



Smart Sustainability

THE ROLE OF AI IN BUSINESS INTELLIGENCE

EDITED BY

Madhusmita Mohanty • Rakesh Kumar • Rajeev Kumar Panda
Rashmi Ranjan Mallick • Kushal Walia

A Productivity Press Book

ROUTLEDGE

Smart Sustainability

This book emphasizes the contribution artificial intelligence (AI) can make to sustainable innovation and business intelligence. It highlights the evolution of smart sustainability and business intelligence practices through AI. AI significantly adds efficiency to sustainable business intelligence practices. This book supports a sustainable development agenda. The book is useful for policymakers, corporate leaders, researchers, industry professionals, and other stakeholders engaged in sustainable business practices.

This book examines the different applications of AI – it can revolutionize green supply chain management, inventory management, and logistics management. Emerging trends are examined, along with problems and their fixes. Practitioners, companies, legislators, and researchers are provided with an implementation framework. In addition, ethical and environmental issues are covered, with a focus on sustainable and responsible behavior.

To shed light on the efficacy of AI applications, the book offers sustainable start-up businesses real-world examples of their use. It also provides guidance on how to strategically incorporate AI into current frameworks for sustainable business practices. For professionals in business, technology, and sustainability, the book also helps with strategic planning. Professionals in waste reduction and resource management might also benefit from their insights. The book helps investors, entrepreneurs, and legislators make well-informed decisions. It increases public understanding of how augmented reality and virtual reality can support sustainable behaviors. The book promotes knowledge progress and sustainable practices across multiple industries by providing interdisciplinary viewpoints and acting as a bridge between theory and practice.



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Madhusmita Mohanty, Rakesh Kumar,
Rajeev Kumar Panda, Rashmi Ranjan Mallick
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Contents

Preface.....	ix
About the Editors.....	xx
List Of Contributors	xxiv
1 Developing Sustainable Business Intelligence through Artificial Intelligence.....	1
GHOUSIA JABEEN, GURUNADHAM GOLI, AND RAKESH KUMAR	
2 Evolution of Sustainable Intelligence Business Practices.....	20
CHUNCHU NAGARAJU, GURUNADHAM GOLI, AND RACHORU HIMANI SRIHITA	
3 AI-Driven Disruption: Driving Business Innovation and Excellence	45
GIRIJA NANDINI, SWARNA PRABHA JENA, PRAMOD KUMAR PATJOSHI, BHANUPRIYA KHATRI, SHIV SANKAR DAS, BIJAY KUMAR PAIKARAY, AND V. S. DAMODHARAN	
4 Green Supply Chain Management with AI and Its Implications	59
DEEPAK HALAN, ARVIND KUMAR JAIN, AND SANTANU PUROHIT	
5 Firm Performance, Innovation, and Government Support in Agriculture SMEs.....	80
SATYABALLAV KAR, SUBHASISH DAS, AND BRAJABALLAV KAR	
6 An Empirical Study on Role of Green Banking and Technology in Sustainable Development	106
JITENDRA SINGH, ANKITA JOSHI, RAVI PRASAD, RAJESH SINGH, AND RAKESH KUMAR	
7 Driving Circular Economy Success: The Power of Collaborative Platforms	130

	PRIYANSHU VERMA, TARUNPREET KAUR AHUJA, DEEPA BISHT, AND MOHAMMED ISMAIL IQBAL	
8	Harnessing Artificial Intelligence in Business Intelligence Systems: Advancing Smart Sustainability in Management	154
	R. PAVETHRA, G. S. MAHESWARI, AND G. CHANDRAMOWLEESWARAN	
9	AI and Sustainability Corporate Governance Reporting	176
	NEERAJ GUPTA, DEBAPRIYA SAMAL, SUNITA JATAV, AND PRITI AGGARWAL	
10	Carbon Taxation and Sustainable Business Practices: A Blueprint for India's Green Economy	205
	RAM SINGH, PRODIPTA BARMAN, ASHUTOSH RATH SHARMA, SHIKHA UNIYAL GAIROLA, JYOTIRMOY BANERJEE, POOJA BANERJEE, VINAY PAL SINGH, AND FAZLA RABBY	
11	A Study on Perception of Gen Z Customers on Artificial Intelligence in Chennai City	228
	K. SANGITHA	
12	The Intersection of AI and Financial Sustainability: Evaluating the Influence of AI-Based Decision-Making, Risk Assessment, and Transparency in Banking: Special Reference to Private Banks in Tamil Nadu.....	249
	K. BINITH MUTHUKRISHNAN, R. SELVAKUMARI, A. SENTHAMIZHSELVI, AND RAKESH KUMAR	
13	AI-Driven Sustainable Logistics and Inventory Management: Bridging Efficiency and Environmental Responsibility	275
	C. V. SURESH BABU AND S. KAHINI	
14	Artificial Intelligence for Sustainable Business Development	302
	GANESAN MURUGANANTHAM, R. S. ASWANTH, AND SEKAR VINODH	
15	Integrating SDGs into Industry 4.0's Sustainable Business Practices: Efficiency and Challenges	325
	TRIPTI SAHU	

