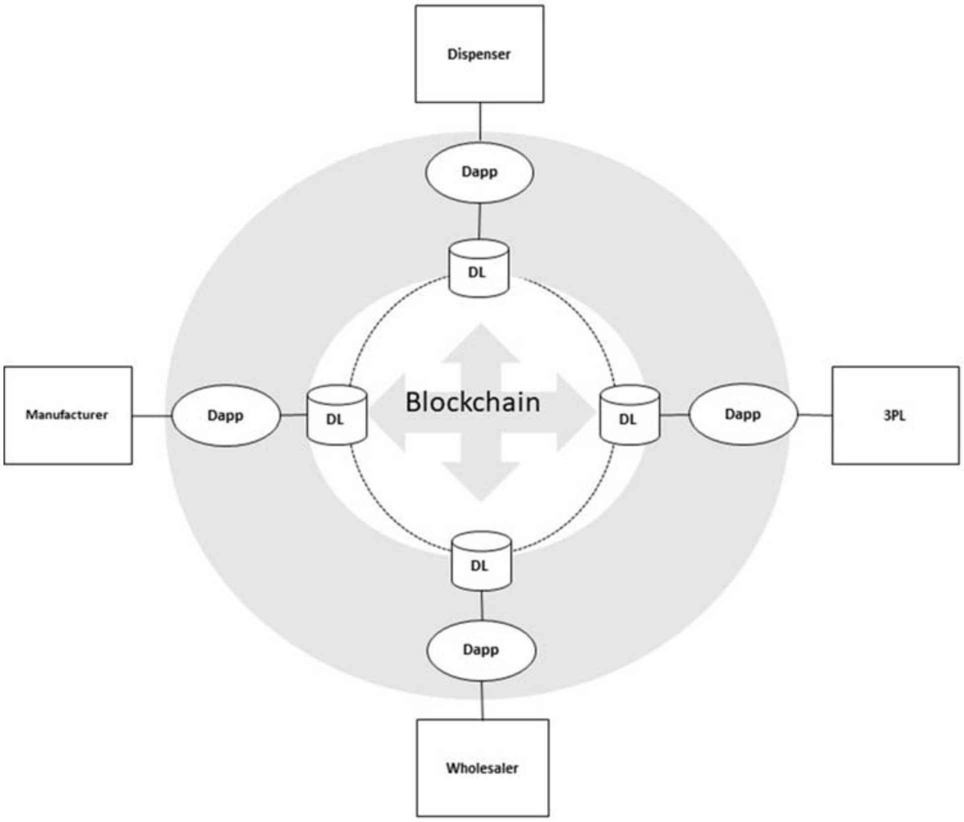


FIGURE 21.3 Illustrative example.

TABLE 21.1 Pairwise daily transactions for illustrative example.

Pair	Partner	Partner	λ
1	Manufacturer	Wholesaler	40
2	Wholesaler	3 PL	25
3	3 PL	Dispenser	15
4	Manufacturer	Dispenser	20
5	Manufacturer	3 PL	30
6	Wholesaler	Dispenser	20
		Total	**150**

and that the time between transaction originations follows an exponential distribution with mean $1/\lambda$. For large values of λ (e.g., $\lambda > 1000$), the Normal distribution is a suitable approximation to the Poisson.

Table 21.1 lists the assumed daily transaction levels between each pair of trading partners. We assume that transactions are exchanged independently between trading partners. In practice, this may not necessarily be the case since partners may decide to restrict information from each other for a variety of reasons. However, a system designed to accommodate transactions between parties, such as an enterprise resource planning system, will likely require the capacity to handle the potential of a wide variety of pairwise transactions.

In a pairwise network where transactions are exchanged independently between N pairs of trading partners, the system capacity x_j required to serve pair j will be $P_j^{-1}(\alpha, \lambda_j)$, where α is the service level or percent transactions to be served by the network and λ_j is the mean transaction rate in pair j. Thus, the system capacity X to serve all transaction pairs in the network can be characterized as

$$X = \sum_{j=1}^{N} P_j^{-1}(\alpha, \lambda_j) \tag{21.2}$$

Similarly, we can characterize the consolidated capacity, $\widehat{X}$, using a DL system as

$$\widehat{X} = P^{-1}\left(\alpha, \sum_{j=1}^{N} \lambda_j\right) \tag{21.3}$$

While this expression implies that capacity and variability are pooled by a centralized DL, in reality the DL is distributed and shared across the network nodes using blockchain.

Applying this model formulation to the illustrative example, we obtain the following results as depicted in Fig. 21.4. Here we show the total transaction system capacity required in both the pairwise and DL scenarios versus the service level α. Overall, it shows how the DL can require far less capacity for the same range of service levels.

In Fig. 21.5 we calculate the percent capacity savings as $(X - \widehat{X})/X$ versus the growth in the mean transaction rate $\overline{\lambda}$ which is the mean transaction rate across all pairs in the illustrative example. Thus, as the transaction rate grows, the percent capacity savings diminish asymptotically across all service levels. In this analysis, we assume service levels α ranging from 0.99 to 0.99999. Greater savings are achieved at higher service levels. The reasoning behind this is straightforward—to provide higher service levels a system will require greater capacity. A system based on a blockchain-based DL replaces direct communication between pairs of trading partners with centralized communication, thus a net benefit is achieved through pooling. But the net effect of this replacement diminishes as the transaction rate and consequently variability grows throughout the network.

6.2 Generalized example

We now extend the findings from the illustrative example to a more generalized situation in order to show how a trading partner network scales with increases in both members, transaction load and consequently variability. In the extreme case there will be $N = n(n-1)/2$ pairs of trading partners in the network, where n is the number of trading partners. In this

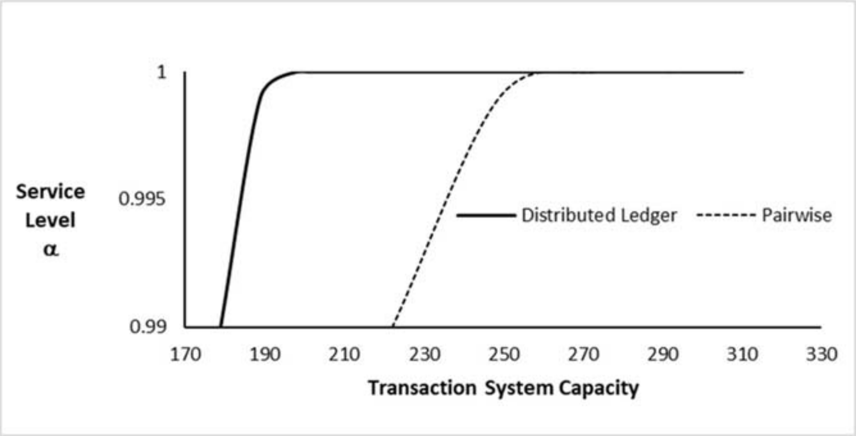


FIGURE 21.4 Distributed ledger versus pairwise performance.

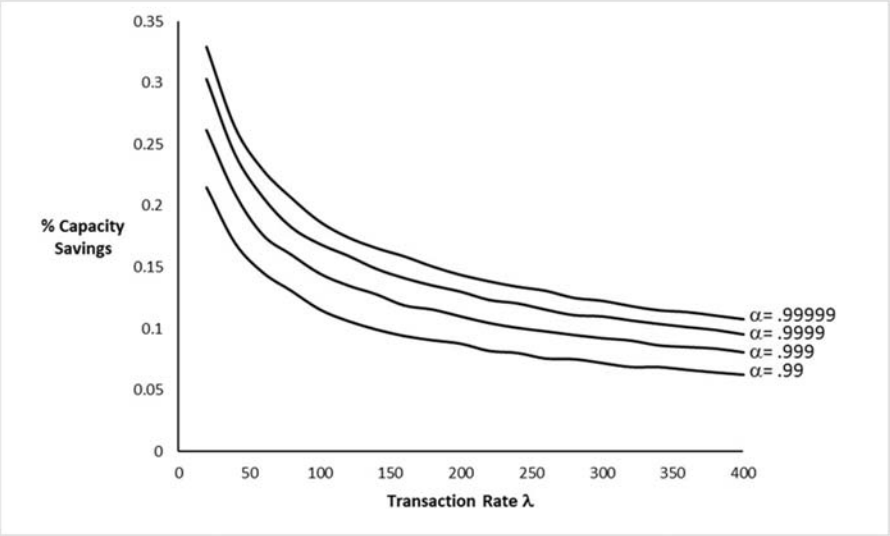


FIGURE 21.5 Capacity savings using a distributed ledger.

example, we increase both the number of trading partners n and the mean transaction rate $\overline{\lambda}$ across all trading partner pairs. Fig. 21.6 and 21.7 illustrate the difference in network capacity scaling between the pairwise and DL scenarios for two different transaction load levels at service level $\alpha = 0.9999$. Comparing both figures, we can see how the capacity differential reduces substantially at higher transaction load levels. In each case, the differential becomes more constant with network size. This behavior is illustrated in Fig. 21.8, where we compare the percent savings in capacity offered by the DL. As seen in the figure, the savings grow asymptotically with network size and decrease with transaction rate, but yet remain significant. The likely parameter values and transaction levels for a typical pharmaceutical supply chain is subject for further research.

The coefficient of variation CV is the ratio of the standard deviation to the mean and is often used to characterize the relative variability of a network (Pound et al., 2014). The impact on variability, as measured by the CV, is shown in Fig. 21.9 for a network of $n = 52$ trading partners for different levels of transaction rates $\overline{\lambda}$ at service level $\alpha = 0.9999$. In the generalized example, the coefficient of variation for the pairwise network is simply $CV = \sqrt{\overline{\lambda}}/\overline{\lambda}$ and for the generalized network is $CV = \sqrt{N\overline{\lambda}}/N\overline{\lambda}$. While CV will naturally decrease with increasing mean, here we compare the relative rate of decrease between the two scenarios. The ability of the DL to dampen variability at various transaction rates is quite evident and diminishes slightly with increasing transaction rates, yielding more stable variability.

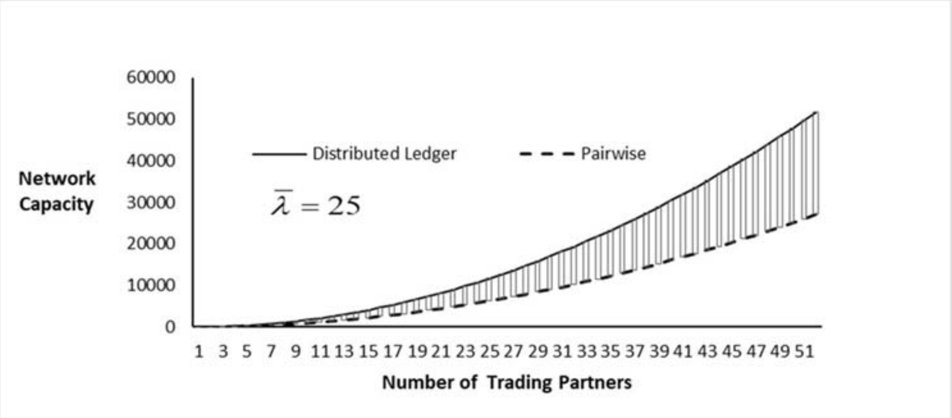


FIGURE 21.6 Capacity differential at low transaction rate.

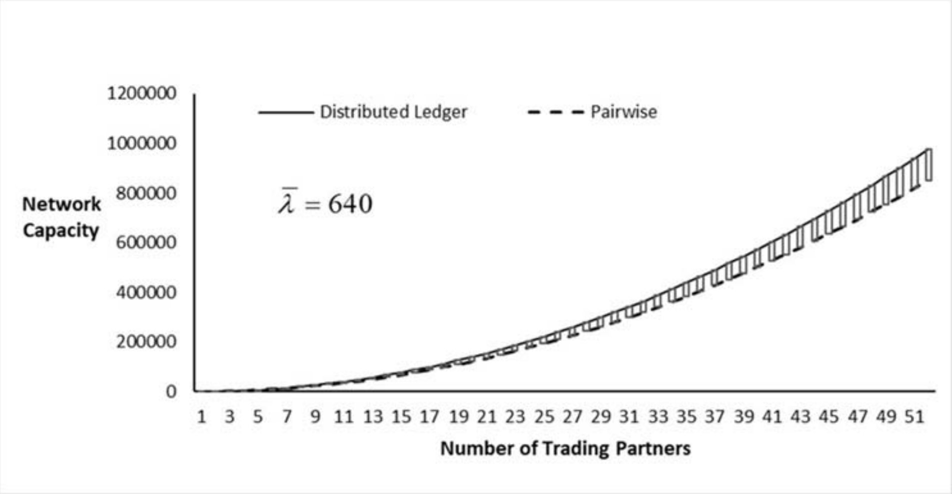


FIGURE 21.7 Capacity differential at high transaction rate.

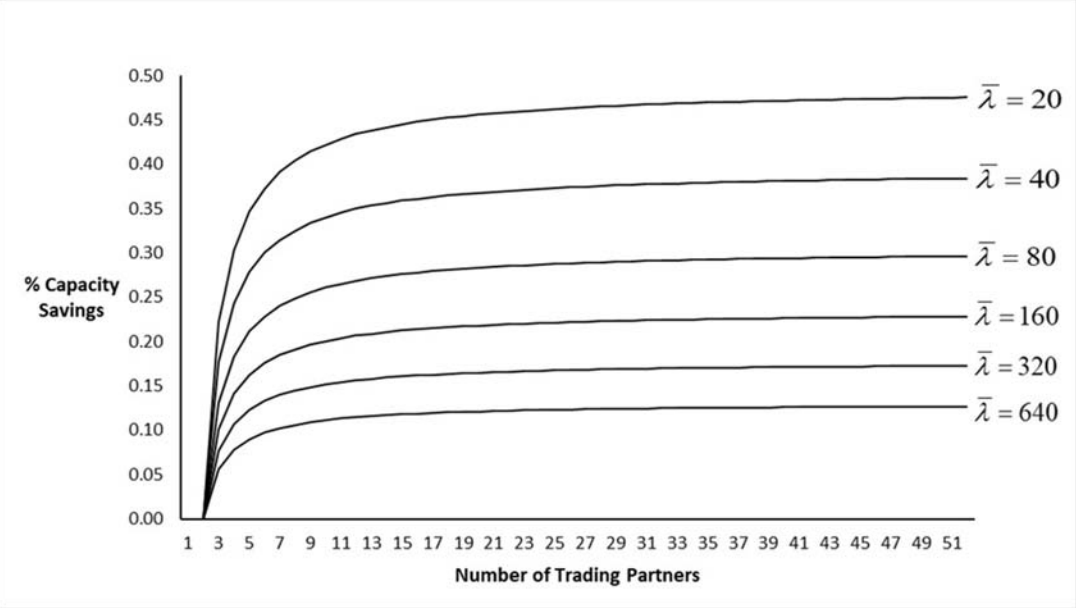


FIGURE 21.8 Capacity savings at different transaction rate levels.

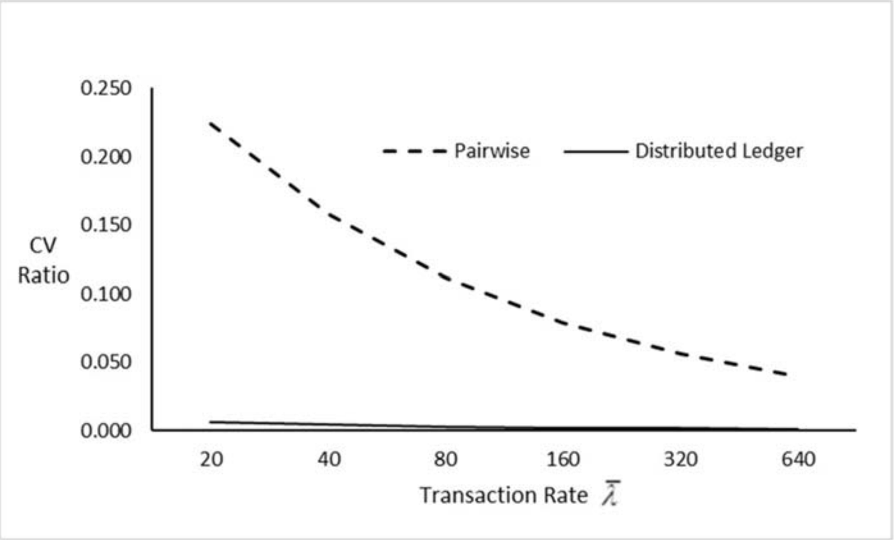


FIGURE 21.9 Effect of distributed ledger on variability.

This analysis demonstrated several characteristics of the ability of a blockchain-enabled DL with regards to its ability to save system capacity due to concentration and pooling effects:

- A DL can provide the same range of service levels using less capacity.
- As transaction rates grows, the capacity savings from the DL will diminish asymptotically across all service levels.
- Capacity savings grow with network size but gradually approach a maximum savings level. The level of savings decreases with increasing transaction rates.
- A DL will also stabilize transaction variability across increasing transaction rates.

In summary, the capacity benefits of using a blockchain-based DL are asymptotic with network size and transaction traffic. Table 21.2 summarizes the results for the generalized example where it is shown that maximum savings of up to 13% can be achieved in a large heavily loaded network. It should be noted that further research is necessary to determine the effects of transaction dependency on these results, since the analysis assumed that transactions were independent.

These preliminary findings can have implications with regard to blockchain justification and deployment offerings, particularly in the logistics field. Blockchain's ability to more effectively realize DL solutions could foster offerings that can more economically support transactions versus systems built for bilateral interactions, that are typical of a multitier supply chain. The savings can translate into greater capacity and reduced per user system licensing costs versus conventional approaches. Additionally, utilizing a blockchain-based DL for very focused applications, such as exception handling, can leverage the features of the technology in a practical way. By enabling interoperability between existing trading partner databases and the DL, information sharing can be enhanced by augmenting, versus replacing, existing capabilities resulting in a more economical and feasible solution approach, thereby facilitating adoption.

TABLE 21.2 **Results for the generalized example.**

Transaction rate $\bar{\lambda}$	Maximum achieved capacity savings	Reduction in variability
20	48%	22%
40	38%	15%
80	30%	11%
160	23%	8%
320	17%	5%
640	13%	4%

7. Research areas for implementation feasibility

The barriers toward the assimilation of blockchain in operations within the pharmaceutical industry center around trade partner collaboration in building, owning, and sharing DLs containing sensitive transaction data, presumed technology onboarding costs, clarity regarding appropriate use cases and scalability, as previously noted. These issues set the stage for some general areas of forward-looking research.

7.1 Scalability and data management

Scalability issues need to be further studied beyond the analysis portrayed in this chapter, using actual or simulated transactions drawn from real-world case studies to identify realistic parameter values and transaction levels. The scalability issue is also accompanied by the question of data storage requirements that might be envisioned, even for transaction exceptions. Blockchain platforms are not currently designed to efficiently store, index, and retrieve vast amounts of data. This has called for investigating architectures that entail locating routine transactional data off the blockchain, yet keeping it accessible to distributed applications on the blockchain. In this scenario, the blockchain DL would be reserved to handle special situations, such as the exceptional events cited above. This would aid in reducing the potential volume of query and retrieval activity on the blockchain through indexing of the DL data to the mainstream data to support track and trace situations. It would also reduce the amount of required resources necessary for supply chain partners in order to trace exceptions.

7.2 Data obfuscation

Data obfuscation is intentionally built into blockchain using embedded hashing to assure transaction immutability. An efficient method of correcting information in an immutable DL can pose a challenge. Erroneous transactions posted in the DL would need to be corrected by creating transactions that would somehow offset, undo, correct, or replace these. The DSCSA is a traceability-only law, prohibiting supply chain trading partners to unobfuscate data. Proper protocols would need to be developed such that a series of transactions can be intelligibly replayed during a trace effort. In concert with this, analysis is required to determine what data can remain unobfuscated on the blockchain. Various obfuscation techniques need to be explored that can obscure certain data items without limiting the ability of approved parties to selectively query the DL.

7.3 Permission and access

Investigation is required in overcoming the permission and access issues to enable relevant supply chain parties to view information on products commissioned and shipped by a manufacturer on the blockchain. This requires developing efficient methods to ensure data confidentiality and sharing data without inadvertently exposing proprietary information in a trustless fashion. Obfuscating vast amounts of transactions can result in a significant key management issue for supply chain trading partners, since any loss of keys could disrupt transaction, and consequently, product flow. Thus, encryption, signing, and digital key exchange and management within the overall data exchange and storage process need to be explored.

7.4 Collaboration

Collaboration challenges between both upstream and downstream nonadjacent supply chain players are an issue which inhibits expediting DL solutions that must straddle multiple companies. These challenges are mainly attributed to issues in sharing data, which is critical to visibility. As blockchain is inherently a collaboration platform, capabilities need to be further explored that can be oblivious to trading partner agreements or conflicts of interests (Center for Supply Chain Studies, 2018). These methods would seek to maintain confidentiality per supply chain trading partner agreements when using a shared DL. Parallel to this issue is the agreement among the sharing supply chain parties on rules governing handling of transactions, for example, which events should be shared or what data elements should be redacted. Such rules would need to be enacted and validated by the software code running the smart contract or DL.

7.5 Cost models

As presumed upfront implementation costs of blockchain are of concern, research is needed to explore the long-term cost-offsets of implementation that would prove it to be viable. Funding a platform that is shared across multiple supply chain players can offset onboarding costs by spreading them across the players, and consequently the risks as well. But possible fiduciary arrangements need to be explored than can enact this sharing. Membership fees, volume-based subscriptions, and transactions are among those models that have been considered, but further work is needed to identify arrangements that are best suited and most viable for different scenarios. These analyses should also be accompanied by identifying the kinds of built-in mechanisms that can be used to support each model to sufficiently pay transaction processing, connectivity, and data storage. For example, since blockchain platforms are not designed to efficiently store, encrypt, and retrieve large amounts of data, many charge a premium for storing and transacting data over a specified limit. Alternatives to such arrangements might need to be investigated.

7.6 Comparative studies

The DCSCA mandate has pressured supply chain players to consider alternative conventional solutions which might seem more cost-effective at first, but can be extremely resource intensive. Small-scale pilots should be encouraged to assess the long run resource utilization and costs associated with blockchain for DCSCA compliance, versus conventional or hybrid solutions involving both traditional and selected blockchain capabilities.

8. Summary and conclusions

While the benefits of blockchain have been widely published, the business case for a blockchain implementation is hard to justify, especially within the pharmaceutical industry sector. There are numerous trials going on in industry to demonstrate the possible benefits and caveats of blockchain use in supply chain and logistics operations (Smith, 2018). In this analysis, we investigated the potential of justifying a blockchain implementation simply on the merits of the capacity saved from consolidating transactions within a DL. While the concept of a DL is not new, blockchain is viewed a cost-effective enabler for a DL versus other approaches. It has been recognized in the case of a pharmaceutical that ledgering all product transactions within a DL may not be practical due to system limitations and information sharing constraints among trading partners.

Instead, ledgering only those transactions related to exceptional situations may be more feasible in enabling compliance with DSCSA. As the previous analysis demonstrated, a blockchain-enabled DL solution to these issues has the potential to provide savings simply with respect to system capacity, and ultimately system costs. Future work should entail further verification of the findings of this analysis using more descriptive models of pharmaceutical networks. This should include examining the impact of product mix on the DL, versus having a distinct DL for a single product or product group. Furthermore, the work should also involve evaluating options for segmenting transactions by trading partner groups or closed user groups based on special agreements, recognizing that trading partners can choose to share data based on their individual business arrangements.