16	Career Exploration and Sustainable Innovation in Tech SMEs: Advancing Employability Readiness and Business Sustainability	345
	R. ALAMELU, K. V. LAKSHMINARAYANAN, AND SAMAR MOUTI	
17	A Bibliographical Analysis of Corporate Social Responsibility and Climate Change through R Studio	374
	SAKSHYARJYOTI MISHRA AND RASHMITA SAHOO	
18	A Study on Behavioural Intention and Actual Usage of Artificial Intelligence among the Select Service Sector Employees	395
	K. SUBHA, M. BHAVNA SRUTHI, HRIDAYA KUMARI, AJIT KUMAR BARAL, AND MRINAL KAUL	
19	Geo-Based Causal Analysis and Risk Evaluation of BOPIS Fee Elimination in Retail Store Rollouts.....	414
	BHAVNISH WALIA, BANANI MOHAPATRA, AND KUSHAL WALIA	
	Index	447



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Preface

This book emphasizes artificial intelligence's contribution to sustainable innovation and business intelligence. It highlights the evolution of smart sustainability and business intelligence practices through artificial intelligence. Artificial intelligence has the potential to enhance the efficiency of sustainable business intelligence practices. This book supports the agenda of sustainable development goals for 2030. The book is useful for academic policymakers, the corporate sector, researchers, industry professionals, and other stakeholders engaged in sustainable business practices.

This book examines different applications of artificial intelligence in sustainable business intelligence. AI has potential in areas such as green supply chain management, sustainable business practices, inventory management, and logistics management. Product life cycle management is an important aspect of marketing. This book examines contemporary case studies of AI in sustainable business practices. Emerging trends are examined, along with problems and their fixes. Practitioners, companies, legislators, and researchers who are interested in using AI to further the objectives of sustainable business intelligence are given useful assistance. Additionally, ethical and environmental issues are covered, with a focus on sustainable and responsible behavior.

In order to shed light on the efficacy of AI applications, the book offers sustainable startup business and real-world examples of their use. It also provides guidance on how to strategically incorporate AI into current frameworks for sustainable business practices. For professionals in business, technology, and sustainability, the book also helps with strategic planning. Professionals in waste reduction and resource management might also benefit from its insights. The book also helps investors, entrepreneurs, and legislators make well-informed decisions. It increases public understanding of the ways in which augmented reality and virtual reality can support sustainable

behaviors. The book promotes knowledge progress and sustainable practices across multiple industries by providing interdisciplinary viewpoints and acting as a bridge between theory and practice.

Overview of Chapters

Chapter 1, “Developing Sustainable Business Intelligence through Artificial Intelligence,” explores the incorporation of AI into sustainable business intelligence (SBI). AI technologies such as machine learning, prognostic analytics, and process robotics enable companies to take better decisions, optimize resource utilization, and minimize their ecological impact. AI helps organizations maintain long-term goals in areas such as efficient supply chain management optimization and waste reduction. However, SBI needs to overcome some significant obstacles before the integration of AI into its operations. The substantial energy consumption of AI models and data centers conflicts with sustainability goals and creates ethical and operational quandaries. Moreover, many industry-specific issues related to artificial intelligence such as data privacy and privacy issues hinder its equitable use.