In conclusion, the DCSCA mandate within the pharmaceutical supply chain has created a real opportunity for implementing blockchain. Small-scale pilots can help discern the benefits and drawbacks of blockchain implementation, and discover opportunities to scale in the future. By pursuing blockchain solutions, the pharmaceutical industry will likely develop capabilities and expertise that may translate to other potential applications within pharma. Blockchain has the potential to enable a more transparent and secure means of handling data across the pharmaceutical supply chain, which can ultimately improve patient safety and bring supply chain players closer together (Ledger Insights, 2019).

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Chapter 22

Digital supply chain surveillance: concepts, challenges, and frameworks

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Abstract

In this chapter, we define and conceptualize the emerging practice of "Digital Supply Chain Surveillance (DSCS)" as the proactive monitoring of digital data that allows firms to track, manage, and analyze information related to a supply chain network using available data and information sources. DSCS has potential applications in risk management, supplier performance management, production planning, inventory optimization, quality management, supplier financing, and cost reduction in supply chains. Artificial Intelligence (AI) is potentially a key enabler and may facilitate a step change in DSCS. We present a framework, SDAR (Surveillance, Detection, Action, Response), to support the design of effective business processes for supply network surveillance. We outline the most important types of AI algorithms and models and discuss their applicability to a range of questions that arise in DSCS. By linking different surveillance data sources and systems, appropriate AI techniques can make surveillance easier, more informative, and scalable. However, AI-based DSCS gives rise to significant technical, ethical, and managerial challenges. These include the decomposition and reintegration of surveillance data and analyses, data imbalances, mitigation of biases in data, algorithms and statistical estimations, and the challenge of embedding DSCS in effective supplier monitoring and auditing processes.

Keywords: Artificial intelligence; Data analytics; Digital supply chains; Machine learning; Resilience.

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1. Introduction

The horsemeat scandal in the United Kingdom and Ireland in 2013 began with the administration of new DNA tests to identify the animal origin of meat in supermarket beef products and quickly led to the discovery that food products from major retailers contained traces of other species (The Guardian, 2013). The scandal raised many concerns about a relatively simple supply chain. How could such contamination occur from farm to fork and who was responsible for ensuring that it did not happen? How should such a supply network be policed to ensure integrity of supply and guard against malpractice? More generally, a wide range of concerns have been raised on ethical and environmental practices in many other supply chains, including chocolate, garments, and minerals (Kim & Davis, 2016; UNECE, 2021; Whoriskey, 2019), which have impaired corporate reputations. The pandemic has revealed the need to monitor and identify potential problems in many globally dispersed supply networks, including pharmaceutical products and semiconductors (Boston, 2021). Here, we consider how such supply networks can be captured and investigated digitally.

While "digitalization refers to the technology of digitalizing information" (Siu & Wong, 2016), the concept has been broadened within the realm of supply chain management (SCM) to encompass "the use of digital technology for supply chain management" (Srai & Lorentz, 2019). The term "digital technology" is itself broad and fluid. A plethora of digital technology tools are being applied in supply chain applications, including the Internet of Things, Artificial Intelligence (AI), digital twins, blockchains, intelligent agents, and robotics. This toolset is likely to expand, e.g., with the use of 5G technologies. The enhanced ability to access accurate and timely data along the chain can facilitate improved monitoring

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and policing of supply chains. In this chapter, we present the concept of *Digital Supply Chain Surveillance (DSCS)* as a necessary but challenging, and potentially controversial, consequence of supply chain digitalization.

Supply chains typically suffer from chronic information challenges, the consequences of which have been well reported in the research literature (Wang & Disney, 2016). A key research topic in the field of SCM has been the study of information sharing, and how to effectively manage operations when working with limited information. Information sharing between direct supply chain contacts improves demand forecasts, reduces inventory costs and the bullwhip effect, and helps coordinate production plans (Lee et al., 1997; Zhang, 2006). However, at a larger scale, companies may be unaware of the interdependencies in their extended supply networks. Hence, they may suffer from disruptions that ripple through their networks, becoming a prominent threat to supply chains (Demirel et al., 2019; Kinra et al., 2020; Ledwoch et al., 2018).

We argue that the increased appetite for digitalization in supply chains brings about unique opportunities to address some of the information sharing challenges observed in SCM. Digitalization may offer organizations a different approach to complement information sharing with specific supply chain partners. A “bottom-up process” may be used where companies seek to capture and analyze available digital data to inform them about previously unknown information without the need to explicitly convince other supply chain actors to share it. Examples could include an Original Equipment Manufacturer (OEM) finding out that one of their suppliers is supplying to a competitor, that an insurance underwriter is keeping a close eye on the financial health of a company’s supply chain dependencies, or that a supplier is seeking to learn about high value contracts awarded to its buyer to increase its leverage in bargaining. While such information gathering and “surveillance” has been informally prevalent in many supply chain contexts, it has, hitherto, been pursued manually or by sharing anecdotal information. The increased use of digital technology makes it possible to automate data capture and analysis at a much larger scale, allowing surveillance to take place in quasi real time, with data obtained from multiple sources (see Demirel (2022) for a review of secondary data sources on supply networks). Digitalization facilitates a step change in surveillance by interconnecting data sources and systems. Hence, surveillance may become easier, may be conducted on a larger scale, and may be potentially more informative. Yet, it presents further challenges, including issues related to data access, data privacy, and data quality.

Surveillance in a personal setting refers to “a close watch kept over someone” (Merriam-Webster dictionary) or “the focused, systematic, and routine attention to personal details for purposes of influence, management, protection, or direction” (Broeders, 2011). The broader term “Digital Surveillance” has negative, or at the very least, controversial connotations. The term is taken to mean: “the acquisition and consolidation of very large volumes of personal data, and its exploitation by commercial enterprises to target advertisements, manipulate consumer behaviour,” or “by governmental agencies to sort and categorise citizens” (Clarke, 2019). Researchers agree that the digitalization of surveillance is significant because of the ubiquity of data, and the speed with which it is generated, which enables algorithmic detection, tracking, sorting, and prediction of individuals in an automated manner (Clarke, 2019). However, within the SCM context, it is not individuals, but rather organizations, activities, products, processes, and events that are monitored.

The gathering, assessment, and evaluation of data and information has always been an important activity in managerial decision-making. In the commercial and business worlds, intelligence gathering, due diligence, and horizon scanning are key parts of many management disciplines including operations and SCM, marketing, new product development, finance, and strategy (Cousins et al., 2011; Recardo & Toterhi, 2014; Rowe et al., 2017). Historically, direct surveillance has been conducted through supplier audits. Several studies have assessed the performance of direct supplier auditing and compared it with other mechanisms such as deferred payment, certification, and product inspection (Babich & Tang, 2012; Chen & Lee, 2017; Mayer et al., 2004). Digitalization allows access to broader sources of data other than on-site audits for monitoring supplier activities.

We define *Digital Supply Chain Surveillance (DSCS)* as the proactive monitoring of digital data that allows firms to track, manage, and analyze data and information related to a supply chain network without the need for explicit consent of firms involved in the supply chain. Essentially, DSCS is formalizing and potentially automating previous manually driven practices. DSCS involves three key phases: (i) data collection and processing, (ii) data analysis, and (iii) extraction of actionable insights.

The first phase requires the selection of appropriate data sources, and devising methods and algorithms for collecting and processing data. The second phase necessitates the application of analytics tools and algorithms to analyze and predict company performance, behavior, and actions. The third phase focuses on extracting applicable and relevant messages, insights, rules, and heuristics that can support appropriate organizational decision-making. While the use of AI is not an explicit requirement for DSCS, it can benefit from AI’s ability to acquire and process large volumes of digital data and supporting decisions in an automated manner. Thus, we assert that two key enablers of DSCS are the availability of digitalized supply chain data and the use of AI techniques. An increasing number of studies (Aziz et al., 2021; Baryannis, Dani et al., 2019; Baryannis, Validi et al., 2019; Brintrup et al., 2018; Kosasih & Brintrup, 2021; O’Leary, 2015;

Wichmann et al., 2018) have proposed ways that combine the two in order to address challenges in SCM. However, DSCS studies are disconnected. We posit that examining the use of AI in monitoring and prediction of supply chain performance and activities under the umbrella of DSCS can help link the extant work on supply chain auditing, inspection, due diligence, and improvement, and indicate future research needs and directions.

In this chapter, we first present a broad framework to support the design of effective business processes for supply network surveillance. We then discuss the processes that may contribute to such a framework. We define the newly emerging field of DSCS, and discuss the role that AI can play within it. We then categorize the types of surveillance activities that can be pursued with extant technology and demonstrate how various sources of information can be brought together using an illustrative case example. We highlight some of the challenges and pitfalls that need to be researched within this area. We conclude with a summary and discussion of key points from our chapter.

2. SDAR—surveillance, detection, action, response

Before discussing particular activities, methods, and challenges for DSCS, we first present a general framework in which digital surveillance can be understood, implemented, and assessed in a SCM context.

While traditional supplier management and development schemes monitor and evaluate an individual supplier's performance directly to decide when and what type of corrective action are required (Krause et al., 1998; Lambert & Schwieterman, 2012), in DSCS we broaden the focus to consider surveillance schemes at the supply network level. Network surveillance activities, whether automated or manual, AI-supported or the result of more traditional intelligence gathering activities such as audits and certification, need to be part of a business process that is enacted in a consistent way. An effective business process allows an organization to benefit from active supply network surveillance. We outline briefly a general framework for the design of an effective business process to maintain awareness about a supply network and take appropriate beneficial actions when necessary. We call the framework SDAR—Surveillance, Detection, Action, Response (see Fig. 22.1).

Surveillance: The first step involves deciding on which entities, activities, and resources to surveil—the unit of analysis. The extent and relevance of the network targeted for surveillance may vary depending on both the primary focus of the surveillance and the nature of the organization conducting it. Different types of organizations may conduct surveillance in a supply chain, including OEMs, retailers/brand owners, regulators, and policy makers. Their reasons for monitoring a supply network may be different. An OEM may wish to concentrate on a specific supply network for a critical sub-system; a retailer may be concerned with ethical compliance in a specific country from which it sources (Kougkoulos et al., 2021); a regulator may need to take a broader perspective on a supply network for a product category for which it is the responsible regulatory authority in a country or region. The supply networks for many products are extensive and deep (Demirel et al., 2019). Hence, defining an appropriate frame of reference for surveillance is important. Data collection is a necessary and challenging step for surveillance activities. Although data may be available, even voluminous, its relevance, reliability, and coverage may be uncertain, creating challenges for DSCS. Hence, the right *unit of analysis* will allow focused surveillance schemes to be devised. The more focused a surveillance scheme is, the better, particularly if seeking to automate or routinely undertake surveillance as a business process. In Section 3, we provide some examples of activities that can be monitored, which can individually or jointly constitute the unit of analysis for surveillance.

FIGURE 22.1 The SDAR framework to embed surveillance as an effective business process.

Detection: In the supply network context, the general detection problem seeks to identify significant changes, dynamics, abnormalities, or nonconformances in the presence of uncertainty and variability in the available data. Deciding when a signal is of sufficient relevance to merit a critical alert or warning is at the heart of effective detection methods. Supply networks may be investigated for a diversity of reasons, ranging from quality and delivery problems to regulatory, ethical or financial compliance issues. Furthermore, the surveillance activity can be targeted to identify interdependencies between suppliers and customers, which can boost cooperation but can also lead to collusion and information leakage (Basole et al., 2018; Lu & Shang, 2017), and more generally to identify opportunities for innovation and cost reduction. The nature of an investigation and the type and amount of available data may help to determine the most appropriate tools to use. In Section 4, we discuss the classes and examples of AI tools and techniques that have potential to detect abnormalities and significant changes and to predict performance in the presence of variability and uncertainty. Notwithstanding the power of AI, informed, experienced, and expert decision makers may often detect abnormalities using human judgment if data are presented and summarized in appropriate ways (Qazi et al., 2018). Hence, AI methods will ideally complement human judgment and other established methods from risk management.

Action: Data have intrinsic value if they can influence decision makers in their subsequent action(s). Where a significant event, change, or abnormality is detected, a strong surveillance scheme will help to identify the area(s) or function(s) in the organization that may be affected, that need to be alerted, or that may need to take action, and the potential options available to decision makers. Surveillance programs need to be linked with an organization's core functions, e.g., the process may sit within the SCM or procurement functions of an OEM but have links with production planning, finance, compliance, governance, and quality functions. For an OEM, the options for dealing with supplier issues may be prescribed by previously developed policies and would typically include options to audit, develop/improve, penalize, or in an extreme case to deselect a supplier (Friedl & Wagner, 2012). For a retailer, actions could include reducing reliance on a specific country for sourcing a specific product category. For a regulator, options might include issuing a cautionary advisory note to companies in a particular sector. Importantly, options might also include actions to monitor more thoroughly or to invest to seek further information to "buy down" uncertainty (Quigley et al., 2018).

Response: Deciding the most appropriate action(s) and initiating it requires an organizational response, as potential options may incur costs, e.g., an OEM incurs cost in auditing a supplier and potentially further costs in undertaking a supplier development initiative; a regulator incurs cost in engaging a consultancy company to investigate further a potential issue in a supply network detected through surveillance. The feasibility and the likely impact of any action need to be evaluated. Some actions may need to be discounted before deciding an appropriate course to pursue for the issue detected (Friedl & Wagner, 2012). As well as determining the nature and the scale of actions to be taken, organizations need to assign responsibility for agreed action(s). This requires the appropriate assignment of authority and responsibility to deal with, and document the organization's responses. Effectively closing the loop can ensure that SDAR encourages beneficial cycles of surveillance monitoring, detection, selection, and deployment of the most appropriate actions. This may lay the basis for future surveillance activities.

In the next sections, we discuss the first two steps of the SDAR framework in more detail. In Section 3, we provide examples of different entities, activities, and resources to *Surveil*, in an endeavor to answer "What are the key surveillance requirements of companies that DSCS can address?". In Section 4, we discuss the AI methods that can be used for *Detection*. In Section 5, we discuss the key challenges that can be encountered in generating appropriate *Actions* and obtaining the desired *Response*.

3. Supply chain surveillance activities

SCM is a cross-functional management approach that involves activities that concern, for instance, demand forecasting, network design, risk management, cost reduction, production planning and scheduling, inventory optimization, and quality management (Chopra, 2019; Tang, 2006). Supply chain surveillance can help to address challenges related to these problems, particularly when there is uncertainty and information asymmetry between different stakeholders. Using the list of stakeholders in supply chain risk monitoring provided by Busse et al. (2017), we can identify five principal supply chain actors with direct relevance to supply chain surveillance: Buyers, Suppliers, Financers, Insurers, and Regulators. Based on a review of the empirical studies in the academic literature as well as discussions with experts from industry, we identify a number of exemplar supply chain surveillance activities, presented in Table 22.1. For each surveillance activity, related SCM problems and the major supply chain actors interested in the activity are noted. The analysis and interpretation are informed by our work with companies on the types of intelligence that could benefit SCM professionals. We note that we do not aim to provide a comprehensive literature review on the SCM areas. We focus principally on studies that use AI methods to support the indicated surveillance activities. While the list is nonexhaustive, it is representative of a broad range

TABLE 22.1 Supply chain surveillance activities.

	Surveillance challenge	Description	Major supply chain actors	Supply chain management areas	References
A	*Supplier lateness prediction*	*Part a from supplier s is likely to arrive (k days) late, with confidence d*	Buyer	Risk management, supplier performance	Brintrup et al. (2020); Chen and Wu (2013); Fang et al. (2016); He et al. (2014)
B	*Supplier disruption prediction*	*Supplier s is disrupted with probability p*	Buyer, insurer	Risk management, supplier performance	He et al. (2014); Kinra et al. (2020); Norrman and Jansson (2004)
C	*Supply network link prediction*	*Buyer b is likely to be connected to suppliers in country X*	Buyer, insurer	Risk management, supply chain visibility, supply network design	Brintrup et al. (2018); Lu and Chen (2020); Sasaki and Sakata (2021); Xie et al. (2019)
D	*Supply network link prediction*	*Supplier s might be a supplier to buyer b*	Buyer, insurer	Risk management, supply chain visibility, supply network design	Brintrup et al. (2018); Lu and Chen (2020); Sasaki and Sakata (2021); Xie et al. (2019)
E	*Supply network link prediction*	*Supplier s_1 might be buying from supplier s_2*	Buyer, insurer	Risk management, supply chain visibility, supply network design	Brintrup et al. (2018); Lu and Chen (2020); Sasaki and Sakata (2021); Xie et al. (2019)
F	*Product contamination detection*	*My product q is likely to contain ingredient j*	Buyer, supplier, insurer, regulator	Risk management, quality management, traceability	Ahn et al. (2011)
G	*Counterfeit-product detection*	*This is a counterfeit product, with confidence d*	Buyer, supplier, regulator	Risk management, fraud, quality management, traceability	Ahmadi et al. (2018)
H	*Purchase order financing decision*	*The supplier s is credit-worthy because it has a purchasing order from reputable buyer b*	Financer	Financial risk management, supply chain financing	Lee (2009); Paul (2015)
I	*Supplier financial risk assessment*	*Supplier s might have financial problems*	Buyer, financer	Financial risk management	Martínez et al. (2019)
J	*Buyer financial risk assessment*	*Buyer b might have financial problems*	Supplier, financer	Financial risk management	Martínez et al. (2019); Valverde and Talla (2013)
K	*Buyer—supplier price negotiation*	*Supplier s has excess capacity*	Buyer	Cost reduction, procurement	Lee (2009)
L	*Buyer—supplier price negotiation*	*Supplier s is likely to offer price p for this product*	Buyer	Cost reduction, procurement	Chen and Wu (2013); Lee (2009)
M	*Buyer—supplier price negotiation*	*Buyer b is likely to accept this bid for this product*	Supplier	Cost reduction, procurement	Yang and Sun (2019)
N	*Demand forecasting*	*Buyer b may order N of part a*	Supplier	Demand forecasting, production planning	Zahedi-Hosseini et al. (2017)
O	*Nonconformance detection*	*Supplier s has quality issues for product q*	Buyer	Quality management, supplier performance	Chen and Wu (2013); Psarommatis et al. (2020); Xiao et al. (2012)
P	*Innovation*	*Supplier s is innovative*	Buyer	Quality management, cost reduction, supplier performance	Liu et al. (2021)
Q	*Sustainability*	*Supplier s is sustainable (ESG)*	Buyer, insurer	Quality management, environmental impact assessment, CSR	Alikhani et al. (2019); Azadnia et al. (2015); Chiou et al. (2008); Klassen and Vereecke (2012); Kuo et al. (2010)

of surveillance challenges arising in contemporary SCM. The DSCS challenges range from strategic supply chain issues such as supply network design (Who is involved in my supply network and should they be?) and supplier selection (Is this supplier likely to be innovative?), to operational decisions such as the identification of possible delays and scheduling issues (How late would my order arrive if I ordered from this supplier?).

Challenges A, B, and P relate to supplier performance. With large-scale outsourcing of manufacturing to suppliers, the management of quality and delivery performance is critical. Typically, companies set up supplier performance measurement and risk management processes, the results of which are fed into supplier selection as well as operational decisions such as safety stock policies (Schmitz & Platts, 2003). A number of DSCS approaches have been proposed to improve supplier performance management, primarily through supplier performance and risk prediction. For instance, Baryannis, Dani et al. (2019), Baryannis, Validi et al. (2019) and Brintrup et al. (2020) develop methods for forecasting supplier delays using times series data available to the buyer. The predictions derived from such data-driven approaches can be used by optimization models to inform supply chain risk management decisions (Tang, 2006).

Challenges C, D, and E pertain to structural supply chain visibility. They highlight the limited knowledge a buying company may have over their supply chain connections. Lack of visibility remains a significant challenge for companies. The lack of knowledge about links in extended supply networks exposes firms to risks (Basole and Bellamy, 2014; Wang et al., 2014). Several studies have shown how lack of visibility can impact supply chain resilience when disruptions ripple through the chain and have highlighted the need for improvement (Kinra et al., 2020). For example, in challenge C, a buyer would like to know how likely it is that their supply network includes suppliers in a certain geolocation, so as to plan for potential location related risks such as natural disasters, social or political unrest. Supply chain insurance underwriters would also benefit from knowing how their client may be affected by disruptions. In D, a buyer would like to know whether its supplier is supplying to a competitor firm, which could be relevant in the case of disruptions where the supplier might prioritize another customer. Furthermore, competitors purchasing from the same supplier might benefit from strategic investments and collaboration with the supplier due to spill-over effects. In challenge E, the buyer would like to know whether its suppliers purchase from each other. If this is the case, the impact of problems and disruptions with the highly connected supplier may get amplified and cascade to further downstream companies (Demirel et al., 2019).

To address these challenges, several studies have investigated how AI-supported DSCS can complement supply chain mapping and monitoring efforts. Wichmann et al. (2018) created a method for extracting supply chain maps from natural language text. Brintrup et al. (2018) analyzed how partial knowledge of the supply network could be used to infer hidden dependencies between suppliers not known to the buyer. Their method incorporated classification algorithms that are trained using topological and production data. O'Leary (2015) proposed the use of Twitter data to monitor supplier disruptions. Hendricks and Singhal (2005) and Wang et al. (2014) discuss the use of risk data, which can be leveraged by firms with increased structural visibility (see Demirel (2022) for a review of databases on supply network data).

Challenge F focuses on product contamination risk in supply chains, as occurred in the horsemeat case discussed in Section 1. The buyer would like to know the ingredients and the composition of the product it procures. Pharmaceuticals and food manufacturing are typical examples where product composition knowledge is essential; hence, traceability is valuable. As labeling regulations differ across the globe, comprehensive information on food products containing multiple processed ingredients is not always available, resulting in problems such as horsemeat in Ikea Swedish meatballs (Falkheimer & Heide, 2015) and nut allergies in sandwiches (Pret Allergy Death, 2019). Similar issues have been observed in toys where toxic ingredients were discovered (China Halts, 2007). Researchers are increasingly exploring machine learning and network science methods to study food supply networks, uncovering patterns relating ingredients to final products (Ahn et al., 2011; Astill et al., 2019) and using AI to identify hidden ingredients not listed for the product.

Challenge G concerns fraudulent behavior by suppliers and anticounterfeiting. Combatting fake products is a global issue in manufacturing. In some countries, it is estimated that up to 40% of automotive parts are counterfeit in some jurisdictions (Dachowicz et al., 2017), which may lead to quality problems in later manufacturing stages. It is imperative that companies have reassurance that the products they procure are genuine. Several AI techniques have been developed to detect counterfeit products. For example, Ahmadi et al. (2018) use computer vision techniques to identify counterfeit microchips (ICs). Dachowicz et al. (2017) capture the microstructure of metal parts using optical microscopy to validate authenticity. The use of known supply chain data in predicting counterfeit products provides further opportunities to combat this challenge. In this vein, Zage et al. (2013) proposed a method to identify deceptive practices within the e-commerce supply chain by analyzing online transaction data to detect fraudulent vendors artificially building a good reputation through fake online reviews.

Challenges H, I, and J are concerned with financial risk and supply chain financing solutions. The buyer is interested in assessing and improving the financial capability of a supplier to adequately source capital to build and deliver its order and the supplier is interested in the buyer's ability to pay on time and in full. Supply chain financing companies and banks are interested in knowing whether a valid purchase order exists from a reputable buyer before lending capital to the supplier. There is a growing literature on the management of suppliers with financial risk (Tang et al., 2018) and supply chain financing solutions (Gelsomino et al., 2016), which are facilitated by the increased visibility, for instance on order quantity, and transparency provided by technological solutions such as blockchain (Chod et al., 2020; Ioannou & Demirel, 2022). On matters that directly relate to the specific prediction problems that we consider, Martínez et al. (2019) use publicly available data on suppliers to predict financial default in supply chain financing. Ye et al. (2015) used asset—liability ratios for Chinese firms to predict likely supply chain disruption based on a firm's financial performance.