Chapter 2, “Evolution of Sustainable Intelligence Business Practices,” deals with the evolution of sustainable intelligence business practices. The evolution of sustainable intelligence business practices has marked a significant shift from traditional business models to those that incorporate environmental, societal, and governance (ESG) principles. Over the past few decades, sustainable practices have grown, driven by technologies, especially in artificial intelligence (AI) and data analytics. By achieving improved resource usage, waste diminishment, and supply chain openness, firms make informed, eco-friendly choices. AI tools, comprising such elements as machine learning and predictive analytics, enable the forecasting of trends, assessment of environmental impact, and streamlined production processes. The outcomes of this chapter highlight the integration of sustainability intelligence into business performance, shifting corporate governance to long-term social and ecological results instead of short-term profits. Consumer demand for sustainable products, combined with regulatory pressure, has encouraged companies to align their practices with ethics and environmental stewardship. Industries, governments, and communities are increasingly collaborating in their role to foster sustainability. This is a sign that the future is one where sustainable business practices are the norm. This chapter reviews

the trajectory of sustainable intelligence and its impact on corporate strategies and the macroeconomy.

Chapter 3, “AI-Driven Disruption: Driving Business Innovation and Excellence,” discusses how AI is reshaping business practices and fostering innovation and excellence. The technology known as artificial intelligence (AI) contributes to the organization’s overall value. AI is being used by many companies to transform their businesses in this digital and competitive environment. On the other hand, many businesses are unable to employ AI to boost their business value and financial performance. There is very little information about how AI can be used to change and improve businesses. Understanding a holistic approach to utilizing AI to transform business will be the primary topic of this chapter. Furthermore, it will assess the impact of AI on growth and the hurdles encountered in its implementation within enterprises. Now more than ever, researchers and practitioners are interested in gaining an understanding of how disruptive technology might be utilized for the growth of organizations. When it comes to business transformation, artificial intelligence has brought about substantial changes in areas such as research and development, analysis and reporting, data management, and the transformation of production and sales. This chapter investigates the applications of AI, the challenges that stand in the way of its adoption, and the revolutionary potential of AI in generating business innovations and operational excellence.

Chapter 4, “Green Supply Chain Management with AI and Its Implications,” explores the integration of AI in green supply chain management and its broader implications. Green supply chain management (GSCM) focuses on embedding eco-conscious practices into conventional supply chain processes to achieve sustainability goals. Recent advancements in artificial intelligence (AI) have provided innovative solutions to many challenges faced by supply chain networks. AI technologies, ranging from predictive analytics to intelligent automation, enhance decision-making, optimize resource use, and boost environmental performance throughout the supply chain. GSCM aligns closely with the United Nations’ 2030 Agenda for Sustainable Development by directly contributing to the realization of various sustainable development goals (SDGs); hence, this study also has social implications. This chapter also explores the transformative impact of AI on GSCM, detailing its advantages, challenges, and future trends, as well as the innovations driving the evolution of sustainable supply chains.

Chapter 5, “Firm Performance, Innovation, and Government Support in Agriculture SMEs,” explores the relationship between firm performance,

innovation, and government support in agricultural SMEs. Agriculture and related practices are firmly rooted in culture and tradition. Food habits are sticky for a region, and output depends on geographical endowments. Under these contexts, agriculture firms must improve productivity, be responsive to environmental sustainability, improve human and social conditions, and be economically viable. Contradictory objectives and constraints demand innovative responses. Given the large and rural employment associated with agriculture, government support becomes necessary. This research investigates how agricultural and related sector firm performance, innovation practices, and government support interact. The findings indicate that innovation explains firm performance significantly but not substantially. Contrarily, firm performance parameters better explain innovation. Quality and customer satisfaction influence innovation significantly and positively, but the profit for the last year negatively influences innovation. Government support factors have a significant positive influence on innovation practices.

Chapter 6, “An Empirical Study on Role of Green Banking and Technology in Sustainable Development,” examines the impact of green banking and technology on sustainable development. Sustainable development aims at the economic growth of a country and the banking sector through sustainable banking services in the global banking industry. In the present scenario, the economy is focusing on the reduction of fossil fuels by enforcing a decline in demand for fossil fuels or by reusing/recycling fossil fuels. Energy conversion is possible through solar energy, wind energy, geothermal energy, hydropower, biomass energy, and nuclear energy. The concept of “green banking” has boosted the banking sector in the development of renewable energy and energy conservation. Green banking usually refers to practices that enhance the operational efficiency of banks and make banks sustainable in economic, environmental, and social dimensions. Green banking makes banking procedures and the use of technology and physical infrastructure more effective. Today, banks attempt to ensure accessible, affordable, reliable, and sustainable banking services for their customers. This chapter identifies the initiatives of Uttarakhand Gramin Bank to make its operations and banking services efficient and effective due to the use of green banking technology.