Challenges K, L, and M are related to cost reduction through price negotiation. Many supply chain actors negotiate contracts with large lists of suppliers and buyers dispersed globally. While procurement officers will often manually analyze price negotiation opportunities, DSCS may help provide automated ways to find patterns in pricing to make negotiation more efficient. There is a rich academic literature that uses game theory to understand the interactions between firms in the supply chain. For instance, Martínez-de-Albéniz and Simchi-Levi (2013) consider multiperiod negotiation games between a buyer and a supplier, showing that the supply chain becomes asymptotically coordinated with the increasing number of periods through strategic ordering by buyers to reduce future price quotes. Zhong et al. (2021) show that supply chain coordination depends on the sequence in the negotiation if more than two tiers are considered together. Historical data on supplier prices have been used in multi-agent systems to model pricing likelihood and negotiations between suppliers and buyers (Boateng et al., 2017; Jiao et al., 2006; Pan & Choi, 2016). Other areas worthy of investigation within DSCS include capacity prediction, pricing anomaly prediction, and price offer prediction.

Challenge N is related to demand forecasting, which feeds into production planning and inventory optimization. The benefits of sharing information between supply chain partners have been well documented in the Operations Management literature (Lee et al., 2000). Collaborative planning, forecasting, and replenishment leads to improved forecasts, reduced uncertainty, and decreased inventory costs (Fliedner, 2003). DSCS can benefit firms along the chain by improved visibility on demand information and identify opportunities for collaborative forecasting and planning. With increased levels of servitization, OEMs need to maximize the useful life of their products, resulting in the need for effective spare parts management, which may encompass a large number of subparts (Baines et al., 2011). In addition to availability and sharing of data, AI could help to plan and optimize for spare parts inventory management in order to ensure that parts are ready when needed, as demonstrated by Zahedi-Hosseini et al. (2017).

Challenge O is about supplier innovation, which is a significant criterion in industries such as the automotive sector, as they undergo frequent innovative disruptions including the current transition to electric vehicles. Manufacturers would like to work with innovative suppliers as they may better adapt to changing product specifications and requirements. Several recent studies in the Operations Management literature have demonstrated the links between supply networks and innovation (Bellamy et al., 2014; Gao et al., 2015). DSCS may help quantify measurements of innovativeness through for instance the use of patent data (Aristodemou & Tietze, 2018; Liu et al., 2021), which can be fed into supplier selection (Trautrims et al., 2017).

Challenge Q focuses on supplier sustainability. The topic of Environmental, Social and Governance (ESG) reporting is gaining traction across all industries, strongly driven by regulatory compliance and reporting requirements. Companies will need to embrace ESG as supply chain performance criteria to thrive in the long run. The supply chain visibility provided by DSCS may enable firms to proactively discover and avoid the use of unsustainable and unethical practice deep in the supply chain. There are several initiatives and studies on conflict minerals and slavery. Researchers are looking into automating aspects of the ESG scoring process (Alikhani et al., 2019) through the use of DSCS. Kougkoulos et al. (2021) combine different data sources and methods to assess modern slavery risk in different regions of Greece. Kuo et al. (2010) look at the interests and rights of employees (IRE) and the rights of stakeholders (RS). Azadnia et al. (2015) study product quality conformation and long-term stability. Chiou et al. (2008) investigate Environmental Management Systems, whereas Klassen and Vereecke (2012) study the management of child labor, health, safety, and discrimination.

Thus, there are a very large number of diverse challenges that DSCS has the potential to help address through automated data collection and analysis of digital data. Next, we review the role of AI in DSCS.

4. The role of AI in DSCS

While AI is not, in theory, a prerequisite for DSCS, many studies in the literature noted in the previous section advocate and deploy AI technology in some way because it enables the collection and analysis of digital data in an automated manner (e.g., Wichmann et al., 2020). In the following, we briefly review relevant AI methods and mention their applications in the context of surveillance.

While many classification schemes for AI exist, we consider the class of problems covered in Russell and Norvig (2009) to classify extant AI approaches relevant to DSCS into the following categories: Classification, Clustering, Prediction, Probabilistic AI, Intelligent Agents, Search and Optimization, Logic and Reasoning, and Graph Mining. We add Graph Mining because of its recent emergence and relevance to DSCS, and its cross-disciplinary perspective that combines network science with machine learning (Cook & Holder, 2006). Table 22.2 shows how these algorithms can be applied to the different surveillance challenges identified in Table 22.1. We note that the list below does not aim to be exhaustive.

Classification is a supervised learning task where the algorithms are used to identify the category, or set of categories, to which a new data observation belongs based on the patterns of relationships between features (independent variables) and labels (dependent variable—categorical for classification). In risk surveillance, classification algorithms can be used to perform a series of binary predictions. For instance, in supplier risk management, the following classification queries may be relevant: Is a given upstream supplier expected to be disrupted or not (challenge B)? Is there a supply dependency between two firms (challenges C, D, E)? Will the delivery from the supplier be on time or tardy (challenge A)? Similar queries can be posed about product conformance and supplier characteristics: Is this product authentic or counterfeit (challenge G)? Does the product contain a potentially allergenic material (challenge F)? Is this supplier innovative or not (challenge P)? Is it sustainable or not (challenge Q)? Lastly, classification can be used to assess if a company is financially healthy or not (challenges I and J). Some examples of how classification approaches are used in practice to address the above have been given by Ahmadi et al. (2018); Brintrup et al. (2020); Martínez et al. (2019); and Psarommatis et al. (2020).

Clustering algorithms are used to find groups of observations that are similar to one another based on their distance to a centroid, density of points, belonging to a distribution, or distance-based connectivity. In surveillance for supplier capabilities, such as innovativeness and sustainability, clustering can be used to group suppliers with similar profiles (challenges P, Q), hence allowing companies to manage them with common strategies. Another classical use case is customer segmentation, i.e., classifying customers into groups based on similarity in profiles and historical purchasing behavior. These clusters add segment-based information that can be useful for demand forecasting (challenge N). Some examples of how clustering is used in practice can be found in Er Kara and Oktay Fõrat (2018) and Murray et al. (2015).

Time Series Forecasting is used to extrapolate trends in historical and current data to make predictions in the future. There is a rich time series analysis and forecasting literature, which is complemented by deep learning algorithms such as LSTM. In supplier risk management, regression can be used to answer forecasting questions such as estimating how many days an order will be late (challenge A)? How much capacity will a supplier have this month (challenge K)? At what price would a supplier offer this product (challenge L)? How many spare parts would a buyer order (challenge N)? Examples include Brintrup et al. (2020); He et al. (2014); and Syntetos et al. (2016). See Carbonneau et al. (2008) for a review.

Probabilistic AI is used to model uncertainty in machine learning tasks. This is often used with classification and regression to measure how confident an AI model is when making predictions. For example, in supplier risk management, we may want to measure the confidence level of a prediction that an upstream supplier is likely to be disrupted (challenge B), how certain we are that a given company is connected to our supplier (challenge C, D, E), and how likely it is for a delivery to be on time or tardy (challenge A). Similarly, any classification/regression task can be combined with uncertainty measures. Examples of how probabilistic AI has been used in DSCS applications can be found in Hosseini and Ivanov (2020); Käki et al. (2015); Lockamy and Mccormack (2012); and Qazi et al. (2018).

Intelligent Agents are used to simulate or automate interactions between independent agents in a supply chain. Simulation models can help decision makers understand emergent behaviors arising out of complex interactions between stakeholders. In DSCS, Intelligent Agent Systems can be used to model bidding processes and answer questions such as the price a supplier/buyer would be willing to offer or accept when negotiating a contract (challenges L and M). The approach may also be useful for inventory modeling, to understand other agents' behaviors and predict whether they have enough capacity to sell or buy products (challenge K). From an automation perspective, Intelligent Agents can be used to automate DSCS, where they are deployed to collect data and monitor events reported on digital media. Some examples of how intelligent agents modeling has been used can be found in Jiang and Sheng (2009); Kara and Dogan (2018); Kosasih and Brintrup (2021); and Oroojlooyjadid et al. (2017).

Search and Optimization is used to find the best solution(s) in the feasible solution space of a problem. This can be used in conjunction with supplier selection criteria, e.g., innovativeness or sustainability (challenges P and Q) to automatically select a list of suppliers that best meet the firms' objectives (Che, 2012; Che et al., 2021). In DSCS, search and optimization can be seen as a follow-on step to take place after intelligence gathering. We do not review the mathematical programming literature here due to the focus of the review on DSCS applications of AI algorithms.

TABLE 22.2 Application of AI for digital supply chain risk surveillance.

	Used for	Example algorithms/frameworks[1]	Possible applications	References
Classification	Identifying to which category or set of categories a new observation belongs through supervised learning	Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, Nearest Neighbors, Adaboost, XGBoost, Naive Bayes, QDA, Neural Network	A, B, C, D, E, F, G, I, J, P, Q	Ahmadi et al. (2018); Brintrup et al. (2020); Martínez et al. (2019); Psarommatis et al. (2020)
Clustering	Unsupervised grouping a set of observations based on their similarities or closeness	K-Means, Affinity Propagation, Spectral Clustering, Agglomerative Clustering, DBSCAN, Gaussian Mixture Model, Birch, OPTICS	N, P, Q	Er Kara and Oktay Fırat (2018); Murray et al. (2015)
Time series forecasting	Analyzing trends and behavioral patterns in current and historical data to make estimations about the future	Recurrent Neural Network (LSTM)	A, K, L, N	Brintrup et al. (2020); He et al. (2014); Syntetos et al. (2016)
Probabilistic AI	Used for a diverse range of problems including reasoning, prediction, planning, and classification/clustering	Gaussian Process, Bayesian Neural Network, Probabilistic Graphical Model	A, B, C, D, E, F, G, I, J, K, L, N, P, Q	Hosseini and Ivanov (2020); Käki et al. (2015); Lockamy and Mccormack (2012); Qazi et al. (2018)
Intelligent agents	Autonomous computational entities that act in pursuit of goals, with tools available to them	Reinforcement Learning, Agent-based Modeling, Multi-agent Systems	K, L, M	Jiang and Sheng (2009); Kara and Dogan (2018); Kosasih and Brintrup (2021); Oroojlooyjadid et al. (2017)
Search and optimization	Finding the best solution(s) from countable/ uncountable feasible solutions	Genetic Algorithm, Tabu Search, Simulated Annealing	P, Q	Che (2012); Che et al. (2021)
Logic and reasoning	Used for knowledge representation and building knowledge bases and expert systems to find solutions to particular problems or for categorizing knowledge to aid a human decision maker	Knowledge Graph, Ontologies, Semantic Reasoning	B, C, D, E, F, H	Chae (2015); He et al. (2014); Tang et al. (2020); Wichmann et al. (2018)
Graph mining	Use of techniques from the science of complex networks to analyze supply chains as directed graphs	Centrality, Link Prediction, Community Detection, Clustering Coefficient, Transitivity, Shortest Path, Minimum Cut	A, B, C, D, E, F	Brintrup et al. (2018); Fang et al. (2016); Kosasih and Brintrup (2021); Lu and Chen (2020); Sasaki and Sakata (2021)

[1] *A number of specific algorithms are listed in Table 22.2 to illustrate how an AI technique could be pursued for the surveillance challenge identified. These should be taken as indicative rather than definitive and exhaustive, given the pace at which new algorithms are developed and applied. Traditional forecasting, optimization, and analytics methods are minimally covered due to space limitations and the focus of this chapter being on AI methods.*

Logic and Reasoning is used to encode and represent human knowledge as relational data that can be used in conjunction with other AI algorithms. In a supply chain context, knowledge graphs could be used to represent relationships between entities/firms in the network, which could then be used to answer questions such as who the suppliers/buyers of a given firm are (challenges C, D, E, H)? What ingredients can be found in a given product (challenge F)? Given news emerging on social media, can we tell if a supplier is being disrupted now (challenge B)? See Chae (2015); He et al. (2014); Tang et al. (2020); Wichmann et al. (2018); and Aziz et al. (2021) for examples of how knowledge graphs and ontologies have been used in DSCS.

Graph Mining is used to extract information from graphs. Several researchers in the past emphasized that supply chains and supply networks can be represented as directed graphs (Brintrup et al., 2018; Demirel, 2022). Doing so can help answer several questions. The first relates to links—understanding the characteristics of the relationship between firms (challenges C, D, and E) or between product and ingredients (challenge F). The second is to model disruption propagation across a supply network, e.g., if a given upstream supplier is disrupted, will the immediate supplier be affected, and how much impact is expected (challenge A and B). Some examples of how graph mining has been used in DSCS are given by Brintrup et al. (2018); Fang et al. (2016); Kosasih and Brintrup (2021); Lu and Chen (2020); and Sasaki and Sakata (2021).

Although AI shows great promise in supporting DSCS, there are many difficult technical, managerial, and business challenges in seeking to exploit its potential. Next, we use an example to illustrate some of the challenges involved in the application of DSCS.

5. Challenges in the application of DSCS—an illustrative example

5.1 Problem formulation and solution approaches

The example considers the detection of supply chain disruptions on the extended network of an OEM that produces complex engineering assets, identified as Surveillance Challenge B in Table 22.1. The OEM is typical of its industry. It forms long-term relationships with its first-tier suppliers that act as system integrators. However, the OEM has limited visibility of its supply chain beyond the first tier. Some of the second and third tiers are known due to the OEM's approved vendor policy for a number of critical parts produced by the second tier. The OEM would like to be able to predict potential disruptions in its supply chain. More specifically, for each product in its portfolio, the following information needs to be predicted: "Supplier x, at tier k, is disrupted, affecting my company, with probability p." The OEM's current data include a complete list of first-tier and a partial list of second-tier suppliers and their product portfolios, and a database pertaining to historical order delivery performance of its first-tier suppliers. The company also has access to private business databases that contain annual company reports and other information for companies in its particular industry.

The surveillance challenge requires three distinct, sequential steps (see Fig. 22.2). *Network Discovery* corresponds to the Surveillance (S) stage of the SDAR framework, i.e., identifying which entities to monitor. This is followed by *Risk Emergence*, i.e., detecting the operational and disruption risks that can affect the focal company; hence the Detect (D) stage of SDAR. The next step of *Risk Propagation* feeds into the Action (A) stage by estimating the likely impact of the downstream propagation of risks on the focal firm, helping to assess the effectiveness of different risk management strategies.

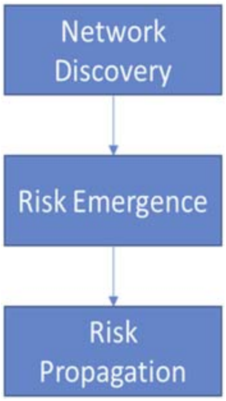

FIGURE 22.2 DSCS steps.

Network Discovery: The OEM has partial visibility over its supply chain. In order to be able to predict disruptions affecting it, each supplier's identity needs to be known to the extent possible from the available data. A data collation exercise needs to be pursued to capture the knowledge the OEM has on its supply network. We call this dataset the "ground truth," as the OEM knows these actors in its supply chain with certainty.

Once ground truth is established, it may then follow a strategy to maximize its knowledge of the network by additional data extraction. The use of Natural Language Processing (Table 22.1) has been proposed as a recent technique to generate supply chain maps automatically that may be augmented with existing maps created from the OEM's own knowledge. They may also be augmented using public databases such as Bloomberg's Supply Chain Suite with additional supplier information from publicly available information sources on the web and privately accessible information from business databases (Wichmann et al., 2018). NLP is a rapidly developing subfield of AI that specializes in the extraction and manipulation of natural language text or speech (Chowdhury, 2003; Kang et al., 2020). NLP extracts are used to construct relational databases and ontologies to structure the extracted information. An ontology captures the relationships between entities and allows further reasoning about the data and information being analyzed. To construct an ontology, classification algorithms are used to categorize text entities (e.g., a company name such as "Bosch") into predefined categories of interest (e.g., a "firm"). Semantic relationships between named entities (e.g., "supplies to") are then extracted. The process typically uses classification approaches (see Table 22.2) that require the creation of a labeled dataset to train the algorithms. Labeling data may involve crowdsourcing via services such as Amazon Turk or exploiting the OEM's own knowledge and expertise. There is increased interest in using NLP for supply chain visibility, with several startup companies such as Versed.ai offering software solutions to companies.[2]

It is important to note that this approach is limited by its nature to companies that report their supply chain information and by the OEM being able to access the relevant media through which the information is reported. Sectors that have high privacy or that outsource to regions where local regulations and/or culture limit the sharing of information may be less accessible than those that have a higher proportion of companies that report relations publicly. Approaches that are more sophisticated could include probabilistic classification (see Table 22.2), where relationships have an associated uncertainty value informed by the date a relationship is reported, the number of times the information was found, and the source of the information. Importantly, the information collected should not simply be accumulative since outdated supply relationships can be still preserved due to a lack of knowledge about the termination of the relationship. Inference techniques may help to identify a relationship that has terminated (Brintrup et al., 2020).

Another interesting proposed approach is "link prediction," which is used to infer supplier interdependencies using the OEM's incomplete knowledge of the supply chain. Here, topological (graph) data are used to train a classifier to predict potential links. The topological data refer to the network structure of "who-supplies-whom." This approach hybridizes Classification and Graph Mining (Kosasih & Brintrup, 2021; Aziz et al., 2021). Additional data such as supplier locations and product portfolios can be augmented to the graph. The resulting graph is then used to "hand-craft" features that are hypothesized to be informative when predicting the existence of a relationship and can be used to complement the NLP extracted data. Brintrup et al. (2018) give an example of a graph mining approach for predicting supplier links. The extracted features include (i) number of existing links of a supplier, (ii) overlaps between supplier product portfolios, (iii) product outsourcing associations, and (iv) likelihood of buyers purchasing from two suppliers simultaneously. The algorithm predicted the existence of links with 71% accuracy measured against random chance. The two approaches combined together may help Network Discovery and help answer the "Supplier x, at tier k" portion of the challenge. However, it is important to note that these approaches are constrained by the availability of data and the adequacy of feature extraction. While this approach typically involves human interaction to guide the algorithm, recent developments propose automated approaches, arguing that heterogeneity and the dynamicity of the graph points are needed for more generalizable methods (Aziz et al., 2021; Kosasih & Brintrup, 2021). Once this phase is completed, prediction of "Risk Emergence" is the next step.

Risk Emergence: Risk Emergence can be categorized into the prediction of low likelihood-high impact and high likelihood-low impact events. Tang (2006) classifies supply chain risks as operational or disruption risks. To predict low likelihood-high impact events, i.e., major disruptions, researchers have used NLP to monitor social media. Chae (2015) and O'Leary (2015) demonstrated that social media can be used to receive and share alerts about potential supply chain disruptions. Twitter has been proposed as a source for detecting events that are happening and will pose supply chain risks, including earthquakes, forest fires, hurricanes, epidemics (Gu et al., 2016; Hughes & Palen, 2009; Sakaki et al., 2010). The extant literature points to significant challenges introduced by endogeneity and data quality (Lazer et al., 2014). Similar

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[2] https://www.versed.ai/.

approaches can be used for local, smaller-scale incidents such as labor strikes, or factory fires (Schulz et al., 2013; Zhang & Vos, 2014). For detecting disruption risks, NLP is used in a similar fashion to its use in network discovery, where named entities are firms and events. A difficulty is the detection of location information, as incidents such as fires are geographically focused, but the recognized entity, if a firm, might not have a location associated with it. This approach will yield useful information only if the OEM has augmented its "network discovery" with precise location information. If location information is absent, a probability of being affected by the disruption can be assigned based on the known locations of the supplier, e.g., extracted from Geographical Information Systems.

High-likelihood, low impact events typically involve operational incidents such as machine breakdowns, logistics delays, and seasonal fluctuations in demand. These types of events are not typically registered on social media or publicly accessible datasets. Hence, the OEM may need to work with information only available to itself. One approach that has been proposed is the use of goods-receipt data to detect patterns that inform potential fluctuations in supply. Brintrup et al. (2020) used a number of classification methods to depict whether a supplier will deliver late by selecting and engineering features that can act as useful predictors from goods-receipt data. Regression models were also used to predict "days late." The approach established good predictors of tardiness, including the requested lead time from the supplier for fulfilling and delivering the order, the supplier's identity, and the characteristics of the product, as well as metrics such as "agility score" that capture the responsiveness of the supplier under fluctuating demand. Since this method is applied to an OEM's existing data, network discovery is not required a-priori.

Risk Propagation: Network Discovery combined with Risk Emergence may help answer "Supplier x, at tier k, is disrupted" portion of the challenge, whereas to detect whether the disruption may reach the OEM, risk propagation needs to be studied. As the OEM knows neither the internal risk containment or risk mitigation capabilities of its suppliers nor whether a procurement relationship exists with complete certainty, the risk propagation involves uncertainty and requires modeling. One option may involve the use of network centrality measures, e.g., percolation centrality, to assign criticality to supplier nodes, combined with an estimated degree of certainty of the existence of the link between each node. The structure of the network and the confidence values on the extracted relationships could provide potentially informative types of data.

The approaches proposed above may inform "Supplier x, at tier k, is disrupted, affecting my company." However, "with probability p" requires further thought. In our three-phased approach, three sources of uncertainty arise. The first is the probability that the supplier in question is being disrupted p_i. Next is the probability that this supplier is connected to the network of the OEM p_{ij}. Finally, the probability of a disruption propagating downstream to the OEM needs to be estimated. We can thus model disruption propagation as a probabilistic graphical model as shown in Fig. 22.3 where nodes are companies and edges are relationships between them, which might represent procurement, logistics, or financial links. The probability that a given node is disrupted is denoted by k_i, the probability that a given node is connected to another company downstream is denoted by p_{ij}, and the probability that a disruption in the node i will propagate to a downstream company is denoted by d_i. Note that the disruption propagation probabilities can also depend on the firm that is at the receiving end of the link.

There are different ways to implement this type of model in practice, including Bayesian networks (Hosseini & Ivanov, 2020; Quigley et al., 2018) and epidemic spreading models (Brauer, 2008). Network simulations can also be used to predict the impact of a given disruption on the OEM under different scenarios and policies. For instance, Zhao et al. (2019) assess the propagation of disruptions under different scenarios where the OEMs restructure their networks either reactively, responding to the disruption, or proactively, anticipating the disruption. The risk propagation probabilities are estimated from ensembles of the network simulations under the specified OEM policies, where the simulations are parametrized using public databases on supply networks and product portfolios of the firms. Such approaches may help to answer the supply chain risk surveillance question "Supplier x, at tier k, is disrupted, affecting my company, with probability p." Once we have an understanding of the disturbances and disruptions and their propagation in supply networks, we should consider their management.

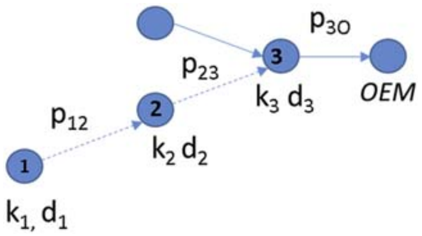

FIGURE 22.3 Uncertainties in network risk propagation.

There may be a number of alternative ways to approach the example challenge. Network discovery may involve manual data collection, or subscription to third-party databases (see Demirel, 2022). Risk propagation may involve simulation models and/or the use of alternative AI algorithms. Any of the steps mentioned here may be avoided if information is already known. The next step needs to consider different risk management policies that involve managing the supply, the demand, the product, and the information at strategic or tactical levels (see Tang (2006) for a discussion of the types of actions).

While the above example presents how AI thinking can be applied to DSCS in a general setting, many technical and managerial challenges will arise for specific cases.

5.2 Technical challenges

The illustrative example showed that a seemingly simple challenge that seeks to detect whether a firm is present in a supply chain and the likelihood of its disruptions affecting a focal buying company, necessitates a decomposition approach where different techniques may need to be developed and applied for different components of the problems. The various forms of uncertainty arising from each investigatory component need to be integrated appropriately. In order to build an effective digital risk surveillance system, companies will have to collect data from real-world operations from multiple interacting subsystems. Data sources may emanate from different platforms with non-uniform data standards. Integrating these different data sources is non-trivial, not only because of the information system expertise required but also because the resulting decomposition involves different analytics approaches that need to be integrated.

We assume here that organizations use either publicly available data sources or data sources to which they have legitimate access. The skill set required for each component of the analysis is different, necessitating a diverse talent base at the focal organization that undertakes surveillance. An additional challenge pertaining to surveillance is data imbalance, particularly when the supply chain disruptions are of the High Impact—Low Likelihood type (Kinra et al., 2020; Tang, 2006). When one is tasked to predict supply chain risk through historical data, there may be a plethora of supply chain data on operational risks but limited samples of disruption data, making prediction hard. To tackle this issue, researchers often use oversampling techniques, for example, by running Monte Carlo simulations built on the underlying models. More research is needed to create frameworks for categorizing and decomposing DSCS challenges and how specific issues such as prediction uncertainty, data fusion, and data imbalance can be tackled.

5.3 Managerial challenges

In Section 1, we noted a number of negative connotations about the general concept of Digital Surveillance, particularly in the context of personal data. Several of these concerns may apply also to the digital surveillance of supply chains, including ethical challenges related to the use of AI algorithms in DSCS. Traditional supply chain surveillance has been a manual, and often opportunistic process, informed by knowledge and data. The process would typically involve data scrutiny and validation before judgments are made by a variety of supply chain professionals in an organization. For example, if a supplier's relations with competitors were of interest, the buyer might directly query the supplier or monitor industrial news sources. At other times, surveillance might be tacit. Procurement officers might collate historical data on supplier performance periodically to assist in future supplier selection. Both of these examples involve a degree of subjectivity and tacit human knowledge.

AI is known to be particularly good at reproducing and even strengthening biases from the dataset on which it is trained (Brennen, 2020). Hence, ethical AI and fairness in machine learning have become important considerations. Cutting human decision makers out of the loop may, therefore, introduce biases inherent in the training data or in algorithm design. These may be difficult to tease out without relevant AI skills and expertise and it is particularly challenging because different algorithmic fairness metrics may not be compatible (Corbett-Davies & Goel, 2018). Lianos and Douglas (2000) discuss that with the rise of Digital Surveillance, "the work of human operators shifts from direct mediation and discretion to the design, programming, supervision and maintenance of automated or semi-automatic surveillance systems." Similarly, in DSCS, AI skills for monitoring and removing bias will be important, especially when applied to financially impactful use cases that could affect supplier selection and insurance costing. Automated algorithms used in DSCS would therefore not replace existing modes of surveillance, but should complement them.

Use cases that DSCS may facilitate, but were not a part of traditional SCM, necessitate further thought into how the obtained information should be incorporated into existing business processes and management practices. For example, the prediction of excess capacity or financial stress at a supplier has typically not been visible to buyers. It is important to design processes that handle new information with care, leading to appropriately balanced action. Graham and Wood

(2003) highlight that the “characteristic of digital surveillance technologies is their extreme flexibility and ambivalence. On the one hand, systems can be designed to socially exclude, based on automated judgements of social or economic worth; on the other hand, the same systems can be programmed to help overcome social barriers and processes of marginalization.” Similarly, in DSCS, prediction of decreasing performance from a supplier could lead to an automatic action where the supplier’s contract is terminated, or to an action that triggers root cause analysis and working with the supplier to develop and improve their performance. A case in point is a supplier delivery performance prediction study conducted by an aerospace company (Brintrup et al., 2020), which found that the main cause for delays was the buyer ordering late rather than a performance issue on the side of the supplier. While much care may be given to validate the data and the training of the model, as well as algorithmic design, it is still possible for invalid conclusions or inappropriate actions to emerge from DSCS, hence the importance of designing an effective Response(R) stage in SDAR.

Linked with questions of ethics in decision-making is the question of explainability of AI (Angelov, 2021). Many state of the art AI algorithms are essentially “black box” methods, which means that interpreting why a certain prediction was made may be difficult. While the explainability of AI may refer to various properties (Brennen, 2020), a key one in SCM is interpretability. Generally, the more complex the models are, the less interpretable the predictions become. Baryannis, Dani et al. (2019), Baryannis, Validi et al. (2019) explore the trade-off between interpretability and prediction performance, demonstrating that a more interpretable algorithm (e.g., a decision tree) may result in lower accuracy than a less interpretable counterpart (e.g., a support vector machine). As they note, research on improved interpretability is vital to the adoption of DSCS. Relatedly, uncertainty quantification is also an imperative for the effective design and use of AI-based decision support systems for DSCS. Predictions and decisions made by AI algorithms need to be given with confidence intervals, to inform human decision makers whether or not the information is trustworthy. From a managerial perspective, the acceptable trade-off between interpretability and performance needs to be investigated before wider adoption of AI practices in DSCS.

6. Conclusions

While surveillance of supply chains is not a new concept, digitalization offers a step change in its potential reach and scale. Large volumes of digital data and a diverse set of AI techniques are available to collect and analyze data, providing an important opportunity to help organizations fill information gaps in their supply chains. In this chapter, we described the emerging practice of DSCS, which we conceptualize as the proactive monitoring of digital data to allow firms to track, manage, and analyze data and information related to a supply chain network. We presented a framework—SDAR—that encompasses Surveillance, Detection, Action, and Response, to support the design of effective business processes for supply network surveillance. A range of DSCS surveillance challenges, such as detecting product non-conformance and fraud, predicting supplier performance, and forecasting demand, are noted and the applications of different classes of AI approaches for tackling these challenges are highlighted. We used an example to illustrate the challenges involved in the application of DSCS, showing that often the surveillance challenge may necessitate a decomposition approach, where the constituting steps of the analysis might require a diverse set of linked AI techniques. The example case highlights that the application of AI to DSCS is non-trivial and further research is needed to understand which techniques are suitable for what types of problems. In addition to decomposition, data imbalance, interpretability, and uncertainty quantification were raised as important issues for the technical advancement of DSCS. A number of ethical concerns were also noted. Digitalizing surveillance in supply chains could remove human discretion but introduce further, hidden, biases. Thus, organizations that want to pursue DSCS may need to invest in AI expertise to ensure bias is removed and plan for business processes that can interpret DSCS findings and circumvent hidden bias.

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Chapter 23

Sustainability and the digital supply chain

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Abstract

The digital transformation of supply chains is happening at the same time as environmental and social impacts are leading to a radical rethink of the very nature of supply chains, how they are designed, and how they are managed. We examine the intersection of digital transformation and sustainability in the supply chain and consider whether they are complementary or in tension. We analyze sustainability in the digital supply chain by combining the supply chain SCOR model with the triple bottom line sustainability perspective that incorporates economic, environmental, and social dimensions. The complexities and trade-offs among these factors can lead to unintended consequences for sustainability initiatives. We consider two illustrative case studies: the emerging supply chains for electric passenger vehicles and the beef supply chain. Automotive and agricultural supply chains have to deal with substantial and complex sustainability issues. We identify how digital technologies may support sustainability initiatives or create unintended negative consequences. We draw insights from the two cases to discuss important issues and questions for both research and practice. Given the importance of sustainability, we highlight the need to consider carefully all the consequences of applying digital technologies in order to achieve intended benefits and reduce unintended harm.

Keywords: Agriculture; Automotive; Electric vehicle; SCOR; Sustainability; Triple bottom line; Unintended consequences

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1. Introduction

The explicit consideration of sustainability is no longer optional in operations and supply chain management (SCM). It has become an essential consideration for citizens, policy makers, and particularly for supply chain managers. Sustainable SCM is no longer a "fringe topic that many of us were actively discouraged from studying" (Pagell & Shevchenko, 2014, p. 44) but a mainstream topic for practice and research. The environmental, social, and economic impacts of many supply chains are demonstrably unsustainable. Our consumption of natural resources has overshot what nature can produce; extreme weather events like floods, droughts, and forest fires are commonplace; while rising temperatures and sea levels are making land less habitable and less arable (Ghadge et al., 2020; Matthews et al., 2016; van Wassenhove, 2019). Our production of goods often creates dangerous working conditions that are hidden within the supply chains of many products, e.g., where people are forced to extract minerals in conflict zones (Timmer & Kaufmann 2017); assemble electronic goods in contact with toxic chemicals (Chan & Pun, 2010); or stitch clothing in factories at risk of collapse (Huq et al., 2016). At the same time, the economic sustainability of many firms and supply chains has been shaken by political instability, and a series of crises including the 9/11 terrorist attacks in 2001, the financial crash a decade later, and the COVID-19 pandemic. As digital technologies reshape supply chains, there is an opportunity to put environmental, social and economic sustainability at the heart of SCM and leverage these technologies for greater good.

The conceptual evolution of sustainable SCM originated from circular thinking, operationalized in reverse logistics and closed-loop supply chains (Fleischmann et al., 1997). Resource scarcity and supply disruptions have given a higher priority to these concepts among researchers, managers, and policy makers at all levels (Lüdeke-Freund et al., 2019; Sarkis et al., 2020). Subsequently, overarching conceptualizations of sustainable SCM (e.g., Pagell & Wu, 2009) have combined social, environmental, and economic performance dimensions, commonly labeled as the "triple bottom line" (TBL) of sustainability. Sustainable development was defined in the influential Brundtland report as "development that meets the needs of the present

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without compromising the ability of future generations to meet their own needs" (WCED, 1987, p. 8). This definition embraces and mutually connects intragenerational and intergenerational justice and, in its generality, enjoys broad consensus among politicians, civil society, and business. It also informs the United Nations' Sustainable Development Goals (SDGs), a set of 17 goals that recognize peoples' right to achieve their social and economic needs, as well as the rights of other species and the urgency to act on climate change (United Nations, 2015). In line with this concept, we seek equal or higher weighting for environmental and social aspects, in our analysis of supply chain sustainability. We also take a broad view of supply chains, encompassing upstream and downstream impacts of digital technology and sustainability in supply chains.

From the basic routines of purchasing introduced in the 1980s to the emergence of SCM in the 1990s and beyond, managing operations and supply has become more cross-functional and interorganizational. Sustainability adds social and environmental perspectives to standard financial and operational considerations. The number and diversity of performance measures across multiple functions and organizations becomes very challenging to manage. Sustainability risks may be hard to identify and manage due to an organization having a restricted "visible horizon" (Carter et al., 2015). Decision makers can be expected to focus on the short term and on those decisions that have the most visible consequences. However, sustainability necessitates a focus on long-term consequences and requires transparency (Carter et al., 2020). The complexity and institutional distance across supply chains makes them potentially opaque, leading to a transparency fallacy (Gold & Heikkurinen, 2018), i.e., it is doubtful how much transparency can be achieved in many supply chains. Even if a focal firm achieves a high level of sustainability performance in its own operations, cascading sustainability through supply chains (Wilhelm & Villena, 2021) and supplier–subcontractor networks (Gold et al., 2020) remains a major challenge. SCM research has started to develop decision-support tools for the high levels of uncertainties that grow with the breadth and depth of sustainability performance dimensions as well as the length and complexity of supply networks (e.g., Awasthi et al., 2018). Despite these advancements, managing supply chains for sustainability means dealing with a lack of transparency arising from complexity, dynamics, fluidity, and embeddedness in geographic, political, and sociocultural contexts (Wieland, 2021).

At the same time as the sustainability and resilience challenges have increased, technological evolution has begun to revolutionize the task of managing supply chains. Steam power, automation, and computing powered previous industrial revolutions, helping to accelerate the global expansion and growth of supply chains. Along with economic wealth and prosperity, they have also left a lasting legacy in social inequalities and environmental degradation. The latest digitally driven industrial revolution is built upon the Internet and the ability to integrate physical systems with increased computing power and huge quantities of almost instantly available digital data. This leads to the Digital Supply Chain (DSC), which can be defined as a "smart, value-driven and efficient process to generate new forms of revenue and business value" (Büyüközkan & Göçer, 2018, p. 157). Here smart refers to systems with sufficient computing power to offer decision-support, autonomous decision-making, and even self-learning. The value offered by these systems is often based on the data generated, captured, processed, analyzed, and operationalized throughout the supply chain. When physical activities like producing and transporting goods are supported by smart technologies, they generate data that can be used to monitor and improve processes. This in turn should enable greater efficiencies, if the wealth of data can be used effectively for making better and faster decisions. An important question, however, is whether the social and environmental impacts of the DSC will be positive or negative (Liu et al., 2020).

Our goal in this chapter is to understand the sustainability implications of the DSC, by unpicking some of the unintended consequences when digital technologies are applied for sustainability reasons. In the next sections we expand on our understanding of digital technologies and of the supply chain, using the Supply Chain Operations Reference (SCOR) model. Next, we discuss the integration of digital and sustainable aspects in a supply chain. To illustrate and investigate these concepts, we explore two case studies. The first concerns electric vehicles (EVs), and how an increasingly digital automotive supply chain could support or potentially hinder sustainability. The second case examines a food supply chain, considering digital technologies that could improve the sustainability of beef production. In both cases, there is acceptance that current supply chains are not sustainable, but altering the end product without considering the entire supply chain is revealed to be ineffective or potentially counterproductive in terms of sustainability. Based on this analysis, we then discuss sustainability implications of the DSC more generally. In particular, we consider the opportunities that business model innovation and disruption might offer for sustainability, and the implications for supply chains as conceived today. Finally, we outline a research agenda and questions for future research and practice related to the impact of digital technology on managing sustainable supply chains.

2. The emergence of a digital supply chain

Digital technologies capture, process, or act upon digital data pertaining to supply chain processes (Büyüközkan & Göçer, 2018; Liu et al., 2020). Sensors capture data by translating events such as changes in location or temperature into electrical signals and ultimately data points. Unlike data recorded physically such as on paper or tape, digital data can be replicated, shared, and processed in multiple places at once, without affecting the original version (Iansiti & Lakhani, 2020). Internet connectivity allows data to be rapidly shared across the world, while established technologies like Radio Frequency Identification (RFID) and Enterprise Resource Planning (ERP) or new ones such as Blockchain help to coordinate and control these data. Software-based analytic tools, from spreadsheets to Digital Twins (DT), Artificial Intelligence (AI), and Machine Learning (ML), combine data points and support their conversion into information or visual representations. These tools may provide instructions to people, for example where algorithms determine the optimal storage location of goods and direct staff to their location in an Amazon fulfilment center. Manufacturing technologies may also be digitally controlled, as in the case of Computer Numerical Control (CNC) tools, Additive Manufacturing (AM), and robotics. These technologies rely on data that are accurate and appropriate in form and content. To maximize their effectiveness, they should also be appropriately combined. For example, Rodriguez-Espindola et al. (2020) demonstrate how a combination of three technologies, AI, AM, and Blockchain, allows flows of information, material, and finance to be managed effectively in disaster response. Data and technology therefore need to be coordinated effectively as part of managing the DSC.

To analyze the DSC, we apply the SCOR (APICS, 2017) model, which is widely used to describe, manage, and measure the critical business activities an organization conducts through its supply and demand chains. The model has been used to structure analyses of digital technology (e.g., Kunovjanek et al., 2020) and sustainable supply chains (Kamble et al., 2020) and offers a useful framework for our analysis. SCOR identifies a number of areas of activity and processes within them that are common to the management of most supply chains. Plan includes supply and demand−related processes and decisions. In our analyses, we incorporate design and new product development as part of the planning process, since these determine what will be supplied. Source includes processes and decisions concerned with procuring materials, goods, and services in the upstream supply chain. Make relates to all of the transformation processes and decisions that create goods and services to meet demand. Deliver concerns the fulfilment processes and decisions including transportation that ensure finished goods and services reach customers. Return relates to the end of a product's life, concerned with recovering, reusing, remanufacturing, recycling, or disposing of what remains.

For an effective sustainability perspective, we add an extra phase to SCOR, which we label as Use. This is concerned with activities occurring during the useful lifetime of a product or service. From an economic perspective, activities performed by customers with a product may not be considered part of conventional SCM. The focal supply chain firm may have no commercial interaction during this time. However, considering the sustainability of a supply chain demands a comprehensive product lifecycle view. Additionally, new business models supported by digital technologies are enabling manufacturers to move closer to their customers. Often referred to as Servitization (Pawar et al., 2009), such business models blur the lines between products and services. They also build closer relationships and data-sharing capabilities between suppliers and customers. These business models can facilitate sustainability by making the use, reuse, and recovery of goods more efficient, more successful, and less wasteful. We illustrate some of the applications of digital technologies to each category of the enhanced SCOR model, in Table 23.1.

3. Sustainability in the digital supply chain

A supply chain normally comprises of a number of interdependent companies that are connected through a sequence of buyer−supplier relationships. As capital, goods, services, and information flow along the chain, each of these companies must demonstrate the value they add, for which they receive payment. The SCOR model and other analyses of SCM often concentrate on a focal company, for example, a brand-owning company. This is helpful in terms of visibility and control. In other words, the scope of a company's decisions and the consequences it experiences are likely to be restricted to the things they directly control (Carter et al., 2015). However, when considering sustainability, the entire chain is relevant. Moreover, DSCs may be self-organized ecosystems, structured around digital platforms and multisided markets (Kapoor et al., 2021), rather than designed and controlled by the most powerful entity. As a result, they are likely to be more flexible and self-organizing, with less control by any one actor. Transparency may be improved through digital technology or, alternatively, reduced by resulting complexity.

Supply chains are increasingly viewed as complex networks (Braziotis et al., 2013), characterized by emergent properties (Choi et al., 2001) such that the actions of suppliers far upstream in the chain may impact on customers downstream. Indeed, the actions of one supply chain may have unintentional influences on other chains (Demirel et al., 2019; Matos et al., 2020). This can be positive, for example, when waste products from one industrial process can serve as a valuable input in another, as a manufacturing material or source of energy. Or it may be negative, where overproduction in one sector leads to shortages in another. For example, increasing use of renewable energy sources such as planting crops for biofuels or construction of wind turbines may have a negative impact on biodiversity, creating risks for wildlife or

TABLE 23.1 The SCOR model used to illustrate applications of digital technologies across the digital supply chain.

Critical supply chain management activities	Illustrative digital technology applications
Plan	• Sensors on products already in use can generate information or directly drive automated design processes • A Digital Twin (DT) can represent every physical product in a computer model, to drive design or service decisions based on real-time or predicted data • Design tools such as topology optimization can automate design decisions
Source	• Integrated systems such as Purchase to Pay (P2P) or Source to Pay (S2P) automate purchasing administration • Cloud manufacturing platforms can enable rapid commissioning with suppliers • Data can be used for supplier auditing and performance management • Blockchain can be used to ensure traceability and communicate the provenance of goods
Make (produce)	• Computer Numerically Controlled (CNC) tools are programmed with digital instructions, which may be transmitted instantaneously through the Internet to any site, globally • Additive Manufacturing (AM), or 3D Printing (3DP) can manufacture directly from computer models • Machine vision can be used to detect defects in production. 5G technology increases the amount of video data that can be captured and processed
Deliver	• RFID and other identification technologies facilitate accurate tracking of goods in transit • GPS enables precision delivery by making accurate location data available to relevant parties • Unmanned Autonomous Vehicles (UAV) can be used for rapid delivery direct to customers
Use	• Big data analysis can identify usage patterns to enable predictive maintenance or detect malicious misuse • Artificial Intelligence (AI) and Machine Learning (ML) convert big data into performance improvement suggestions and recommendations • Augmented Reality (AR) can facilitate product maintenance by giving users real-time instructions
Return	• Digital passports and traceability (e.g., applying blockchain and RFID) allow components and materials to be separated for reuse and recycling • Internet of Things (IoT) and DTs help capture product history and facilitate decisions on reuse or disposal at end of product life • Multisided platforms can help broker exchange of materials and end-of-life products

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reducing affordability or availability of food for human consumption. Consumers downstream in the chain will often hold a brand responsible for social and environmental issues occurring upstream in its supply chain, such as in contract manufacturing or raw material extraction (Eltantawy, 2016). Sustainable SCM can therefore be understood as managing supplier performance and risk, in addition to managing the sustainability of the products and services being created.

Academic debates continue over what sustainability should mean. The TBL approach, which considers environmental, social, and economic sustainability, is widely but not universally accepted. Some academics argue that true sustainability should prioritize sustaining the planet at the expense of people and profits (Pagell & Shevchenko, 2014). Others (e.g., Barkemeyer et al., 2014) bemoan the neglect of the world's poor in a corporate-driven sustainability agenda that prioritizes profit and planet at the expense of human development, including alleviation of poverty. Meanwhile focusing on people through stakeholder management may fail to acknowledge planetary boundaries (Matthews et al., 2016). Some scholars have called for radically rethinking business in line with an ecologically dominant logic (Montabon et al., 2016) or a socially dominant logic (Gold et al., 2020) to challenge the dominant business logic (Silva & Nunes, 2021). While recognizing these wider debates, TBL does at least identify critical dimensions of sustainability in a supply chain context. In this study, we therefore apply a combination of SCOR and TBL in order to conceptualize and understand sustainability in the DSC.

4. Building a sustainable digital supply chain

An increasing number of activities, including shopping, education, and maintaining friendships, are now performed through technology mediation with often minimal physical interaction. Such "process virtualization" (Overby, 2008) can lead to the idea that digital technologies are inherently more sustainable because of the dematerialization that is expected and intended when physical goods are transformed into information. It may be possible to reduce excessive consumption and production of physical goods (Womack & Jones, 2005) through services, such as the leasing, renting, or sharing of resources. Producing goods has many visibly unsustainable impacts, from consumption of scarce resources to exploitation of low paid workers. However, replacing goods with digital technology rarely happens completely, as seen in the "myth" of the paperless office (Sellen & Harper, 2003). Additionally, the unintended consequences of digital solutions may create greater sustainability challenges, such as when low-carbon LED lighting increases light pollution (Carter et al., 2020) or digital platforms move work into unregulated and potentially more exploitative contexts (Curchod et al., 2020).

An illustration of these complex interactions can be seen in the production and consumption of music. Moving from physical production of vinyl records, cassettes, and CDs to digital streaming and downloading reduces the need for raw materials, production, logistics, and warehousing. At each stage, energy use and carbon footprint may be reduced. Additionally, the accessibility of online streaming platforms can democratize the production of music through disintermediation, allowing anyone to produce and distribute music without relying on record companies or distributors. Yet lifecycle analysis (Ayres, 1995) of music streaming presents a more complicated picture. For example, one analysis found energy use is lower overall if a digital song is only listened to once, but if it is repeatedly played many times, a physical copy would eventually have a lower environmental impact (Wadsworth & Forde, 2011).

Physical and digital aspects of supply chains are almost always intertwined. For example, digital technologies enable traceability and precise location of goods in transport. This helps consumers know the arrival time of parcels, retailers to co-ordinate stock, and manufacturers to audit the provenance of parts. In recent years, literature has made strong arguments that the digital nature of supply chains should lead to more sustainability along with efficiency and innovation (Yang et al., 2021). McGrath et al. (2021) argue for a link between (digital) technologies and sustainability via an increase in supply chain transparency through monitoring and relationship building. Balakrishnan and Ramanathan (2021) demonstrated a connection between the use of digital technology and resilience as well as sustainability. This is supported by Rapaccini et al.'s (2020) evidence that navigating the COVID-19 pandemic was aided by, and served to accelerate the adoption of digital technology and sustainable business models. However, O'Rourke and Lollo (2021) underline that while data-driven supply chain governance in sustainable apparel helps measure environmental performance, it may not motivate the supply chain to improve its performance.