Chapter 7, “Driving Circular Economy Success: The Power of Collaborative Platforms,” explores the role of collaborative platforms in driving success in the circular economy. The world is moving towards a circular economy, and in this chapter, we investigate the steps that we can take to realize this objective while handling worldwide challenges, society’s needs, and caring

for the environment. We begin by looking at shared economy models, squander trade stages, and the product-as-a-service framework, investigating the different shapes of modern collaborative stages which allow for feasible utilization and waste reduction. Throughout the chapter, we examine how inventive innovation and collaboration have changed the way things are consumed and produced by taking real-world examples such as the Article of Clothing Collecting Activity by H&M, Patagonia's Worn Wear, the Repair Café Development, and the Fabric Trade Platform or Material Exchange Platforms (MEP). These ventures highlight the success of collaborative stages as they strive to make financial openings whereas lessening the affect on the environment and assets devoured. Whereas carefully investigating these case studies, it is similarly imperative to consider the limitations, such as information security, coordination, and administrative boundaries. To overcome these challenges, smart advances such as internet of things (IoT), blockchain, and data analytics can be used. Finally, this chapter emphasizes the need for coordinated effort among businesses by stating that accomplishing a circular economy is a shared goal for all financial performing artists.

Chapter 8, "Harnessing Artificial Intelligence in Business Intelligence Systems: Advancing Smart Sustainability in Management," opens up a discussion on how AI integration enhances smart sustainability. AI is fast becoming part of BI systems, and this is changing how organizations tackle sustainable development issues. Due to the increasing environmental and social pressures that business entities experience currently, even more intelligent BI systems present new approaches to reconciling the organization's operations with sustainable management. Thus, this chapter discusses how AI supports the concept of "smart sustainability" by leveraging big data techniques to inform and improve resource decisions and environmental results. With big data self-learning, AI systems find patterns, predict effects in the future, and provide recommendations for sustainability in several domains, including energy use, waste management, and supply chains.

Chapter 9, "AI and Sustainability Corporate Governance Reporting," deals with the role of AI in enhancing corporate governance practices. Artificial intelligence (AI) in sustainability reporting is currently transforming corporate governance in today's business environment. With pressure from investors and regulators to become more transparent with their environmental, social, and governance (ESG) reporting, companies across the globe are using AI to inscribe sustainability into operations that are transparent, efficient, and effective. In this chapter, the key role played by AI in shifting the paradigm of sustainability reporting is highlighted, i.e., the automation of

data collection and the usage of huge, real, useful, and action-driven data to move decision-making forward. It explains how AI tools and technologies such as machine learning, natural language processing, and predictive analytics can be leveraged to provide added value to ESG reporting, suggest new measures towards sustainability, and facilitate stakeholder engagement through user interactive and responsive platforms. However, the arrival of AI in sustainability reporting also faces certain difficulties. The chapter addresses some of the key governance concerns, including ethical concerns, quality of data, risk management, and disclosure of AI systems. In addition, the study on regulatory evolution, emerging technologies, and the actors' viewpoints on the development of the future of AI-enriched sustainability reporting is also proposed. This chapter, by offering an integrative model for the responsible use of AI in corporate governance (CG), can contribute valuable information to business managers, professionals in corporate sustainability, and legislators who wish to harness the benefits of AI while being mindful of ethical, transparent, and efficient sustainability applications. What makes this work innovative is the interdisciplinary approach (AI and sustainability reporting, corporate governance, and so on) adopted in the present study in an attempt to offer hands-on solutions for companies who want to make measurable long-term value.

Chapter 10, "Carbon Taxation and Sustainable Business Practices: A Blueprint for India's Green Economy," deals with the role of carbon taxation in promoting sustainable business practices. The escalating urgency to address climate change has prompted nations worldwide to adopt carbon taxation as a policy tool to reduce greenhouse gas emissions. For India, this challenge is particularly nuanced, requiring a delicate balance between its developmental priorities and environmental sustainability commitments under frameworks like the Paris Agreement. Sustainable business practices, integrated with carbon taxation, can serve as a cornerstone in the country's transition to a green economy. This study investigates the role of carbon taxation in fostering sustainable business practices in India, aiming to establish a comprehensive framework that aligns environmental and economic goals. Employing a mixed-method approach, the research combines qualitative case studies of Indian industries adopting green initiatives with quantitative assessments of carbon tax impacts on emissions and economic performance. Policy simulations and stakeholder interviews further enrich the analysis. The study anticipates revealing that a well-designed carbon taxation system, complemented by incentives for sustainability, can achieve significant emission reductions without hindering economic growth. Insights into

sector-specific challenges and opportunities will provide actionable guidance for policymakers and businesses. The findings emphasize the transformative potential of harmonizing carbon taxation with sustainable business strategies. A phased implementation, sectoral differentiation, and strong regulatory mechanisms are highlighted as essential for ensuring effectiveness and equity. Uniquely tailored to India's socio-economic realities, this research presents a novel blueprint for achieving a low-carbon economy, offering practical pathways to integrate environmental stewardship with economic resilience.

Chapter 11, “A Study on Perception of Gen Z Customers on Artificial Intelligence in Chennai City,” relates to the simulation of human intelligence processes by computer systems, known as artificial intelligence. It involves teaching machines to learn from data and make decisions with minimal human intervention. AI's potential benefits promise continued advancements and integration into various aspects of life. Individuals born between 1997 and 2012 are the most influential consumer group, known as Generation Z consumers. These individuals have grown up in a digital world where artificial intelligence and themselves are commonplace. A unique perspective on the role of artificial intelligence in the lives of Gen Z customers is characterized by an affinity for technology, social consciousness, and diverse interests. This study investigates the perceptions of Gen Z customers on AI in Chennai. Data was collected through a structured questionnaire distributed among 400 respondents, out of which 386 questionnaires were found suitable for the study. The findings ultimately suggest that, to engage effectively with Gen Z customers, businesses need to focus on practical benefits and ease of accessibility with data security. Overall, this study underscores the importance of awareness and trust in the unique perspectives of Gen Z customers to harness the full potential of AI.

Chapter 12 is “The Intersection of AI and Financial Sustainability: Evaluating the Influence of AI-Based Decision-Making, Risk Assessment, and Transparency in Banking: Special Reference to Private Banks in Tamil Nadu.” Artificial intelligence (AI) technology changes banking operations through its application in financial management by strengthening risk evaluation and decision-making processes while improving financial transparency. The research investigates how AI financial strategies affect sustainable financial performance (SFP) through the mediating influence of financial transparency and governance (FTG). Researchers used structural equation modeling (SEM) in AMOS to analyze responses from 600 banking professionals employed at five private-sector banks located in Tamil Nadu. The study

shows that AI-based financial forecasting (AFF), automated decision-making (ADM), and AI-driven risk assessment (ARA) improve sustainable financial performance (SFP) through full mediation by financial transparency and governance (FTG). Sustainable credit scoring (SCS) failed to produce significant results, which indicates limitations within current AI-based credit models. The results indicate that strong AI governance structures are essential to fully harness financial benefits from AI technologies. The research provides managerial insights and recommends more investigation into the extended financial effects of AI adoption.

Chapter 13 is “AI-Driven Sustainable Logistics and Inventory Management: Bridging Efficiency and Environmental Responsibility.” The study explores the transformative role of artificial intelligence (AI) in sustainable logistics and inventory management, aiming to enhance efficiency while minimizing environmental impact. Targeting logistics companies, supply chain managers, and sustainability advocates, the research employs a mixed-methods approach, combining AI-driven predictive analytics, machine learning, and real-time tracking technologies. Key findings highlight AI’s ability to optimize route planning, reduce waste through precise demand forecasting, and enhance supply chain transparency via blockchain integration. Additionally, AI-powered automation improves inventory tracking and reduces carbon footprints through optimized transportation strategies. The study concludes that AI-driven logistics fosters economic benefits, operational resilience, and sustainability compliance. However, challenges such as data quality, integration with legacy systems, and regulatory constraints require strategic mitigation. Future research should explore AI’s role in circular economy supply chains, quantum computing for logistics optimization, and autonomous vehicles for sustainable transportation.