While the DSC is arguably more sustainable in theory, the complexity of supply chains makes the connection between digital and sustainable less clear in practice. Digital technologies can be misused, resulting in human rights violations, deepened inequalities, and perpetuated marginalization of societal groups; for example, AI-based systems for screening victims of modern slavery may be maliciously turned against the individuals they are supposed to protect (Thinyane & Sassetti, 2020). Without a clear association between data, knowledge, and ethics, the DSC may be more transparent, but not necessarily more responsible (Gold & Heikkurinen, 2018). A growing body of research has pointed to unanticipated outcomes, tensions, and unintended consequences of sustainable SCM (e.g., Carter et al., 2020; Matos et al., 2020). These may be positive, for example if digital technologies are implemented to achieve servitization or lean operations, creating win-win by reducing waste and environmental harm or by supporting smaller suppliers. Or the unintended consequences may be negative, such as when the added cognitive pressure on logistics workers are not considered during digital transformation of warehouses (Gruchmann et al., 2021). To illustrate the synergies, complexities, and tensions involved, we examine two cases of supply chains that are being transformed. This helps to show how digital and sustainable transformations can be complementary, conflicting, or even both.

5. Driving down urban emissions—the case of the Electric Vehicle (EV) supply chain

EVs are viewed as a zero (tailpipe) emission form of transport, which appear to have won the battle for passenger vehicles and are likely to be the dominant technology for the foreseeable future (De Paulo et al., 2020). EVs represent a change in product architecture compared to Internal Combustion Engine (ICE) vehicles, which creates opportunities for both sustainability and digital transformation throughout the emerging EV supply chains. With such opportunities, however, there may be unintended consequences, which necessitate a broader perspective.

Automobiles, and by association automotive supply chains, are among the most important economic drivers in many nations but are also among the greatest contributors to carbon emissions. Despite economic and social benefits, they have become unsustainable from an environmental perspective (Jasinski et al., 2016). Automotive production entails intensive use of land, energy, and water (Nunes & Bennett, 2010). Emissions from the use of ICE-based cars have a detrimental impact on air quality, particularly in urban areas (Orsato & Wells, 2007). Disposing of vehicles at the end of their life contributes to contamination of land and water. The environmental impact has led to numerous initiatives to reduce traffic, reduce congestion and ultimately to ICEs being phased out. The Glasgow declaration commits to all new cars and vans being zero emissions by 2040 globally and not later than 2035 in leading markets (UN, 2021). Some nations, including India, Singapore, Sweden, and the United Kingdom, will ban the sale of new petrol or diesel vehicles from 2030. Additionally, many of the most crowded cities have implemented restrictions or planned bans on use of such vehicles. These policies contribute to the rising demand for EVs. In the coming decades, we can expect to see EV numbers gradually overtake those of ICEs. This should improve air quality in cities and reduce greenhouse gases (GHGs), but EVs also rely on the efficiency and sustainability of the electrical grid that powers them.

5.1 Historical perspective

Automobile manufacturing in developed countries is viewed by some as an old, slow, polluting sector, ripe for disruption by dynamic digital startups (Economist, 2015). Yet the automobile was itself once a new, disruptive technology, promising enormous social and even environmental advantages. At the end of the 19th century, some commentators looked forward to "the entire banishment of the horse from city streets—a measure much to be hoped for on the score of cleanliness and health" (Fotsch, 2021, p. 13). In the 1890s, urban pollution was an enormous problem, with horses powering industrial growth across the world's great cities. In addition to cleaning the huge quantities of manure (the tailpipe emissions of their day), the hundreds of thousands of horses required stables and food (fuel production), brought flies, disease, and foul smells (air pollution), while traffic accidents resulted in frequent horse deaths (end-of-life problems). In contrast, ICE powered vehicles became cheaper, safer, more efficient, and cleaner than their horse-drawn equivalent, while improving social connections and enabling livelihoods.

The introduction of automobiles helped drive innovation and economic growth as well as creating jobs in new types of business activities. New infrastructure such as roads and fueling stations, new production methods including mass production, and new business models such as drive-through fast food, made the automobile a symbol of modern development. Viewed over 100 years later, the unintended consequences give a very different picture. Extensive road networks have replaced many natural landscapes, with harmful effects for flora and fauna. Mass production methods are often associated with wasteful overproduction and exploitation of workers. The history of the transition from horse power to horsepower (Morris, 2007) offers a cautionary tale as we consider the transition from ICE to EV. Today, the superiority of the latter, in sustainability terms, seems unequivocal. Replacing fossil fuels with electric batteries will drastically reduce air pollution and other environmental impacts. Yet this assumes that production of vehicles and the energy they consume are sustainable, rather than shifting the source of pollution from use to production. Moreover, there are political implications associated with a reliance on oil and gas. Oil producing nations risk losing the considerable global influence they have held over recent decades. As the value of rare minerals used in batteries increases, a battery "arms race" is under way (Pattisson & Firdaus, 2021), leading to concerns over human rights abuses in Congolese mines (e.g., Sovacool, 2021). Care must be taken to avoid environmental sustainability becoming a driver for adverse social impacts including modern slavery in the EV supply chain.

5.2 EV supply chain (un)sustainability

Over the past century, automotive supply chains have become economically vital for many nations. The automotive sector accounts for around 5% of global manufacturing employment (OICA, 2019). Global production of automobiles was around 70 million vehicles before the 2008 economic crisis but increased to almost 100 million as nations gradually recovered (OICA, 2019). China became the largest producer in 2009 and had an output of around 27.8 million units in 2018, compared to 11.3 million in the United States, 9.7 in Japan, and 5.1 in Germany. In short, the automotive sector both 'drives' and reflects the economic growth of a nation. This leads to many governments offering incentives to manufacturers, such as tax reductions and other favorable terms, to stimulate growth throughout their economies. For example, the UK government has offered investment and support for electric battery 'gigafactories' to stimulate growth in EV automotive manufacturing (Reeves, 2022). Every new vehicle produced is likely to create more jobs upstream and downstream throughout the supply chain, in distribution, maintenance, financing, and the entire supply chain of economic activity illustrated in Fig. 23.1. This simplified illustration of the ICE vehicle supply chain indicates the key activities both upstream and downstream, connecting its various links from design to the final use or disposal. It also indicates connections beyond the immediate supply and demand of vehicles, including the supply of fuel, finance, and transportation, which can influence sustainability.

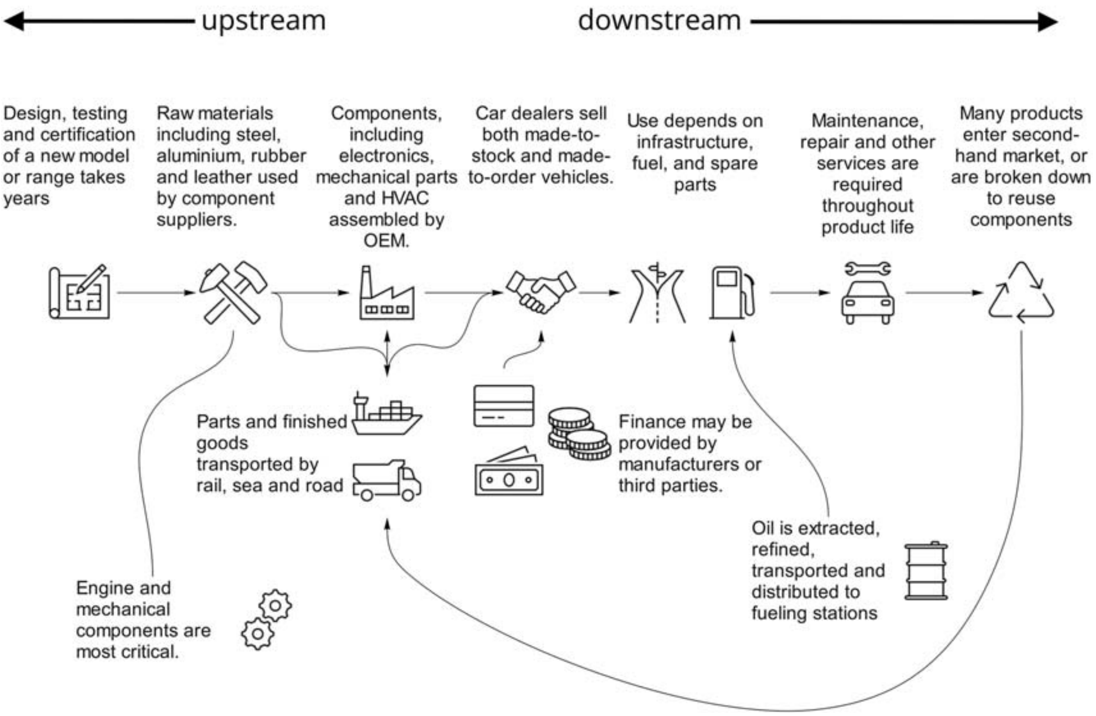

FIGURE 23.1 A simplified illustration of the supply chain for ICE vehicles. *The Authors.*

The jobs and wealth created by the automotive sector have often pushed environmental concerns to a low priority. However, manufacturers have increasingly been scrutinized over the performance of their products and their production methods. From an economic perspective, overproduction continues to be a problem, despite the prevalence of lean management and make-to-order strategies. Moreover, as legislation has pushed manufacturers to improve their performance, they have had to explore a range of possible technologies and powertrains.

5.3 Product architecture

As a vehicle, EVs and ICE vehicles look deceptively similar. Indeed, manufacturers may offer electric, conventional or hybrid powertrain versions of the same vehicle in their product range. When in motion, the difference in noise hints at the substantial differences between these vehicles. EVs typically have fewer moving parts, and generate less vibration, noise, and emissions since they run from DC batteries rather than burning fuel to generate motion. ICEs burn fuel to move a piston vertically, using a relatively complex mechanism to convert vertical motion into rotation of the wheels. The movement creates several undesirable by-products, including heat, noise, and vibration caused by the inefficiency of the mechanisms, and emissions at the tailpipe that result from burning fuel. In comparison, EVs produce far less vibration, heat, and noise, since they produce rotation directly from the energy stored within a battery, and with no tailpipe emissions. Two important consequences of EVs compared to conventionally powered vehicles are shorter supply chains for a smaller number of components, and potentially longer vehicle life due to less movement and wear.

The battery is the biggest contributor to the cost and weight of an EV, as well as being the biggest constraint on its distance. One EV lithium-ion battery can contain almost 80 kg of metals including lithium, nickel, manganese, and cobalt (Castelvecchi, 2021). These batteries are now 30 times cheaper and have a far higher capacity than at their introduction in 1991 (Ziegler & Trancik, 2021). Yet, rapidly rising production volumes will increase demand on these precious metals. Thus, batteries will also be one of the key contributors to social and environmental impacts. There are environmental concerns associated with lithium extraction from rocks or water and likely shortages of other metals such as nickel. Meanwhile cobalt, which can be toxic to handle, is mostly mined in the Democratic Republic of Congo, where human-rights concerns have centered on child labor in particular (Sovacool, 2021).

The change in the power source will reshape the automotive supply chain. While an ICE contains over 100 moving parts, an EV motor (assuming single speed transmission) contains as few as 3 (Fleming et al., 2019). Moreover, the complex mechanisms that regulate airflow and provide additional oxygen to the engine or remove waste gases are no longer required. While suppliers of these moving parts will continue to produce spares as long as there is sufficient demand, the production volumes can be expected to decline. Meanwhile, the move toward electrical and electronic components will shift the greater share of value away from mechanical parts toward those related to connectivity and driver assistance. Not only what is produced but also how it is produced faces potential disruption. This entails risk for existing suppliers but gives rise to opportunities elsewhere in the supply chain.

5.4 Digital technologies in EVs and EV supply chains

As illustrated in Fig. 23.2, the EV supply chain is likely to incorporate a number of different actors around the manufacturing operations. New entrants are not always traditional automotive companies with a legacy of ICE supply chains. For example, Dyson, Apple, Google, and, most prominently, Tesla have all sought to disrupt the automotive sector with EVs (Nunes et al., 2016). The new entrants may have a digital mindset, which values data over material. While the first ICEs followed the metaphor of a horse-drawn cart, digital companies may take inspiration from smart phones, in which the greatest value comes from constantly updated software, connectivity, and the feedback generated by users. For example, smart phone users are offered regular updates, which are periodically and automatically installed to refresh the functionality of the hardware. Similarly, Tesla offers customers regular software updates that provide additional functions, including safety features (Tesla, 2022). Such features may not accord with the mindset that designed a traditional ICE vehicle, where the engine is the pinnacle of engineering, but are important for designers of EVs, who may be more concerned with the user experience offered by engineered products.

Digital technologies also extend into the supporting infrastructure for EVs, particularly the charging stations required by batteries. Tesla invested in charging infrastructure to incentivize vehicle purchases with the offer of free charging for its customers. It then moved toward requiring payment for vehicle charging, but also announced plans for a “non-Tesla supercharger pilot” (Tesla, 2021), i.e., making it possible for vehicles from other manufacturers to access a number of Tesla superchargers in the Netherlands. Digital technologies are applied to access the service through a mobile phone application that allows users to pay for their use of charging stations. Digital monitoring of usage requires smart devices to detect how much charge is required and software may be configured to optimize the rate of charging. The interoperability

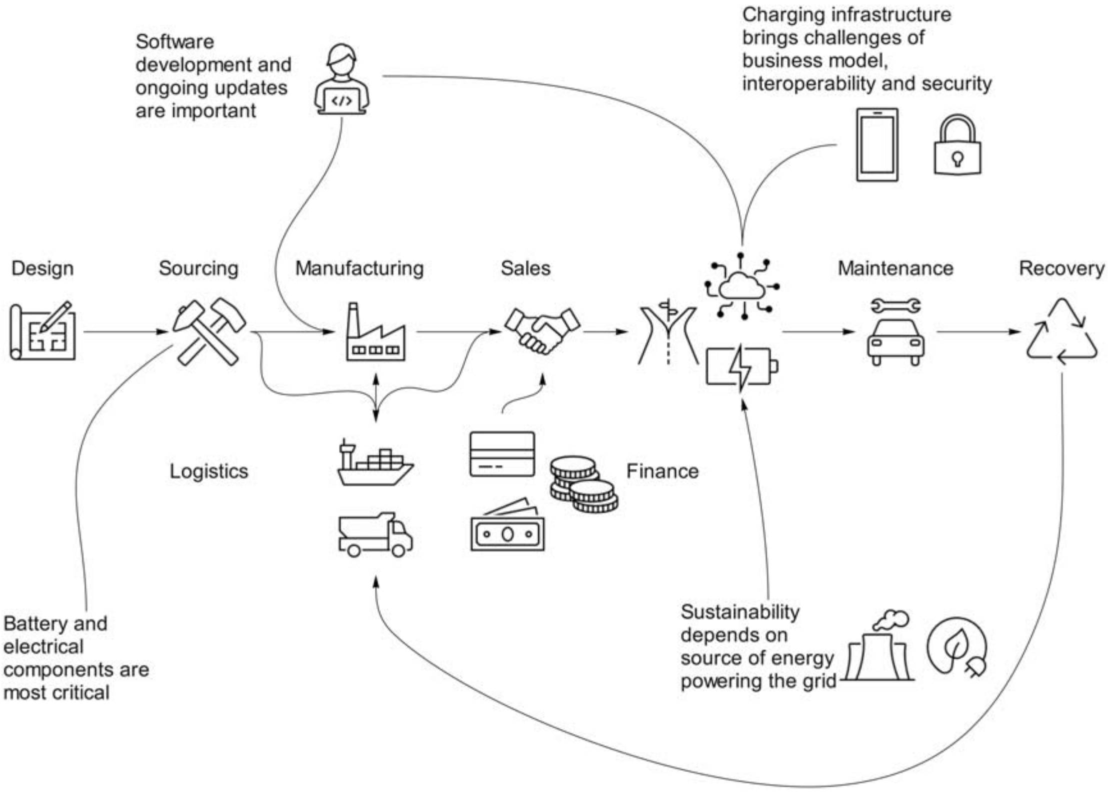

FIGURE 23.2 A simplified illustration of the supply chain for EVs. *The Authors.*

challenge is then one of ensuring that vehicles from different manufacturers can make the most effective use of the same charging devices. The smart digital technologies applied to some EVs create opportunities but new risks as well. Connectivity enables access to use data, which can help improve performance through software-enabled optimization, as well as to enhance decision-making in production. For example, gathering and analyzing data on a large fleet of vehicles enables accurate prediction of physical faults and better demand forecasting, improved design, or preventative maintenance (Beltagui, 2018). Whereas manufacturers traditionally had limited interaction with customers, digital devices and innovative business models allow them to generate more knowledge and enhance value creation. This also creates unprecedented data protection and cybersecurity risks. For example, if the user's privacy is not respected, their data may be misused. If users' data are not carefully protected, they may be abused by third parties.

5.5 Sustainability and the digital EV supply chain

International agreements and industry standards will lead to EVs replacing ICEs, and this offers a platform for digital technologies in particular through the use phase. There is a need for improved sustainability in the new and emerging automotive supply chain. Table 23.2 uses the SCOR model as the basis for identifying some of the sustainability challenges involved throughout the automotive supply chain. For each of these, digital technologies are proposed to offer a potential solution. However, we also highlight the risks of unintended sustainability consequences, some positive but many negative overall.

6. Global food supply chains—the case of the beef supply chain

To support a growing human population, it is estimated that 60% more food must be produced by 2050 (Porter et al., 2014), yet food production is one of the key contributors to climate change. The effects of climate change have stimulated concerted efforts to improve sustainability of food production systems. Food production is part of the problem, and its importance means it must also be part of any solution to sustainability challenges. The negative contributions to ecological sustainability of food production include loss of soil health, pollution associated with pesticides and fertilizers, as well as GHG emissions (Nelson & Coe, 2014). Conversely, climate change has a negative impact on farming and food production, affecting crop productivity and food security, as well as leading farmers to abandon vulnerable crops (de Vrese et al., 2018). In addition, global food production has frequently been linked to labor and land rights violations (Gold et al., 2017). The sustainability concerns around agriculture and food therefore extend to social and economic, as well as environmental issues.

One food supply chain that is noteworthy is beef production. Beef, particularly in the form of hamburgers, has been a symbol of economic growth and technological ingenuity. The production system that creates efficient, high quality, affordable protein for customers across the world has long been a benchmark for operations management (e.g., Levitt, 1972). Yet it has also become a symbol of corporate greed and social harm, as customers are encouraged to "supersize" (Spurlock, 2006) their meals, at the risk of their health. Moreover, the carbon footprint of the cattle herds required, and the welfare issues of the cattle themselves are considerable (e.g., Capper, 2012).

6.1 Historical perspective

Agriculture has been integral to human societies throughout recorded history. Until the 20th century, meat was produced only in small quantities, on-demand, and often affordable to only a relatively small segment of society. The growth of cities in North America, along with the railroads that connected them, helped to drive the industrialization of meat production, which came to be dominated by the meatpacking plants in Chicago. Among the leading firms in the industry was Swift and Company, which revolutionized logistics through the use of refrigerated train carriages in the early 20th century, allowing beef to be distributed and consumed far from where it was prepared and from where the cattle were raised (e.g., Teece, 2010). As a result, beef became affordable to rich and poor alike, across the United States, and increased supply drove increased consumption. The volume of meat production led to waste, such as blood and bones, becoming a source of pollution. The working conditions in meat production were described by the United States Committee on Agriculture (1906) as "entirely unnecessary and unpardonable … not only a constant menace to their own health, but to the health of those who use the food products prepared by them." In subsequent years, the welfare of workers has arguably not improved much, but the welfare of livestock and the health impacts of excessive meat consumption have now become greater concerns (Bonnet et al., 2020).

TABLE 23.2 Analysis of digital solutions to sustainability challenges and their potential unintended consequences in the EV supply chain.

Supply chain activities	Illustrative sector-specific activities for automotive industry	Wider sustainability issues (economic, environmental, and social)	Potentially supporting digital technologies	Intended sustainability benefits	Unintended consequences
Plan	• Design of vehicle architecture • Design of components and parts • Software	• Lack of manufacturability; Low speed/high cost of design • Low environmental impact but design has a large influence on other phases of the product lifecycle • Product ergonomics and accessibility; Creation of high-skilled jobs	• CAD systems • Rapid prototyping through 3D-printing	• Increased manufacturability (i.e., making designs more feasible) • Reduction of time and cost in design • Reduced material waste in prototyping	• Planned obsolescence and increased material waste (environment) • Distributed manufacturing enables dealers and customers to create and customize parts • More opportunities for disassembly—by OEMs or by rivals
Source	• Production and delivery of parts and components: e.g., batteries	• Depletion of resources and land use • Energy and water consumption • Hazard waste • Large amounts of pollution in end-of-life • Shared/distributed revenue • Job creation in the supply chain	• Blockchain and RFID for tracking material provenance, stock, location, movement, and transparency in sourcing and in-bound logistics	• Lower bullwhip effect • Better (more accurate) environmental accounting and reporting • Increased transparency on working conditions across the whole supply chain	• Some digital technologies such as blockchain may be energy intensive • Limited accessibility to new technologies to smaller supply chain players
Make	• Press-shop • Assembly • Paint-shop • Final inspection	• Depletion of resources and land use • Energy and water consumption • Hazard waste • Large amounts of pollution	• Advanced manufacturing • Industry 4.0 • Machine to machine communication • High-precision sensors	• Avoiding defective goods (lower waste) • Reduced recall and consequent reduced emissions and costs	• Increased automation can reduce flexibility and resilience • Sensors and digital monitoring can give false sense of accuracy • Reduction of nondigital jobs and employment opportunities (e.g., manufacturing and administration)

Deliver	• Out-bound logistics	• Packaging • Emissions from logistics • Traffic, waste	• Online sales and tracking systems • Potential for distributed manufacturing and assembly	• Better cash flow, lower waste of finished goods, optimized out-bound logistics	• Higher risk of disruption through overreliance on digital systems
Use	• Driving (movement of people and things) and maintenance	• Land use (roads, parking, etc.) • Accidents (human health) • Increased individual productivity • Traffic jam (lower productivity) • Air pollution • Noise	• Embedding artificial intelligence for autonomous vehicles in EVs	• Less accidents and deaths from car collisions • Optimized routes and lower emissions per journey • Availability of cars for vision impaired drivers, elderly people, etc.	• More accidents at pedestrian crossings due to quieter vehicles • Lack of privacy • Higher exposure to cybersecurity risks • Fewer opportunities for self-maintenance
Return	• Removal of end-of-life vehicles from the road • Reverse logistics flow • Recall systems for defected products and parts • Final disposal of materials, parts, and components	• Value capture from residual vehicle • Material waste and pollution • Waste of valuable materials • Contamination of land, air, and water resources and their consequent effects on human health	• Online auction systems • Digital industrial symbiosis • Portable diagnosis systems • Augmented reality devices	• Larger opportunities for disassembly • Increased levels of refurbishing, remanufacturing, and recycling, particularly of batteries • Reduced risk of inappropriate disposal	• Prolonging vehicle life may delay adoption of more efficient newer technologies • Facilitates identification and repair of inappropriate final disposal of end-of-life vehicles

The Authors.

6.2 Beef supply chain (un)sustainability

Today, Brazil has become the world's largest exporter of beef, partly driven by the illegal replacement of large sections of rainforest with grazing land for cattle (Rajão et al., 2020). The concerns over this activity are numerous. The loss of biodiversity is irreparable, with many species facing extinction as land is used to feed cattle with crops such as soy. Additionally, deforestation both contributes to the emission of GHGs and removes a source of carbon storage that trees provide. Using the categories identified by Xu et al. (2021), Fig. 23.3 illustrates sources of GHG in the beef supply chain. Significant among these is environmental impact of cows' digestion, from the large quantities of methane produced. Beef contributes an estimated 25% of all GHG emissions associated with global food production (Xu et al., 2021), while lifecycle analysis puts the contribution of livestock in general at 18% of all global GHG emissions (O'Mara, 2011). Indeed, it is estimated that cattle contribute more GHG than cars (GreenPeace, 2020; UN, 2006) even before EVs have reduced automotive emissions.

Agricultural policies arguably contribute to unsustainability by favoring economic and social development at the expense of preserving natural capital. There are also ongoing concerns regarding labor exploitation in Brazilian beef production (Emberson et al., 2021). Brazil was ranked among countries at highest risk from climate change impacts (IPCC, 2014). Government policy supports large-scale producers that export foods including chicken and beef (Nunes et al., 2014) as well as the small, family-owned farms, which provide 70% of food consumed in Brazil (MDA, 2015). Rural areas that would benefit from the sustainability potential of digital technologies face a barrier in the lack of infrastructure as well as information on what is possible. Farmers, particularly in small farms are likely to rely on nonelectronic information sources, have limited IT skills and very little understanding of how the DSC might support their operations (Nunes et al., 2021).

From an environmental perspective, beef production is increasingly unsustainable, but the same may be true of its consumption by humans. The World Health Organization has classified red meat (including beef) as probably carcinogenic (WHO, 2015). Additionally, health risks related to practices in the supply chain undermine public confidence. For example, the emergence of "mad cow disease" (Bovine Spongiform Encephalopathy, or BSE) in the 1980 and 1990s had a widespread and long-lasting effect on demand for British beef (Washer, 2006). Food and agricultural supply chains often conceal negative social practices (Gold et al., 2017), including child labor or modern slavery (Emberson et al., 2021). Other food scares, from salmonella in chocolate to melamine in milk and horsemeat in ready meals, have serious effects on consumer confidence, and result in monetary and reputational losses for businesses. Most businesses faced with such scandals have found the solution lies in transparency, to help drive improvements in communication and performance of all participants in the supply chain (Nunes et al., 2021). Pressure on costs and profit margins often drives risk-taking practices that can ultimately be harmful to human health. This makes the notion of shared value throughout the supply chain important. Supply chain transparency can be supported by digital technologies such as RFID that help to monitor every process and track every product in a supply chain (Liang et al., 2015).

6.3 Sustainable alternatives to beef production

As is evident above, the current beef supply chain is environmentally and socially unsustainable. Additionally, the price of beef has fallen as production volume has increased availability and consumption. Considering sustainability in the DSC,

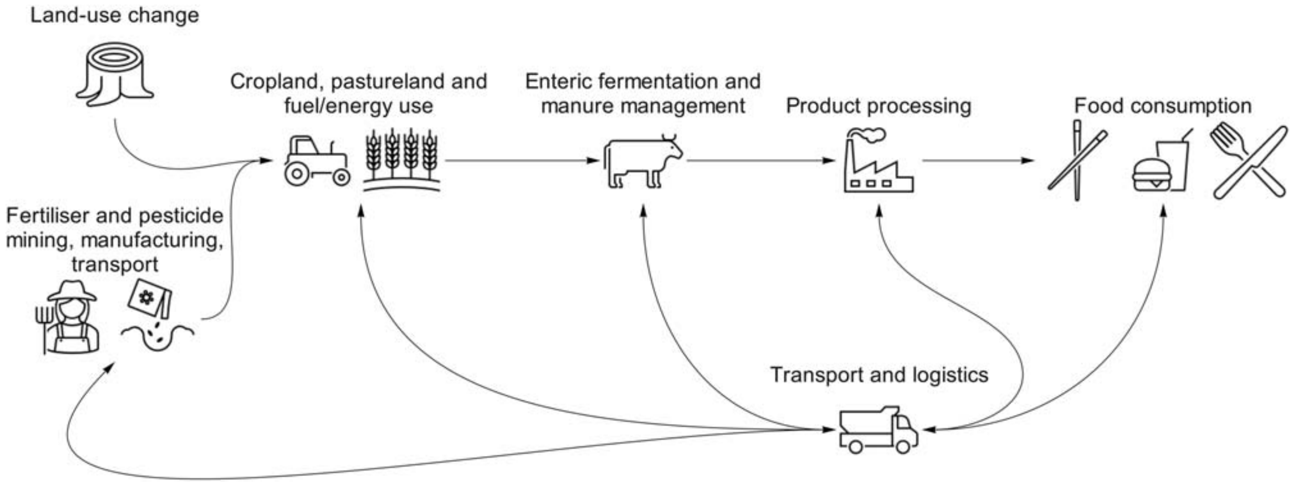

FIGURE 23.3 Main sources of GHG in the beef supply chain (categories based on Xu et al., 2021). *The Authors.*

our starting point is the end-product. Three alternatives can be considered. The first is to introduce technologies and practices that improve the efficiency, sustainability, and quality of beef. The second is to replace meat with plant-based alternatives that mimic the taste, texture, and nutritional characteristics of beef. The third, and most technologically challenging, is to produce cultured meat, which involves growing beef protein artificially, without the need to raise and slaughter animals. These considerations are at the plan or design phase of the meat supply chain when considering the protein needs of consumers and their taste preferences.

Research on Swedish milk and beef production suggested profitability can be maintained by improving efficiency to achieve economic and environmental sustainability (Hessle et al., 2017). This effect is enhanced by a supply chain approach that considers recirculation of plant nutrients to minimize environmental impact. Additionally, there may be simple solutions such as supplementing animal feed with seaweed, which has been found to reduce methane emission by 80% (Roque et al., 2021). Using data on US beef production, Eshel et al. (2018) calculated that sustainable beef would require rewilding a portion of current grassland, as well as producing more plant-based foods that provide "2- to 20-fold more calories and protein than the replaced beef" (Eshel et al., 2018, p. 81). Unless existing nonarable land becomes suitable for livestock and crop production, this suggests that current levels of land-use are unsustainable while hinting at the trade-offs or sacrifices required, and the need for a mix of food sources to avoid overreliance on meat.

A comparative study of consumer preferences in the United Kingdom, Brazil, and the Dominican Republic (Gómez-Luciano et al., 2019) found that interest in plant-based alternatives to beef are increasingly attractive. Moreover, the study suggested that cultured meat would be considered much more attractive if it could be shown to be healthy, safe, and nutritious. Cultured meat (Heffernan, 2017) has become a focus of attention from Silicon Valley, home of disruptive startups such as Impossible Burger, to Singapore, which gave regulatory approval for sale of lab-grown meat in December 2020 (Ives, 2020). The objective is to create a realistic imitation of meat, including the taste, texture, and nutritional profile, without requiring animals to be slaughtered, hence reducing the need for animal feed, fertilizers, and pesticides. Production costs have decreased considerably as the technological challenges have been gradually overcome leading to global market estimates as high as $25bn by 2030 (Brennan et al., 2021). While reducing reliance on farming and animal slaughter would be expected to reduce environmental impacts, this is not a given. For example, a comparison of conventional and cultured meat production estimates the energy use could actually increase GHG emissions and have a detrimental environmental impact (Lynch & Pierrehumbert, 2019).

6.4 Sustainability and the digital food supply chain

Over centuries, technology has made agriculture more efficient, capable of feeding more people on less land. The DSC has the potential to continue this trend, yet a number of barriers have so far limited widespread adoption of digital technologies. These include a lack of appreciation of the climate change risks and technological solutions; limited infrastructure in rural areas where many farms operate out of range of Internet or mobile phone coverage; low acceptance by stakeholders lacking familiarity with digital technologies, and lack of investment by consultants and technology vendors in the sector (Aubert et al., 2012). In particular, food supply chains often depend on small, independent, remotely situated farms with limited resources and technological infrastructure (Nunes et al., 2014). In this context, frugal innovations can help, for example, cheap IoT devices have utilized 3DP to support farms growing coffee (Beltagui et al., 2021).

Digital technology is likely to be critically important in making agriculture and food production more sustainable. Indeed, sustainable agriculture is now recognized as a knowledge-intensive activity that relies on information for decision-making and management (Nelson & Coe, 2014). For example, Precision Agriculture (PA) describes a suite of digital tools that allow farmers to monitor soil and crop conditions, analyze treatment options and optimize their use of resources (Aubert et al., 2012). PA enables farmers to make decisions about the type of crops to plant, the quantity of fertilizer required and the timing of feeding and watering, to maximize yields. Data collection and analysis may support sustainable decision-making in individual farms and the transfer of these data across the supply chain can enable traceability and optimization at a system level.

Blockchain technology in particular is considered to have potential to improve sustainable supply chain performance (Nayal et al., 2021) despite limited evidence in practice to date. Meanwhile AI can be applied to optimize irrigation and protection of crops (Talaviya et al., 2020). For example, AI combined with robotics (Duckett et al., 2018), drone swarms (Spanaki et al., 2021), and machine vision (Mavridou et al., 2019) can be used to detect and automatically respond to threats such as weeds. Cameras on drones can be used to rapidly capture what is growing, which can be analyzed automatically to identify undesirable weeds that can be quickly and selectively removed by specialized robots. Satellite images can be used to track illegal modifications to forests, rivers, lakes, or dams (Kim, 2016). Such technologies have the potential to sustain struggling farmers and deliver both environmental and social benefits. However, if digital technologies are applied solely with the intention of maximizing yields, they may even increase environmental harm by reducing biodiversity. If only one type of crop is grown, at the expense of all else, the natural ecosystem loses diversity, health, and resilience when a disease affects this crop. Therefore, a holistic perspective, which maximizes the environmental as well as social and economic sustainability of food production, is important. Table 23.3 uses the SCOR model again to identify some of the sustainability challenges of the beef supply chain, potential solutions through digital technologies, and their intended and unintended consequences.

7. Implications for theory, practice, and policy

In both the automotive and food cases, there is acceptance of a need to rebalance and reconcile the focus on economic growth with wider and more fundamental considerations of social and particularly environmental impacts. In both of these cases, new digital and manufacturing technologies can support more sustainable alternatives. EVs powered by batteries rather than ICEs burning fossil fuels should reduce emissions, just as cultured meat produced in a laboratory can potentially reduce the harmful effects of current meat production. Alternatively, these solutions may simply shift problems elsewhere if energy production and raw material extraction are not affordable, scalable, and sustainable. To guard against such risks, a supply chain perspective, which encompasses all of the associated activities, is essential. Such a perspective is inconceivable without the use of digital technologies to provide visibility, transparency, and efficiency throughout the supply chain. The DSC therefore offers many opportunities to improve the sustainability of existing supply chains.

Supply chains can be very difficult to change, resulting in the persistence of unsustainable practices. There may be little incentive to move away from socially or environmentally unsustainable practices (Shevchenko et al., 2016) until either legislation or consumer demand reduce the commercial viability of these practices. At such points, when practices become economically unsustainable, alternatives are needed. Digital technologies can be disruptive in the sense that they may threaten the market leading products, but they can also have a similar effect on prevailing supply chain practices. Digital technologies can help startup companies to introduce more sustainable practices and potentially disrupt an existing supply chain. This is evident in the two cases above, in which the incumbents such as automotive companies and food producers must respond to the emergence of disruptive startups capturing market share with a promise of sustainable alternatives (Beltagui et al., 2020). Startups seeking to challenge and improve existing supply chain practices face difficulties in gaining a foothold in the market. Digital technologies and the supporting structures they enable can help. This includes open innovation supported by crowdsourcing and crowdfunding (Stanko & Henard, 2017), through various online platforms such as KickStarter, 3D Hubs, Amazon Marketplace, Ali Baba, or eBay. The DSC therefore offers an opportunity for new entrants to disrupt and improve the prevailing SCM practices in favor of sustainability.

Digital technologies can improve sustainability at each stage of the supply chain. Using the SCOR model, we identified activities including planning, sourcing, making, delivering, using, returning, and reusing. It is possible to not only identify sustainability risks at each stage but also indicate how decisions in one part of the supply chain create constraints or impacts elsewhere. For example, the decision to use lithium-ion batteries in EVs or to grow cultured meat in a liquid derived from animal blood constrains the options for those designing, sourcing, and making products. It can be difficult to understand and predict the consequences of such technological disruptions, especially when these activities are performed across organizational and geographical boundaries. There are trade-offs and tensions within and between all of the actors in the supply chain (Wannags & Gold, 2021). These can be increased by attempts to introduce sustainability or digital technologies in a supply chain, since each actor may be affected in different ways. Some may benefit from increased opportunities, while others find their roles diminished. For example, the introduction of digital cameras created more demand for producers of camera lenses but eliminated the need for film processing. Similarly, the growth of EVs will create increased demand for battery producers, while drastically reducing the market for other components that will no longer be needed or not replaced as often. Introducing services for mobility may benefit an automotive manufacturer but will have a detrimental impact on the dealer network and may therefore face internal resistance.

Intended improvements can often have unanticipated negative (or occasionally positive) side effects (Matos et al., 2020). The unanticipated consequences should be included in any analysis to make it comprehensive and sound. This is where digital technologies may help. Jonsson and Holmström (2016) argue that supply chain decisions should be based on evidence with regards to whether plans were realized or not, and therefore whether or not the intended and unintended outcomes were achieved. The complexity of supply chains and the differing responses of each actor to encourage or inhibit change are very difficult to fully capture. However, the availability of reliable performance data throughout the supply chain that DSC promises and the possibility to simulate future scenarios can help to analyze possible results and inform decisions.

TABLE 23.3 Analysis of digital solutions to sustainability challenges and their potential unintended consequences in the beef supply chain.

Supply chain activities	Illustrative sector-specific activities (beef)	Wider sustainability issues (TBL)	Potentially supporting digital technologies	Intended sustainability benefits	Unintended consequences
Design/ Plan	• Choice of beef cuts • Forecasting demand • Choice of country of origin (location factors)	• Potential implications from choice of animal breeds, plant feed, and other needs in the production system	• Software analysis of nutrition needs • Communication with other links of the supply chain	• Optimizing animal health and yields • Lowering environmental impact	• Inaccurate data inputs can affect results • Affordability issues
Source	• Production and delivery of machinery, animal feeds, genetic manipulation of animals, etc.	• Animal feeds require large-scale production of grains usually in monoculture environments	• Satellite images • Precision agriculture • Low-cost mobile devices to analyze soil composition	• Avoid deforestation, land erosion, and other negative impacts • Efficient use of water • Better equilibrium between land–plant–animal	• Property and data privacy issues • Water conservation in absolute terms (opposed to relative efficiency) • Ability to produce meat closer to consumption point
Make (produce)	• Slaughterhouses • Packaging • Cultured beef	• Welfare of animals • Intensive use of land • Nonconforming animals • Radical change of production system	• Blockchain and RFID to track material provenance, stock, location, movement, and transparency in sourcing and in-bound logistics • Wearable technology • 3D food printing	• Prevention of diseases, increased efficiency, or supply of beef • Improved animal welfare • Enabling smaller more sustainable farms • Radical reduction on the use of land, water, energy, and other resources	• Increased supply can lead to increased consumption • Wider acceptance of beef • Lack of market acceptance or affordability of lab grown (cultured) beef
Deliver	• Transporting final products to supermarkets, butchers	• Emissions from refrigerated transportation and storage	• Advanced manufacturing • (Industry 4.0) • Machine to machine communication • Logistics optimization and tracking systems • Cold chain monitoring	• Reduced emissions from logistics • Increased shelf-life • Reduction of bullwhip effect	• Pressure on truck drivers and consequent stress, physical and mental health issues
Use	• Consumption at home, restaurants, etc.	• Health risks of beef overconsumption	• High-precision sensors • Online sales and tracking systems • Diet/nutrition apps	• Mindful consumption and healthier population	• Higher variability in demand and increased waste
Return	• Reverse flow of materials, including packaging or food waste • End-of-life from processes and final production	• Packaging waste, including plastics, etc. • Antibiotics and hormones can flow through sewage systems and affect biodiversity	• Loyalty cards, promotions, influence purchase behavior • Sensors • Intelligent waste treatment system	• Reduction of discarded beef due to date expiration • Management of price and higher revenues • Increased affordability • Reduced pollution—solid residues and liquid effluents	• Higher variability in demand and increased consumption

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An important note of caution, however, relates to the data. Aside from questions over the quality of data, for example their accuracy and completeness, the transparency that data provide does not automatically ensure responsibility or sustainability (Gold & Heikkurinen, 2018). Technologies such as RFID in the beef supply chain and blockchain technology for tracing conflict minerals can increase transparency but must be used as more than "tick boxes" for complying with minimum standards (e.g., Liang et al., 2015). Digital technologies can be used to include and give voice to marginalized groups, whether through mobile phone applications seeking to reduce labor exploitation (Gallo & Thinyane, 2021) or open-source 3D printers that democratize innovation (Beltagui et al., 2021). Yet care must be taken to deploy these technologies without amplifying preexisting inequalities and issues (Thinyane & Sassetti, 2020). In both the automotive and food cases, there is acceptance of a need to rebalance and reconcile the focus on economic growth with the need to consider social and particularly environmental impacts. In both supply chains, new technologies offer more sustainable alternatives.

Both transportation and food production are intrinsically material in nature. Unlike books, music, or business meetings, entirely digital alternatives are not available. Yet new business models, enabled by digital technologies, may offer an alternative way of providing transport or food. In recent decades, there has been a move toward what some refer to as the experience economy (Pine & Gilmore, 2019) or the age of access (Rifkin, 2001) in which people are less concerned with owning goods and more concerned with the outcomes these goods help them achieve. Sharing Economy Services (Apte & Davis, 2019) allow people to access the outcome of transportation (e.g., Uber, Lyft, Mobike). While acknowledging the risk that easy access results in more consumption or exploitation, there is at least the potential that services focused on achieving outcomes can be more sustainable. For example, Heat as a Service (HaaS) is a business model with the potential to improve the environmental impact of domestic heating and to make more environmentally friendly heating technologies more affordable (Schroeder et al., 2020). Providing customers with the outcome of the technology—a warm home—over the lifetime of the product makes it easier for a manufacturer to introduce high-capital investment products such as heat pumps to the market. Digital technologies such as IoT and Digital Twins enable the outcome by monitoring, managing, and optimizing performance to ensure the service is both profitable and affordable. Taking responsibility for the product over its life encourages the manufacturer to make it more reliable and operate more efficiently, captures data to improve performance and future design, as well as the opportunity to reuse end-of-life products in a more circular manner (e.g., Lüdeke-Freund et al., 2019). The DSC therefore offers an opportunity to completely change production and consumption at the supply chain level, by enabling the delivery of sustainability focused outcome-based services.

8. Conclusions and research agenda

Digital technologies and sustainability should be complementary and mutually supportive concepts in SCM, but there is more than meets the eye when the full implications of applying digital technologies are considered. The complexity of supply chains means there are likely to be hidden interactions and implications of any action. The result is that well-intentioned technology-driven changes may have harmful unintended consequences. Replacing a product that has clear environmental impacts, such as ICE cars with a more sustainable and more technologically advanced alternative, such as EVs appears on the surface to be a sustainable move. Likewise, exchanging plastic audio CDs with streaming services or slaughtered meat with cultured meat seems to be more sustainable and responsible. However, without considering the entire supply chain, each of these examples can have potential negative consequences that are not immediately obvious.

We have combined the SCOR model to capture supply chain activities with the TBL perspective to examine the sustainability performance of a production or supply chain system. These two approaches are well established and understood in research and practice. Based on this approach, we outline a number of conclusions and directions for further developments in research and practice.

8.1 Harnessing data for sustainability evaluation

Data and transparency should give decision makers more complete evidence to support their decisions. On the other hand, sustainability multiplies the performance dimensions that must be managed. In addition to quality, speed, cost, flexibility, and delivery, supply chains must also maximize environmental and social performance. Given the inherent trade-offs and complexities, there may quickly be both too much information for decision makers to process, as well as not enough information to predict the consequences of actions. A range of tools are widely applied by researchers, for example Analytical Hierarchy Processing to deal with the uncertainty around performance measures (e.g., Awasthi et al., 2018) and Systems Dynamics to evaluate the consequences of actions on complex supply chain systems over time (e.g., Beltagui et al., 2020). A valuable contribution to practice would be to integrate these techniques and produce tools that can be widely applied by managers, to improve the decision-making on sustainability performance of supply chains and identify opportunities for the effective use of digitalization.

8.2 Transparent may not always mean sustainable

Transparency is a key element of sustainability. Collecting, storing, and processing accurate and reliable data at each stage of a supply chain can help shed light on whether processes have been carried out appropriately. This can and often does help to reduce exploitation of people by tracing who did the work, whether they did so in safe environments, and whether they were appropriately remunerated. It may help to reduce overuse of natural resources by tracing how much has been taken, when, and by whom. Yet data alone are not sufficient without regulations and institutions that maintain and actively apply appropriate standards. Furthermore, digital technologies may be used proactively to help strengthen partnerships throughout the supply chain and support a collaborative approach to sustainability. Just as a successful lean management approach should include supplier development to improve efficiency and benefit the whole supply chain, the same approach can be applied to improve sustainability performance. Transparency may be used not just to comply with regulations but to improve the quality and sustainability (Montecchi et al., 2021). Further work can contribute to knowledge and practice by embedding data-driven partnership practices to allow all actors in a supply chain to contribute positively toward sustainable development.

8.3 Tensions and paradoxes

Managing sustainability is rife with paradoxes, for example, balancing the needs of the present with those of the future. Resources can be kept secure for the future if they are not used in the present, but with the risk that organizations or people may not survive to the future without using resources in the present. Reconciling the needs, goals, and interests of people with requirements of technology may raise similar paradoxical tensions (Gruchmann et al., 2021). There is a need to better understand how and when such paradoxes become salient (Wannags & Gold 2021). In particular, when digital technologies are introduced into a supply chain, where might the tensions emerge, when and how should they be managed? Digital transformation is a priority for businesses and policy makers, in large part to improve productivity, resilience, and growth. An important question, however, is how to shape digital transformation in a way that supports a sustainable change (Hanelt et al., 2017). For example, one may use the SDGs as a guide for sustainable supply chain initiatives, but it is almost impossible to avoid trade-offs when trying to contribute to 17 different goals. A sense of priority is needed, which makes sustainability in supply chain strongly context dependent, particularly when it is geographically dispersed. Thus, an interesting question for future research is how procurement departments are considering SDGs in their purchasing decisions.

8.4 New solutions, same problems

A key concern that has been highlighted throughout this chapter is the danger of unintended consequences. The introduction of new technologies often brings hope of radically changing conditions for the better. We can imagine the promise of a clean and quiet future that the automobile offered in horse-filled cities, just as we have experienced the excitement of apps and platforms offering flexible work and shared resources. Yet the technologies may reinforce the environmental problems and social inequalities they were intended to overcome. Worse, they may create bigger problems than those they have solved. For example, the so-called "gig economy," which is largely digitally driven, reinforces and further deepens economic divisions (Demirel et al., 2020). Ride sharing or package delivery platforms, for example, offer flexible extra income for a car owner with spare time. Yet those who see them as a primary source of income are offered challenging work with limited rights to minimum wages or other statutory benefits. As the digital landscape becomes all-pervasive, there is an ongoing need for research to understand how and why technological solutions become problematic, how technology use is shaped by institutional contexts, and whether technologies can reshape rather than reproduce existing institutional structures.

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Chapter 24

Reconceptualizing supply chain strategy for the digital era: achieving digital ambidexterity through dynamic capabilities

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Abstract

The concept of the digital supply chain (DSC) has gained prominence across industry, business, and commerce, as it opens up new business opportunities and new business models and has the potential to revolutionize supply chain performance. Accordingly, supply chain managers are viewing the DSC as a critical source of value creation and competitive advantage. Yet, many firms are still in the early stages of adoption and there is a lack of understanding of how the DSC can develop supply chain capabilities or improve supply chain performance. The DSC concept has not yet been appropriately theoretically grounded. Drawing on dynamic capabilities and ambidexterity, we present a set of six propositions showing how digital ambidexterity can be achieved to generate high levels of supply chain performance. We introduce a conceptual framework that underlines the importance of dynamic supply chain capabilities, including visibility, agility, and flexibility, in the design of the DSC-building process. We highlight the need to possess these capabilities to create ambidextrous supply chain capabilities. The conceptual framework explains how digital technologies support and interact to enable digital ambidexterity. This chapter sets the stage for an ambitious research agenda focused on Digital Supply Chain Strategy to achieve sustainable performance gains.