Chapter 14 is “Artificial Intelligence for Sustainable Business Development.” Artificial intelligence (AI) technology provides businesses with creative approaches for addressing issues related to sustainability and making data-driven decisions. AI can optimize the utilization of energy, minimize waste, and improve supply chain efficiency by analyzing massive volumes of data, enhancing sustainable practices. As businesses try to balance their environmental and social duties with their need to maintain a distinct brand identity, AI in sustainable business development has become an emotive subject. This chapter presents the potential of AI in linking sustainable practices with brand identity, emphasizing the significance of explainable artificial intelligence (EXAI) in assuring credibility and responsibility. AI will preserve product uniqueness and market positioning. Businesses could

leverage AI solutions based on their core values and marketing strategies to reinforce their brand identities.

Furthermore, the concept of EXAI is critical in the ethical implementation of AI. EXAI will enable humans to comprehend and interpret AI systems. Integrity in AI algorithms and decision-making processes builds trust and gives people insight into the reasoning behind AI model outcomes. As consumer expectations for accountability and ethics develop, this degree of communication is crucial for sustainable businesses. Companies can effectively integrate their brand identities with existing sustainable initiatives by employing AI in sustainable business growth and assuring the clarity of AI systems through EXAI. This chapter addresses the importance of AI for sustainable business development, EXAI in building trust and transparency, and the potential benefits and challenges of incorporating AI in sustainable business practices.

Chapter 15 is “Integrating SDGs into Industry 4.0’s Sustainable Business Practices: Efficiency and Challenges.” Technological advancements continuously reshape the way people live, often leaving significant impacts on the environment, particularly when development is unplanned. In the context of the United Nations’ Sustainable Development Goals (SDGs), this chapter explores the initiatives undertaken by Industry 4.0 and the challenges they face in achieving their goals. A literature review approach was adopted for this research, relying on open-source data from the internet to compile information on corporate initiatives aligned with SDG requirements. To ensure data relevance, only articles published from 2018 onward were considered, and studies lacking empirical evidence were excluded. Examples of organizational practices were supplemented with information collected from official company websites. The findings reveal that while many companies in India are making efforts through corporate social responsibility (CSR) initiatives to contribute to SDGs and establish themselves as responsible corporate citizens, a significant number struggle to create meaningful societal impacts. Achieving SDG targets within the given time frame remains challenging due to multiple obstacles.

Chapter 16 is “Career Exploration and Sustainable Innovation in Tech SMEs: Advancing Employability Readiness and Business Sustainability.” Indian technology small- and medium-sized enterprises (SMEs) are experiencing swift digital transformation, requiring workforce flexibility and sustainable business strategies. This study investigates the influence of organizational career and skill enhancement (OCE and SE) ecosystems on employee career exploration (CE) and their contribution to promoting

sustainable employability readiness (SER) and sustainable business practices (SBP) in technology small- and medium-sized enterprises (SMEs). As digital SMEs undergo rapid expansion, structured career development frameworks—comprising career architecture, workforce management, performance management systems (PMS), skill profiling, and talent management—are essential for equipping employees with skills suited for the future. Sustainable innovation (SI) is a crucial factor in synchronizing career development with long-term business sustainability by incorporating environmental factors into human resource practices. Career exploration serves as a crucial intermediary, connecting social capital, career anchors, and network capital to sustainable employment preparedness. Despite comprehensive research on sustainability and career development, the interaction among SI, CE, SER, and SBP in technology SMEs remains insufficiently examined. This study addresses the research gap by emphasizing the strategic significance of sustainable innovation in career trajectories and business sustainability. Research indicates that integrating sustainability-focused career frameworks and business practices within IT SMEs enhances workforce resilience and bolsters competitive advantage in a changing digital economy.

Chapter 17 is “A Bibliographical Analysis of Corporate Social Responsibility and Climate Change through R Studio.” The climate change (CLC) phenomenon is not unknown to anyone in the world and is likely to influence every sector—economic, social, political, cultural, and other sectors—directly or indirectly. No industrial organization is immune from the effects of CLC, and so are their actions. Corporate social responsibility (CSR) can be traced as an action of the industrial or corporate world towards society as their corporate responsibility. CLC has changed how CSR activities divest the compulsorily emboldened legal responsibility assigned by the Indian Company Act of 2013. This chapter tries to emulate the bibliographical activities involving CSR and CLC. In this study, we show how the CSR activities of corporations have evolved over the years with CLC, specifically after the Paris Climate Agreement, by using the Scopus database in R Studio. The latest two decadal periods of study showcase the various outputs using R Studio for annual scientific production (ASP), the significant sources, the keyword plus heatmap, the country collaboration, and other significant outcomes required for a bibliometric review of any topics in research of interest and for future contribution.