Keywords: Ambidextrous supply chains; Digital supply chains; Dynamic capabilities; Dynamic supply chain capabilities; SCM construct

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1. Introduction

A supply chain may be defined as the network built between a company and its suppliers for the production and distribution of specific products (Büyüközkan & Göçer, 2018). Management of the supply chain system comprises the planning, sourcing, manufacturing, delivery, and return processes required to deliver a product or service to customers. Supply Chain Management (SCM) involves the optimization of supply chains to reduce costs and maximize customer service and has become a source of competitive advantage for many companies (Attaran, 2012). Supply chains and their management are affected by the introduction of digital technologies. The arrival and continuing development of such technologies provide opportunities for radically new supply chain designs and approaches to manage supply chains.

Both academics and practitioners consider the emergence of Digital Supply Chains (DSCs) to be an important phenomenon (Nasiri et al., 2020). Some authors (e.g., Mussomeli et al., 2016; Yang et al., 2021) argue that they have become a strategic imperative, as they may raise performance to new levels. Many organizations, however, are not taking advantage of the opportunities provided by DSCs, due partly to a lack of understanding. This chapter addresses this gap by exploring conceptually how companies achieve supply chain digitalization in today's dynamic business environment.

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Firms cannot unlock the full potential of digital technologies without reinventing their supply chain strategies (Gezgin et al., 2017). Competitive pressure necessitates the creation of ambidextrous supply chains, a strategic approach that encompasses both exploitation (e.g., cost reduction or improved reliability) and exploration (e.g., leveraging of supply chain—wide resources to develop new knowledge and competencies) (Kristal et al., 2010). This chapter is grounded in the concept of organizational ambidexterity, which has emerged as a valuable theoretical lens for the explanation of innovation, organizational learning, and supply chain performance improvement (Lee & Rha, 2016). Moreover, an organization cannot successfully implement ambidextrous strategies over the long term without dynamic capabilities (O'Reilly & Tushman, 2008; Kriz et al., 2014), defined by strategic management scholars as a "firm's ability to integrate, build, and reconfigure internal and external competences to address a rapidly changing environment" (Teece et al., 1997, p. 516). Our objective is to present a theoretical perspective explaining how ambidexterity based on dynamic capability building improves competencies (Lee & Rha, 2016) and thereby helps firms to incorporate digitalization and build DSCs. In addition, ambidexterity (considered itself as a dynamic capability; Jansen et al., 2009) can lead to supply chain empowerment via the use of new-generation technologies (e.g., robotics, Artificial Intelligence, and big data) to improve supply chain connectivity, intelligence, scalability, and speed relative to traditional supply chains. The chapter argues that combining the concepts and theories from the well-developed ambidexterity and dynamic capabilities domains provides a highly relevant theoretical lens for the study of DSC design and construction.

Consistent with the research of Lee and Rha (2016), Aslam et al. (2018), and Kristal et al. (2010), we propose that DSC construction is modeled by a framework with three dynamic supply chain capabilities—visibility (sensing), agility (seizing), and flexibility (transforming)—which are the antecedents of ambidextrous supply chain strategies. We argue that firms can develop such strategies for DSCs and leverage them to create the higher-order supply chain capability of transparency, leading to the generation of significant and sustainable performance gains. We also argue that only those firms that build and hold dynamic capabilities can successfully exploit digital supply chain capabilities (DSCCs). We expand on each of these capabilities, explaining how each contributes to competitive advantage. We argue also that the possession of any two dynamic capabilities is valuable, and that the possession of all three certainly enables a firm to build an ambidextrous supply chain and then a DSC, leading to sustainable competitive advantage.

The remainder of this chapter is organized as follows. In Section 2, the conceptual framework and theoretical foundations informing this work are presented. In Section 3, the theoretical framework is presented, and propositions are developed to link dynamic supply chain capabilities and ambidextrous supply chain strategies with the essential constructs of SCM to the DSC concept. The impacts of DSCs on firms' supply chain performance are also discussed in this section. In Sections 4 and 5, the implications of the model are described. Section 6 contains concluding remarks and proposed directions for further research.

2. Literature review

2.1 Dynamic capabilities

Dynamic capabilities theory is derived from the resource-based view (RBV) (Daniel & Wilson, 2003; Peteraf et al., 2013), in which firms are seen as collections of specific physical, human, and organizational assets, or resources. This strategic paradigm considers that an organization's performance is created from the capabilities provided by, and the differences in the resources that it holds. With valuable, rare, imperfectly imitable, and nonsubstitutable capabilities and resources, firms can achieve a sustainable competitive advantage (Barney, 1991). Moreover, resources are distributed heterogeneously, and the differences in distribution persist over time (Barney, 1991). However, the RBV involves the assumption that a firm's environment is static and relatively unchanging (D'Aveni & Gunther, 1994), which is not applicable to today's dynamic business environment.

Dynamic or high-velocity markets are characterized by unclear boundaries, frequent change, nonlinear and unpredictable movement, and players that are not always clearly discernible (Eisenhardt & Martin, 2000). The assumptions of the RBV do not transfer to such markets because the advantage of a resource might dissolve or become less important over time in an unstable environment (Teece, 2007). The use of a dynamic capabilities framework to study strategic change and explain long-term competitive advantage is more appropriate in this context (Beske, 2012; Schilke et al., 2018). This approach is linked strongly to consideration of an organization's capacity "to sense and shape opportunities and threats, to seize opportunities, and to maintain competitiveness through enhancing, combining, protecting, and when necessary, reconfiguring the business enterprise's intangible and tangible assets" (Teece, 2007, p. 1319). Dynamic capabilities "can enable an enterprise to upgrade its ordinary capabilities and direct these, and the capabilities of partners, toward high-payoff endeavors" (Teece, 2018, p. 45). As dynamic capabilities are difficult to replicate (Teece, 2014), the organization that uses them sooner, more astutely and more fortuitously than the competition achieves competitive advantage (Eisenhardt & Martin, 2000).

2.2 Organizational ambidexterity

Ambidexterity is the capability that can help firms utilize existing knowledge to improve profitability and seek new knowledge. This new knowledge contributes to the development of competencies. Firms that seek to remain competitive must explore new market opportunities while also exploiting existing operational efficiencies (March, 1991; Wu et al., 2017). Exploration encompasses activities such as the search for new opportunities, the flexibility to respond to such opportunities, and the discovery of innovative ideas. Exploitation refers to the use and refinement of existing knowledge; it includes activities such as the selection, refinement, and implementation of standardized procedures to achieve operational efficiencies (Im & Rai, 2008). Conventional wisdom, however, posits that organizations do not have the capability to pursue exploration and exploitation simultaneously; due to the scarcity of firm resources and limitations of managerial scope, they must choose between flexibility and efficiency, often to the detriment of the unselected option (Kristal et al., 2010). The Operations Management perspective has long held that firms would benefit from the pursuit of a low-cost competitive strategy supported by efficient operational process, or a strategy of differentiation underpinned by more flexible processes (Hill, 1993). Being "stuck" in a situation falling between efficiency and flexibility has been argued to lead to high switching costs (Markides, 2006).

However, another school of thought has emerged, positing that the development of an ambidextrous strategy can allow firms to be simultaneously flexible and efficient (Gibson & Birkinshaw, 2004); arguing that exploration and exploitation are complementary competencies (Gupta et al., 2006; Im & Rai, 2008). Firms possessing ambidextrous operational capabilities can simultaneously explore new processes and exploit existing processes, enhancing operational performance (Tamayo-Torres et al., 2017). The general concept of ambidexterity has been advanced in other disciplines, such as organizational theory and the study of networks, innovation, and interorganizational relationships (Kauppila, 2007). Its introduction to the supply chain management literature has changed this field of research (Blome et al., 2013).

2.3 Supply chain theory foundations and evolution

Numerous researchers have contributed to the development of supply chain theory, with the advancement of postulates explaining how organizations create form, time, and place value through supply chain design and management (e.g., Carter et al., 2015; Mentzer et al., 2004). Supply chain research emerged after the manufacturing sector began to take advantage of advancements in Information Technology (IT) and Operations Research (OR). Perspectives on quality, logistics, business organization, and partnerships have changed immensely with the advancements in IT and OR with a strong trend of rationalization (Papadonikolaki, 2020). First, a supply chain was represented by a set of flows. The first scheme depicting the materials and information that flow through the main components of the physical distribution channel including suppliers, warehouses, factory distribution warehouses, and final customers was introduced by Stevens (1989).

Cooper et al. (1997), and more recently Oettmeier and Hofmann (2016), proposed three general constructs: (1) supply chain management components (SCMCs), (2) supply chain management processes (SCMPs), and (3) supply chain network structures (SCNSs). SCMCs are managerial tools used to integrate and manage business processes across supply chains. They include work and organizational structures, as well as information and communication structures. SCMPs are activities that produce specific value outputs for customers, including those related to customer and supplier relationships and demand and manufacturing flow management. SCNSs concern member firms and the links between them. This construct encompasses supply chain actors such as upstream suppliers and downstream customers.

The ways in which academic researchers conceive of supply chains have also evolved. Initially, supply chains were considered to be linear systems. Given the multiple organizations participating in supply chains and the multiple, diverse streams of information flowing simultaneously along them, Christopher (2005, 2011) and Harland et al. (2004) proposed that supply chains be considered as networks, and more specifically as supply—demand networks or complex and distributed networks of organizations, otherwise known as supply networks (Braziotis et al., 2013). In the "analog era" in which SCM emerged, companies operated in contexts in which supply was often scarce relative to demand; the technology available to capture, move, and analyze information within reasonable timeframes was limited and relationships among supply chain actors were adversarial (Bowersox, 2002). Most supply chains are, in fact, networks (Chopra et al., 2016). Garay-Rondero et al. (2020) called attention to a fourth construct of supply chain flows (SCFs), which describe systematic interactions between specific actors in the SCNS. SCFs encompass goods and services, information, knowledge, financial, and return flows.

2.4 Contemporary supply chain challenges

Despite the successful achievement of integration, collaboration, and digitalization with the modern wave of automation and the rise of SCM as an accepted managerial discipline, the connection of various processes associated with physical flows within and across businesses in supply chains remains characterized by linear and hierarchical interactions, with limited real-time visualization. Traditional linear supply chains are characterized by a lack of agility, flexibility, and visibility; they also lack real knowledge about return, risk, and value flows or the optimal streaming of flows among supply chain components. A traditional design limits the potential of SCM practices in many ways and renders managerial decision-making difficult (Sinha et al., 2020). Moreover, archaic practices (e.g., autocratic leadership) continue to be used for management components such as planning, slowing the capabality to respond to external changes (Garay-Rondero et al., 2020). In traditional supply chains, transparency is "siloed" throughout the network system, despite considerable efforts of some companies.

Indeed, many weaknesses of supply chains stem from the lack of end-to-end visibility, information traceability and transparency; in other words, problems related essentially to visibility and interoperability (Pan et al., 2021). Traditional supply chains have various communications and information systems that tend to converge in one, or they are affected by problems with the updating of information or achievement of real-time communication; knowledge management is usually not available to all actors. In such supply chains, collaboration on SCM practices has limited potential (Mussomeli et al., 2016). Process execution within and across them is based on preoptimization and scenario-derived information. Thus, great effort is needed to attain horizontal and vertical integration of these chains. Real long-term interdependence across network structures cannot be achieved (Garay-Rondero et al., 2020). The sequential and manually intensive nature of classical supply chain activities are key sources of the challenges faced in this context. Together with the large number of weakly connected stakeholders, it prevents the design and development of agile supply chains. Speed is among the most critical factors for the success of a supply chain. In traditional supply chains, many customers are not well integrated with companies' SCM processes and have very little involvement in the creation and delivery of services and products (Sinha et al., 2020; Kracklauer et al., 2004). Traditional supply chains are characterized by low or moderate degrees of integration of their workflow activity and organizational structures.

As contemporary supply chains have been subjected to the trends of economic globalization and offshore production, they are more complex and strained, and the challenges faced are greater than before (Ivanov & Dolgui, 2020). The COVID-19 pandemic brought many contemporary supply chains to a halt, thereby exposing their vulnerability. SCM activities should support efficient, effective, agile, resilient, and sustainable operations. They are increasingly interdependent and interconnected, with high levels of collaboration, which must be underpinned by rapid, efficient, and effective communication (Pan et al., 2019, 2021).

The paradigm shift toward the data-driven, digital transformation of supply chains and services emphasizes the enhancement of digital interoperability (Hofmann & Rüsch, 2017). Digital solutions and tools can aid the transformation of contemporary supply chains to become secure, interoperable global supply chains. However, the current use of numerous, heterogenous, proprietary systems prevents the achievement of global interoperability. Not all current technology architecture solutions are interconnected, which may lead to information "siloing".

2.5 The supply chain of the future and the shifting theoretical foundations of SCM

Characteristics such as the sustainability, effectiveness, and efficiency of supply chains and information flows, and horizontal and vertical collaboration, underlie the expected move toward the massive utilization of digital technologies in future supply chains. Such utilization offers a new paradigm for SCM theory and practice. The dynamic view that comes with these practices of real-time supply chain integration is an interesting contrast to the more static perspective of traditional SCM (Dallasega et al., 2018; Liu & Rong, 2015). This concept needs to be enhanced through clarification of the role that the new generation of digital technologies will play in future SCM activities. Digital technology has changed the ways in which supply chain stakeholders manage their production, logistics, distribution, and marketing activities (Li, 2020). The emergence of customization that requires rapid responses are changing the whole structure, including supply chain processes, managerial components, and flows. Digital technology capabilities provide new opportunities related to the effectively mobilize quintillions of bytes of data flows and processes. Data, information, and knowledge have become crucial for supply chain managers' decision-making ability.

The domination of supply chains by digital technologies means that SCM decisions and solutions will focus heavily on two criteria: time and process efficiency. SCM activities will be underpinned by an interoperable and flexible digital infrastructure, in which the digital and the physical are integrated to improve SCM, and thereby, supply chain performance. In increasingly interconnected, dynamic supply chains with greater information enrichment, SCM performance relies heavily on the 'self-thinking' capabilities of the supply chain (Calatayud et al., 2019). In such a context, digitally enhanced SCM activities contribute to the improvement of execution speed and process design. This new way of viewing SCM strategy development and resources does not emphasize costs or services, as before; attention is focused more on concepts such as the time and place value required to optimize the cost/service balance, and maximization of the profitability of each transaction (Stank et al., 2019). The acceleration of information flows and the reduction of inefficiencies represent the future of SCM. Supply chains do not remain static. They evolve and change in terms of size, shape, configuration, and the manner in which they are coordinated, controlled, and managed (MacCarthy et al., 2016).

The structure referred to in the practitioner literature as the supply chain "control tower" facilitates SCM decision-making, and may lead to the innovation of supply chain models and strategies (Devlin, 2021). Hence, a focus on the solutions that an individual digital technology can provide for competitive advantage is less important than a focus on the ways in which digital technologies are combined and utilized. Henceforth, the technology needed to capture, move, and analyze information within reasonable timeframes will be readily available; and relationships among supply chain entities will be increasingly collaborative.

SCM activities are undergoing significant changes due to the adoption of new digital technologies (NDTs) (Wu et al., 2016). These technologies are contributing to the creation of DSC models in which information that was previously created by people will be increasingly machine generated. Thus, factors such as consumer trends and expectations, may alter key SCM concepts and their complex interrelationships (Stank et al., 2019). Supply chains will be more connected and include parts, products, and smart objects that will aid chain monitoring (Liu et al., 2021). As we transition from the analog to the digital age, SCM as we have known it may be fading away (Lyall et al., 2018). A new paradigm that considers the impact of digitalization on SCM is thus needed to advance scholarly discourse (Stank et al., 2019). As technological innovation continues to drive immense changes in SCM practices, academics and practitioners must seek to understand how new forms of SCM process execution can confer sustainable competitive advantage. Such challenging work is necessary to reap the benefits of the concept of SCM practices underpinned by, for instance, smart technologies. More generally, digital technologies are helping to transform the value chain as we know into a virtual value chain (Müller, 2019; Sony & Naik, 2020; Srai & Lorentz, 2019).

2.6 New digital technologies (NDTs) to create higher-order capabilities for supply chain components, processes, networks and flows (SCMCs, SCMPs, SCNSs, and SCFs)

A DSC has been defined as "an intelligent best-fit technological system that is based on the capability of massive data disposal and excellent cooperation and communication for digital hardware, software, and networks to support and synchronize interaction between organizations by making services more valuable, accessible and affordable with consistent, agile and effective outcomes" (Büyüközkan & Göçer, 2018, p. 165). Although the DSC concept and its characteristics are still emerging, the digitalization phenomenon is already disrupting all types of supply networks, necessitating the development of new manufacturing strategies (Holmström & Partanen, 2014). Hence, digitalization of operations and logistics processes has begun in recent years in retailing, steel production, food packaging, manufacturing, and construction industries (Strong et al., 2018). DSCs' design involves more than the simple digitalization of all operations management and supply chain processes while maintaining the traditional form of supply chain management. The transformation from a traditional supply chain to a new-generation DSC needs to provide greater flexibility and efficiency (Büyüközkan & Göçer, 2018), with movement beyond the traditional focus on cost, quality, and delivery. DSCs are "accelerated, adaptable, smart, [with] real-time data gathering, transparent, globally connected, scalable, and clustered, breakthrough, inventive and sustainable" (Garay-Rondero et al., 2020, p. 899). They embrace innovation and growth, connect customers' consumers with suppliers' suppliers, and are designed to recognize and respond to needs and opportunities. They may enable new and faster access to markets, enable the creation of new business models, support smart-production products, and drive more flexible processes (Barata et al., 2018).

DSCs can be considered as having a physical SC scope and a digital data value chain scope (Hofmann & Rüsch, 2017) to make more informed decisions and create organizations to adapt and learn from the systems in which they are involved. They are interconnected, dynamic, open systems with a high level of ubiquity. With the integration of information from many sources and locations, businesses provide DSC members with a holistic view of what is taking place in real time (Calatayud et al., 2019). In this context, the ways in which supply chain actors create, move, and manage physical and informational flows are transformed (Ardito et al., 2019; Sundarakani et al., 2021). In addition, Büyüközkan and Göçer

(2018) point out that DSCs impact product development through increased information provision upstream and downstream of supply chains, which contributes to better integration with customers' needs and, thereby, efficiency.

IT can help firms improve logistics performance and supply chains, thereby enhancing their competitive advantage (e.g., Lai et al., 2008). IT-based competitive advantage can be attained through three paths: the continuous reinvention of IT advantages through avant-garde IT innovation, the use of IT to attain unassailable first-mover advantages, and the use of IT in a way that generates valuable and sustainable resources (Lai et al., 2010). Given the short development cycles and rapid obsolescence of IT, the first two paths are considered in the information systems management context to provide unsustainable competitive advantage (Sager, 1988). The third path is more likely to lead a firm to improve its supply chain, thereby generating performance gains. A firm requires a set of digital technology resources to combine with its human and infrastructure resources (Queiroz et al., 2021). By implementing this type of strategy, a firm opts for a bundling approach, rather than focusing on single IT applications in managing supply chain activities (Lai et al., 2010).

Firms' bundling capability has been found empirically to engender sustainable cost and service advantages (Kettinger et al., 1994), and to enable DSCCs development. A DSCC is "a set of ICT resources that an organization uses to interact with their network in order to shift physical activities to digital, applied in an integrated form both in physical and digital activities to minimize resource consumption and support productivity improvement, network visibility, and real-time feedback, including tools for custom production and suppliers' production in all stages of the network, supported by strong data-management techniques and skills" (Queiroz et al., 2021). We consider that DSCCs capture the collective effects of new IT applications on firms' business performance through the enhancement of the SCM structure. Indeed, NDTs are changing the core of supply chains, including SCMCs, SCMPs, SCNSs, and SCFs. This trend is generating new forms of management, processing, and interaction among actors in the SCM structure, integrating physical and digital operational approaches in the virtual and physical worlds. Consequently, DSC extends beyond the digitalization of all knowledge and information flows; it involves multidimensional, nonlinear interaction among all elements (i.e., management components, processes, network structures, and flows). The most important output in any DSC is virtual value creation. According to Garay-Rondero et al. (2020), in a digital technology paradigm, the supply chain consists of six continuously interconnected dimensions—SCMCs, SCMPs, SCNSs, SCFs, digital technologies, and value creation. These six dimensions interact constantly in the physical and virtual supply chains (Graham & Hardaker, 2000; Hofmann & Rüsch, 2017).

3. Conceptual framework and system of relationships

We build our conceptual models (Figs. 24.1 and 24.2) and (Table 24.1) by drawing on the extant literature on the dynamic capabilities' theory of competitive advantage (Teece et al., 1997; Teece, 2007), dynamic supply chain capabilities (Kristal et al., 2010; Aslam et al., 2018), ambidextrous supply chain theory (Lee & Rha, 2016), DSCs (Garay-Rondero et al., 2020) and DSCCs (Büyüközkan & Göçer, 2018; Queiroz et al., 2021). We follow a narrative literature review approach (Secundo et al., 2019), which has been used in several fields for different purposes (Neumann, 2017). It enables broad exploration of research questions, with the development of conceptual frameworks and propositions and consolidation of background information from the literature (Christenson et al., 2017). We have performed an open search of leading databases, including Emerald Insight, ScienceDirect, and Taylor & Francis Online, using the term DSC with filtering by title. We did not restrict the search to specific years and considered articles, white papers, proceedings, and book chapters published in English. This approach yielded hundreds of publications, which we filtered by abstract, retaining those related directly to DSCs, operations management, and logistics. To develop the framework (Fig. 24.1) and a set of six propositions related to DSCCs (Fig. 24.2), we have considered that DSC development is in its early stages and that awareness of DSC strategies is limited in the supply chain management literature.

We argue that:

- the ambidexterity of a supply chain depends on a firm's dynamic supply chain capability—building process (Lee & Rha, 2016).
- Organizational capabilities can be divided into two levels (Winter 2003): a base level of operational and ordinary capabilities, routine activities, administration, and basic governance, and an overlying level of dynamic capabilities.
- Dynamic capabilities, in turn, can be divided into microfoundations and higher-order capabilities (Teece, 2007).
- Microfoundations are second-order dynamic capabilities that concern the adjustment, recombination, and novel creation of a firm's ordinary capabilities (Teece, 2018).
- A firm with stronger dynamic capabilities is better able to maintain profitability over the long term, and to design and adjust its supply chain.
- The dynamic supply chain capabilities of *sensing*, *seizing*, and *transforming* have crucial roles in this framework.

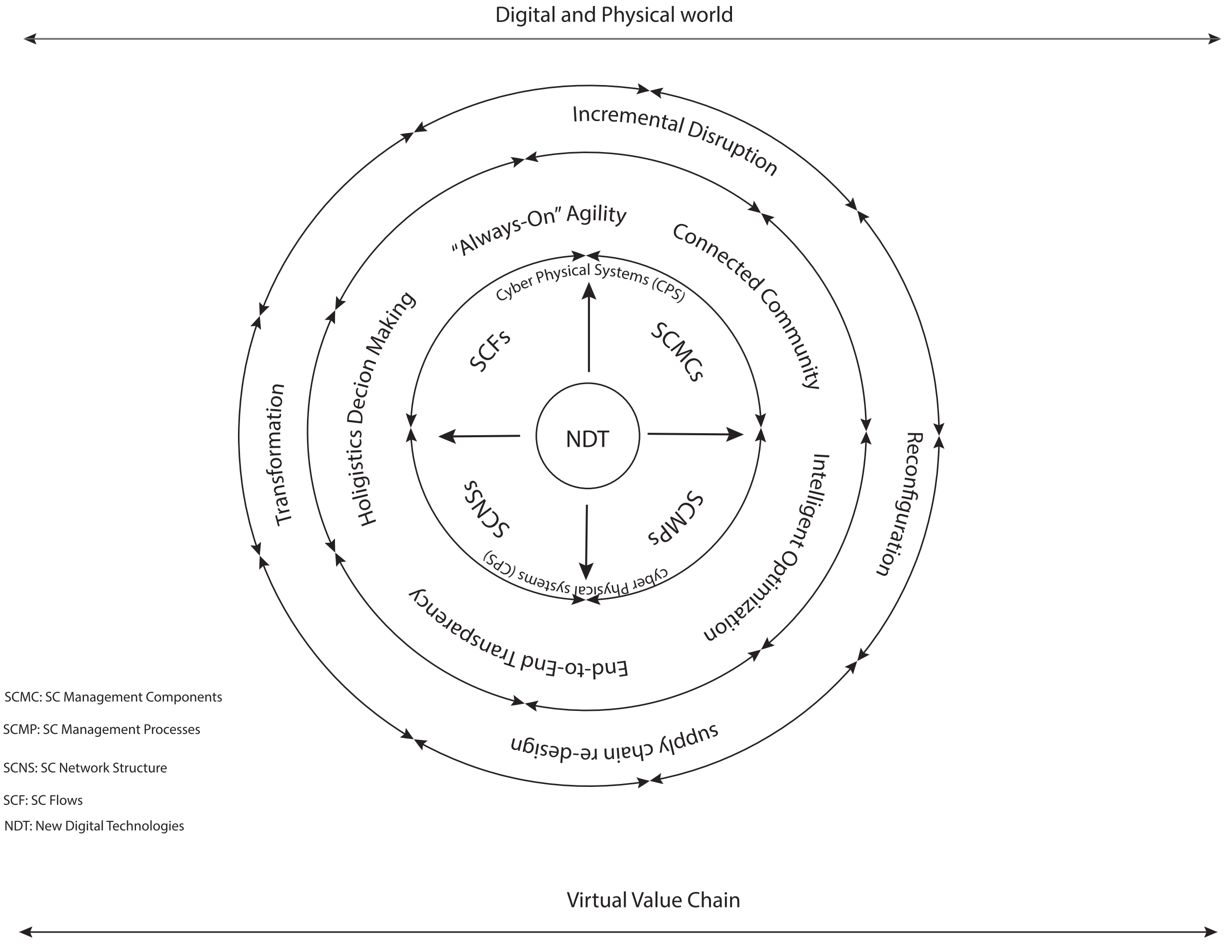

FIGURE 24.1 Digital Supply Chain model showing the impact of New Digital Technologies (NDTs) on SCM constructs.

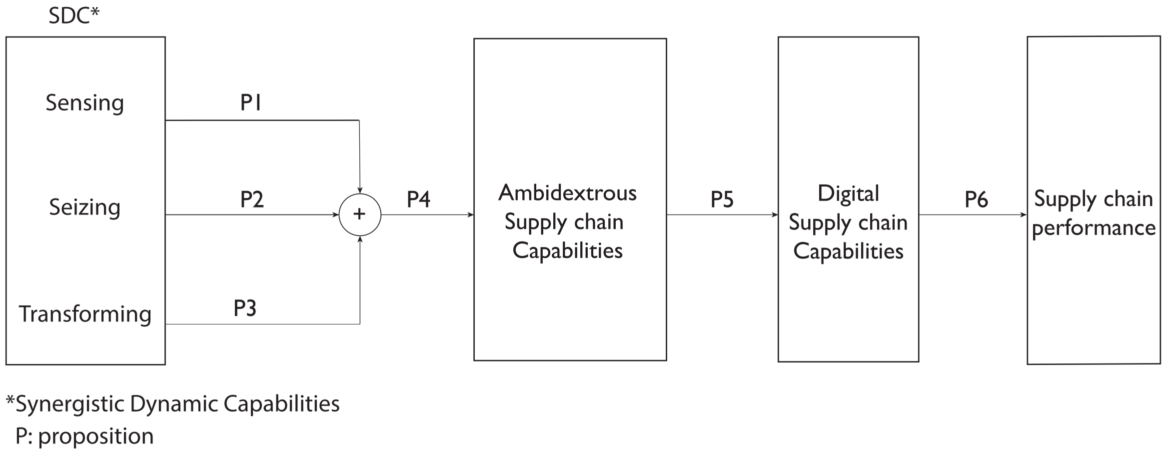

FIGURE 24.2 The process of digital supply chain capability building influencing supply chain performance.

TABLE 24.1 Glossary of acronyms for Digital Supply Chain Capabilities.

Acronym	Meaning
DSC	Digital Supply Chain
DSCCs	Digital Supply Chain Capabilities
NDTs	New Digital Technologies
SCM	Supply Chain Management
SCMCs	Supply Chain Management Components
SCMPs	Supply Chain Management Processes
SCNSs	Supply Chain Network Structures
SCFs	Supply Chain Flows

Following Teece et al. (2016), we argue that dynamic supply chain capabilities are about doing the right thing at the right time. Thus, the dynamic capability—building process is the necessary antecedent of supply chain ambidexterity. Hence, we propose that the construction of an ambidextrous supply chain contributes to the creation of a DSC, thereby improving supply chain performance. We argue that our framework is relevant as a foundation for firms to build DSCs.

4. Building digital supply chain capabilities (DSCCs)

Dynamic capability building can be viewed as a process, which must be routinized and embedded in the organizational structure for effective supply chain development. For supply chains, this process encompasses three interrelated capabilities: visibility (sensing), agility (seizing), and flexibility (reconfiguring) (Lee & Rha, 2016). Hence, we define this process as a synergistic dynamic supply chain capability.

4.1 Supply chain visibility capabilities (sensing)

From the supply chain perspective, sensing is associated with visibility, or the ability to monitor precise information about inventories, demand, supply conditions, production, and purchasing across a supply chain (Christopher & Peck, 2004). Sensing enables the development of supply chain capabilities, thereby improving outcomes and operational performance (e.g., in terms of shipment accuracy, customer service, inventory turnover, and competitive advantage) (Wei & Wang, 2010). Scanning and searching can strengthen responsiveness, planning, and decision-making in the supply chain context (Barratt & Barratt, 2011; Patterson et al., 2004). Based on these characteristics, we derive the following proposition:

Proposition 1. Strong supply chain visibility capabilities (sensing) will positively affect a firm's dynamic supply chain capability—building process.

4.2 Supply chain agility capabilities (seizing)

In the supply chain context, seizing corresponds to agility, or firms' speedy and effective responses to supply chain problems resulting from, for instance, changes in the marketplace environment (Swarford et al., 2006). Improvements in adaptability and flexibility thus play key roles in this agility. Authors such as Gligor and Holcomb (2012) and Yusuf et al. (2014) have shown that supply chain agility is associated positively with operational capabilities, allowing firms to reduce inventory, efficiently tackle market variations, promptly respond to customer demand, and integrate smoothly with suppliers and supply chain members (Mason et al., 2002). From the seizing-based perspective of Teece and colleagues (Teece et al., 1997; Teece, 2007), supply chain agility can be seen as the ability of supply chain stakeholders to make timely decisions to develop new opportunities. We thus make the following proposition:

Proposition 2. Strong supply chain agility capabilities (seizing) will positively affect a firm's dynamic supply chain capability—building process.

4.3 Supply chain flexibility capabilities (transforming)

The ability to recombine, redeploy, and reconfigure assets corresponds in the supply chain literature to flexibility, or the ability to restructure supply chain assets, strategies, and operations in adapting to changes in, for instance, information systems, products, and customers without altering the performance level (Candace et al., 2011). Thus, firms that possess supply chain flexibility capabilities are able to improve their operational outputs and organizational performance (Malhotra & Mackelprang, 2012). Thus, we derive the following proposition:

Proposition 3. Strong supply chain flexibility capabilities (transforming: recombining, redeploying, and reconfiguring) will positively affect a firm's dynamic supply chain capability—building process.

4.4 Dynamic supply chain capabilities as a prerequisite of supply chain ambidexterity

The value creation, delivery, and capture components of a supply chain must be in equilibrium to ensure efficiency, effectiveness, and sustainability. Supply chain elements must be internally aligned and coherent with a firm's overall management model. Extreme supply chain transitions, such as those involving new technologies, very different customer bases, organizational reengineering, and/or disruptive change, are likely to fail in the absence of major financial resources and managerial commitment (Teece, 2018). Transition to a supply chain design similar to an existing one is much easier, but is rarely sufficient, although it may enhance value capture to build long-term competitive advantage for firms whose dominant market share is under attack. An organization with dynamic supply chain capabilities (i.e., supply chain design management, asset orchestration, and learning) can successfully implement a new or reengineered supply chain. Hence, the strength of such capabilities plays a key role in a firm's capacity to choose from a full menu of supply chain management practices. Firms with weak dynamic capabilities are more likely to adopt supply chain strategies that rely solely on past investments and existing organizational processes and routines, and thus will struggle to create value or overcome disruptive changes in the business environment. Firms with strong dynamic capabilities are much more likely to design supply chains that entail radical shifts in resources and/or activities. Thus, dynamic supply chain capabilities that enable the mixing, remixing, or orchestration of supply chain components are particularly salient. We therefore make the following proposition:

Proposition 4. Strong dynamic capability building, such as mixing, remixing, or orchestration will positively affect a firm's supply chain ambidexterity.

4.5 Supply chain ambidexterity and DSCCs

The concept of supply chain ambidexterity, or a firm's strategic choice to simultaneously pursue efficiency and flexibility (Kristal et al., 2010), is not consistent with some perspectives found in the supply chain literature. For instance, some scholars have argued that firms should select the right supply chains for their physical flows, leading to the design of efficient supply chains for functional products and flexible supply chains for innovative products (Fisher, 1997). Exploration refers to practices that refine and extend a firm's existing skills and resources (e.g., to reduce costs and increase reliability) away from the supply chain management perspective, to experimentation and the acquisition of new knowledge and resources that contribute to practices enabling a firm to develop new supply chain capabilities (Kristal et al., 2010). Although ambidextrous supply chain strategies can help firms enhance their business performance and technological innovativeness (Blome et al., 2013), their implementation can be challenging. Firms attempting such implementation must carefully balance exploration and exploitation. Excessive focus on exploitation can trap a firm in a suboptimal stable equilibrium, making it very difficult to adapt quickly to changes in the business environment, whereas excessive focus on exploration can lead to loss of efficiency characterized by the inability to reap the benefits from too many projects and/or innovations (March, 1991; Kristal et al., 2010). Firms that can address this issue of balance gain competitive capabilities. Our theoretical model reflects our argument that organizations must develop infrastructural capabilities to support their DSC strategy construction (Quieroz et al., 2021). DSCCs cannot be designed or built without harnessing employees' capabilities, the management of which can enhance supply chain performance; these capabilities should be considered critical resources for DSC transformation (Gunasekaran et al., 2017).

Based on our review of the literature and the authors' knowledge of operations and supply chain management practices, we argue that firms' ability to build DSCs is attributable to their supply chain ambidexterity capabilities. The continuing success of a supply chain requires the reconsideration of connections, processes, and interorganizational alliances among stakeholders, which we believe ambidexterity can address. In DSCs, the linkage of physical and digital assets generates high levels of connectivity and replaces the separation of processes that is typical of traditional supply chains, thereby, altering the nature of supply chain management. Such integration and interaction confer simultaneous availability of information to all members, natural development of deep collaboration to capture intrinsic supply chain value, and the ability to rapidly assess end-consumer demand and respond in real time at the planning and execution levels. We thus formulate the following proposition:

Proposition 5. Supply chain ambidexterity, as a dynamic capability, will positively affect a firm's Digital Supply Chain Capabilities.

4.6 The relationship between DSCCs and business performance

As rapid positioning with regard to customers' preferences and greater cost-effectiveness can bring competitive advantage, supply chains that can enable this have come under increasing focus (Alfalla-Luque et al., 2018). Competition among companies has evolved to competition between supply chains for many products. DSCs provide a potentially great and sustainable advantage in this context (Ketchen et al., 2014). They allow rapid response to short-term changes in immediate and ultimate customer demands, adjustment to long-term changes in economies and markets through supply chain restructuring, and the integration and coordination of business and operations processes to achieve equitable sharing of risks, costs, and benefits among all supply chain stakeholders (Lee, 2004). Accordingly, NDTs are seen as a promising means to improve supply chain functions, such as procurement, logistics, scheduling, and planning (Arunachalam et al., 2018; Hallikas et al., 2021).

Our conceptual framework is illustrated in Fig. 24.1. Digital technology application is essential for intra- and inter-organizational business processes; the digitalization of logistics operations and activities enhances logistics performance (i.e., reduced costs via information sharing and improved services via enhanced organizational responsiveness), and thereby overall supply chain performance (Scuotto et al., 2017). Furthermore, our model indicates that digital technology must be bundled appropriately at the firm and supply chain levels; whether a DSC can deliver the expected performance depends on how well the digital technologies are implemented collectively and across business activities within a supply chain; in other words, an organization's DSCCs. Our conceptual framework also argues that DSCCs lead to the development of the higher-order capability of supply chain process integration, enabling firms to unbundle information flows from physical flows and to create information-based approaches for highly accurate execution of processes such as demand planning and the movement of physical flows.

We consider that DSCC competitiveness is linked deeply to the integration of internal and external capabilities, with the intersection of digital technology capabilities, workers' capabilities, and stakeholders' capabilities, contributing positively to organizations' supply chain performance (Queiroz et al., 2021). Improving supply chain relationships through digital technology can benefit operational performance, transaction costs, and delivery times (Ataseven & Nair, 2017; Paulraj et al., 2006). Thus, to achieve superior performance with supply chain digitalization, key performance indicators such as cost, quality, flexibility, and time are very important to consider. Multilateral (internal and external, functional, and geographical) integration within chains and networks, including via IT, is also required (Oh & Jeong, 2019). Moreover, to leverage the power of the supply chain network, suppliers' suppliers and customers' customers should be included in the integration process. Supply chains with high levels of digitalization enable the creation of services that provide customers with convenience, choice, and control. In other words, interconnectivity and mass customization efforts improve the customer experience (Garay-Rondero et al., 2020).

DSC characteristics such as transparency, communication, collaboration, real-time responsiveness, accuracy, and flexibility play key roles in digitalized supply chain performance. Accordingly, each player involved in value chain delivery should be ready to leave aside the approach involving connectivity just between adjacent actors in a linear supply chain structure. Supply chain actors engaged in the improvement of supply chain performance through digitalization must adopt a multidimensional organizational strategy. A key goal of digitalization is to build visibility in supply chain (Hallikas et al., 2021). Supply chain visibility is the major outcome of external integration and entails access to high quality information. Accordingly, visibility enabled through digitalization is fundamental to improved performance (Williams et al., 2013). We thus derive the following proposition:

Proposition 6. DSC characteristics such as transparency, communication, collaboration, real-time responsiveness, accuracy, and flexibility will positively affect supply chain efficiency and effectiveness, and thereby supply chain performance.

Fig. 24.2 shows the relationships between the six propositions and how dynamic capabilities generate ambidexterity, which is enabled through DSC.

Our framework (Fig. 24.1) illustrates the cooperation that occurs among essential SCM components. All of this is made possible by "always-on" agility, a connected community, intelligence optimization, end-to-end transparency, and holistic decision-making. We developed this framework with the aim of reducing some of the technological and managerial barriers that managers face during the transformation of traditional linear supply chains to DSCs. For instance, it brings to light the essential components of real-time NDT interaction with all SCM constructs. It also enables the visualization of SCM dimensions with the inclusion of physical and digital flows, which is difficult to achieve with traditional SCM constructs.

Continuous research and innovation in all SCM constructs, along with NDTs, have brought about a new system in which the real and digital worlds meet, with symbiotic interaction. The effects of NDTs on some or all components of a company's supply chain structures generate value for the organization. The framework (Fig. 24.1) indicates that NDTs can be leveraged for incremental adjustment or improvement of SCM elements to aid organizations' redesign, or to the reconfiguration of SCM constructs and components, and in some situations to radically transform SCM. NDTs form a core, enabling the effective handling of digital and physical DSC management components. They encompass all managerial methods by which a business can achieve real-time integration. They bring about different degrees of change, which is distributed unequally across SCM activity dimensions. Each organization may approach NDT application across their essential SCM elements differently, depending on the complexity of the products and services that they wish to design and offer to their customers (Calatayud et al., 2019). NDT enables the establishment of macro-interconnectivity among all elements of the DSC model. Multiple DSCs can be connected in real time through a cyber-physical system (Shirkin et al., 2015), which provides the key elements linking the physical world with the global digital data value chain and NDTs (Strange & Zucchella, 2017). Moreover, the virtual value chain is a key mechanism of integration via dynamic information, enabling the visualization of the entire chain. Each DSC component is related closely to the virtual value chain dimension, which contributes to the maintenance of transparency, communication, collaboration, flexibility, responsiveness, and accuracy across the entire structure (Garay-Rondero et al., 2020).

5. Theoretical implications—achieving digital ambidexterity

Although DSCs represent the next frontier in supply chains and supply chain management, the concept of the DSC is emergent for both practitioners and academic researchers. The theoretical perspectives we present can aid understanding of the way in which firms build capabilities from DSCs. To the best of our knowledge, this is the first effort to conceptualize this construction process. Although articles from practitioners and consultancy reports on this topic are accumulating, their content is mostly descriptive; scientific or conceptual investigation is lacking. Our models highlight the rich interplay among dynamic supply chain capabilities (visibility—sensing, agility—seizing, and flexibility—transforming), supply chain ambidexterity as an additional dynamic capability, and the essential constructs of SCM to show how DSCs influence supply chain performance.

These conceptual models have significant implications for researchers and practitioners. First, the very few studies of DSCs conducted to date have focused on concept enablers, rather than on supply chains, and most articles have been industry and consultancy reports. Thus, more scientific research on the developmental framework required for DSC creation and the impacts of DSCs on firms' supply chain performance is needed. Second, we direct attention to the roles of the three dynamic supply chain capabilities—visibility, agility, and flexibility—and argue that they are compulsory for the successful development of supply chain ambidexterity. We argue that the lack of one of these capabilities seriously compromises a firm's ability to achieve ambidexterity, and in turn to build an effective DSC and thereby improve its competitive advantage. Third, we highlight the prerequisite of supply chain ambidexterity as a dynamic capability resource that plays an important role in the construction of DSC. We show that the dynamic capabilities perspective is an appropriate lens to explain the dynamic supply chain capability—building process.

6. Managerial implications

Our conceptual framework can prepare supply chain managers for DSC construction, helping them to understand that the mere deployment of digital technologies, although now numerous and readily available on the market, is not sufficient; digital ambidexterity is required. Supply chain managers should understand that their organizations' dynamic supply chain capability building needs to be strong, as it plays a central role in DSC construction via ambidexterity; this interdependence has important managerial implications and provides important insights into the process of DSC construction. Managers must recognize the need to change or replace their supply chains, and understand how to do so successfully by grasping the DSC process and relationships among its components, to gain competitive advantage for their firms in today's dynamic business environment.

Our conceptual framework further emphasizes that the achievement of competitive advantage through the use of digital technologies in the supply chain is based definitively on an organization's ability to use these technologies strategically and synergistically. DSC building will likely fail when organizations have insufficient dynamic capabilities. The gap between what organizations expect (and could reap) from DSC design and their preparedness for that implementation may be wide. Our conceptual framework indicates that operations and supply chain managers should resist the temptation to focus just on digital technologies or cost. They should give a central place to dynamic capabilities including supply chain visibility, agility, and flexibility; sensing and seizing; and supply chain ambidexterity. In considering DSC building, managers should go beyond the traditional "trade-off" view and adopt ambidextrous supply chain strategies. This recommendation is in line with the findings of Kristal et al. (2010), Lee and Rha (2016), and Aslam et al. (2018).

Supply chain evolution does not occur solely due to the implementation of physical and digital network structures or traditional information and communications technology systems; supply chain actors must generate a culture of change focused on digitalization to create a proper environment. Supply chain transformation thus requires special attention during the implementation of new forms of administration. It requires the introduction of elements such as project management to digitalize and manage the organization's cultural behavior in SCMCs, the establishment of human−technology relationships in SCMPs, and the formation of a technology infrastructure for digital and physical SCNSs. Wide-ranging digital and physical SCFs need to be established providing the right level of digitalization and the deployment of the right digital technology (Garay-Rondero et al., 2020).

7. Conclusions and further research

This chapter has sought to reconceptualize supply chain strategy in the context of building DSCs, a topic of great interest to practitioners and researchers. We highlight the importance of meaningful interactions of strong dynamic supply chain capabilities with ambidexterity in DSCs for the ability to achieve overall strategic priorities and, most importantly, SCM competitive advantage. We identify factors that are critical for success, including supply chain visibility, agility, and flexibility. Researchers and supply chain practitioners must recognize that digital technologies play a fundamental role in firms' competitive advantage, but that their adoption is not just a means by which to develop more efficient solutions for known issues. As excitement about digital technologies has spread in the logistics and supply chain industry, operations and supply chain managers are searching for ways in which to utilize these technologies. Firms must understand how to configure, design, and use digital technologies to develop simultaneously efficient and effective DSCs. There is no simple explanation for how a given firm should utilize or implement digital technologies across its operations and supply chain management practices. Nevertheless, we posit that firms can go a long way toward the development of the right approach to digital technology and DSC implementation by considering dynamic supply chain capabilities and ambidextrous supply chain strategies.

This chapter sets the stage for an ambitious and new research agenda focused on Digital Supply Chain Strategy to achieve sustainable performance gains. We encourage researchers to critique, illustrate, expand on, and test the concepts, propositions, and framework presented here to improve knowledge about DSC construction and, in turn, generate supply chain performance gains for firms.

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THE DIGITAL SUPPLY CHAIN

Edited by
Bart L. MacCarthy | Dmitry Ivanov

The Digital Supply Chain is a thorough investigation of the underpinning technologies, systems, platforms, and models that enable the design, management, and control of digitally connected supply chain networks.

The book examines the antecedents of the digital supply chain, showing how and where the virtual and physical supply chain worlds interact. It reviews the technological and systems building blocks for the Digital Supply Chain, considering how supply chains can be re-conceptualized for research and practice in the digital era (e.g. Digital Platforms, Cloud Manufacturing, Internet-of-Things, and Blockchain). The book examines how the discipline of supply chain management is affected by digital connectivity, collaboration, and visibility using case studies of current digital practices and the challenges faced across different industrial and business sectors. The book concludes with highlights from critical research frontiers, both academic and industrial, to enable future adoption of and engagement in digital supply chains.

Key Features

- Coverage from both theoretical and practical point of view.
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- Comprehensive thematic perspective examining the whole digital supply chain journey in depth.
- Up to date critical insights on the technology, design, management and control of digitally connected supply chains.
- Written by experts with strong backgrounds in the field.

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Bart MacCarthy is Professor of Operations Management at Nottingham University Business School. His research interests include supply chain evolution, and the impact of digitalization, cloud-based systems, and platforms on Operations and Supply Chain Management. He works with a wide range of industries and business sectors in both his research and teaching. He is a Fellow of the Institute of Mathematics and its Applications, the Institution of Engineering and Technology, and the Chartered Institute of Logistics and Transport. He is currently Vice President for Europe for the Decision Sciences Institute (DSI). He has published widely in the Operations, Supply Chain, and Management Science literatures and serves on the Editorial Board for the *International Journal of Production Economics* and the *International Journal of Operations and Production Management*.

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