Chapter 18, “A Study on Behavioural Intention and Actual Usage of Artificial Intelligence among the Select Service Sector Employees,” explores the factors that impact behavioral intention and actual usage of AI and the

moderating role of gender in these relationships, utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT) model. A structured survey was conducted among 120 employees from the Indian IT and banking sectors to collect data. Structural equation modeling (SEM) review was run using SmartPLS V4 to inspect the influence of social influence (SoIn), performance expectancy (PeEx), effort expectancy (EfEx), and facilitating conditions (FaCo) on behavioral intention (BeIn) and actual usage (AcUs) of AI. It was found that EfEx, PeEx, and SoIn have a positive influence on BeIn, while FaCo has no substantial impact on BeIn and AcUs. However, the interplay between gender and FaCo was observed to influence the intention and adoption of AI. The findings of the research can be applied in organizations by leaders and managers as organizational strategies to motivate employees to leverage AI, thus improving the efficiency of the employees and the organization.

Chapter 19 analyzes the impact of removing pickup fees on sales within a buy-online-pickup-in-store (BOPIS) retail model using a novel geo-based causal analysis. Traditional A/B testing is not directly applicable for evaluating features in physical stores due to the inherent challenges of retail experimentation. Retail physical stores operate in interconnected networks, where changes in one store can influence nearby locations. This complicates the isolation of test and control groups. The logistical constraints, such as fixed store locations and variations in customer demographics and operational capacities further complicate experimentation. The solution to these challenges was to implement advanced clustering methods and causal inference techniques to create precise test-control groups while minimizing network effects. A two-step clustering approach—DBSCAN for spatial grouping and K-means for operational attributes—was implemented to ensure effective store segmentation and reduce bias and spillover effects. The treatment's impact was evaluated using a Difference-in-Differences (DiD) methodology, which validated the parallel trends assumption and controlled for pre-treatment biases. The results showed a 2.2% increase in average sales, driven by a 7.7% rise in average pickup sales. The results demonstrated clusters where removing pickup fees significantly increased sales and pickup adoption but also flagged stores where delivery orders were cannibalized. This study establishes a scalable framework applicable to omnichannel pricing strategies resulting in e-commerce innovations by detailing advancing methodologies in retail analytics and geo-based decision-making.

About the Editors



Madhusmita Mohanty is currently working as an Assistant Professor Senior Grade (Finance and Analytics) at VIT-AP School of Management (VSB), VIT-AP University. She earned her doctoral degree from the National Institute of Technology, Rourkela, Odisha, India. Her areas of expertise include financial management, security analysis and portfolio management, project analysis and control systems, financial and financial modeling, and financial market with relation to AI, ML, and blockchain applications. She has 12 years of experience in teaching and research.

She received a Gold Medal “AIMS J L Batra Best Research Paper Award” for the paper titled “An Empirical Analysis of Volatility Spill-Over Effect on Indian Financial Market Efficiency: U.S. Fed Policy or International Capital Flows” during the 32nd AIMS Annual Management Education Convention from 26 August to 28 August 2021. She has presented papers at various reputed national and international conferences. She is proficient in STATA, E-Views, and data analytics using Advanced Excel, R Statistics, and Python. She is optimistic about delivering the best of theoretical and technical knowledge with practical applicability in the recent world.



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Rashmi Ranjan Mallick, Director, KPMG Middle East, Cities, Infrastructure, PPP, Riyadh, Saudi Arabia, has 16 years of management consulting experience in developing business and leading several large-scale infrastructure, PPP, cities, and real estate projects from structuring to financial close to delivery across the Middle East, Philippines, and India. He brings a unique profile with a background in management, planning (Masters), and economics (Masters). He has a track record of developing and leading multicultural teams to drive business

growth. He has successfully closed billion-dollar infrastructure project deals. He played a key role in the structuring of high-quality winning proposals to secure advisory projects worth over \$50 million to developing lasting relationships with clients. He successfully developed the New Cities Advisory Practice within the Infrastructure Group at KPMG Saudi to expand the group's service offerings. Currently, for Cities Advisory, he is expanding the business, expanding the multicultural team, and leading the delivery of large-scale projects. Earlier, he led the delivery of large-scale infrastructure, real estate, and PPP projects in the Kingdom.



Kushal Walia is a Senior Technical Product Manager with extensive experience in artificial intelligence, cloud computing, serverless computing, and distributed computing. He has developed deep expertise in enhancing the developer experience for cloud computing services, focusing on security, governance, and fraud containment on serverless platforms.

Kushal's technical leadership in cloud computing extends to building supply chain, logistics, people analytics solutions, and AI. Kushal has led initiatives to improve the efficiency of supply chain and logistics systems which directly relate to the compute asset infrastructure management for a large cloud provider. Kushal's work on AI and machine learning in real-world problems extends to improving the employee experience at a big tech company. By leveraging large-scale data and people analytics, Kushal has driven meaningful changes in our global workforce's engagement and satisfaction. Kushal's origin in computer science has foundations in software engineering and big data engineering. As Software Development Engineer, Kushal built solutions

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Chapter 1

Developing Sustainable Business Intelligence through Artificial Intelligence

Ghousia Jabeen, Gurunadham Goli, and Rakesh Kumar

1.1 Introduction

Business intelligence (BI) and artificial intelligence (AI) are two crucial concepts in today's business analysis, where AI supports BI at every step of the process. A computer system that duplicates human brain capabilities through learning features, self-adjustment functions, and reasoning processes is defined as artificial intelligence (Rane et al., 2024). On the other side, BI is marked by the processes and tools through which an enterprise gathers, processes, and analyzes data to gain historical, real-time, and prognostic visions of the company-wide activities. Artificial intelligence is a catalyst for transformation across most sectors in the age of technological innovation. Its ability to analyze huge datasets, recognize patterns, and streamline intricate processes has rendered it essential not only in the field but also inside business consulting industries. With increasing pressure on businesses to adopt sustainable practices, the convergence of AI and sustainability has given birth to a new paradigm: sustainable business intelligence (SBI) (Di Vaio et al., 2020). This concept focuses on leveraging AI-driven insights and tools to meet environmental, economic, and social sustainability goals while maintaining a competitive advantage. SBI

represents a strategic approach wherein AI technologies are used to optimize resource allocations, reduce waste, and enhance decision-making processes for sustainable development. With AI to identify and implement solutions aligned with sustainability objectives, sustainability solutions can be achieved in supply chain efficiency, in manufacturing energy management, and many more. Such technologies help businesses to respond to global challenges such as climate change, resource scarcity, and social inequities while ensuring long-term profitability. However, the integration of AI with SBI is challenging (Toniolo et al., 2020). The energy-intensive nature of AI systems coupled with ethical concerns about data privacy, algorithmic bias, and equitable access to AI technologies poses significant hurdles. The balance between technological innovation and ecological sustainability demands thoughtful strategies and a robust governance framework.

The emerging trends and case studies provides actionable insights for businesses to adopt AI as a tool for sustainable progress (Ahmad et al., 2021). The incorporation of AI into BI has revolutionized the way data have been processed to eradicate barriers to efficient decision-making. Here is an elaboration of the paper's definition in relation to AI and BI (Table 1.1).

Although AI and BI are separate concepts, they merge to alter several business environments through improved decision-making. However, the issues of the ethicality of AI in BI, such as data privacy and algorithm fairness, are of crucial importance for ensuring credibility and neutrality in the BI system, as pointed out by Goswami et al. (2024).

The tender of AI and BI remains momentous in current business models, especially when aligned with sustainable development objectives. AI, also called artificial intelligence, mimics the human brain and its processes on machines, especially computer systems, whereby they can learn, reason, and criticize themselves, and business intelligence (BI) is more about the utilization of data tools and procedures to make the right business decisions (Nwaimo et al., 2024). Sustainability within organizations relates to the ability to deliver value to the current group without jeopardizing the standard of future groups' quality of life, while also addressing environmental, social, and economic aspects (Karthik, 2024). To that effect, it is vital that AI plays a central part in sustainable BI to improve some of the decision-making activities for the purpose of sustainability objectives.

Table 1.1 Draft Definitions Based on Existing Documents

	<i>Artificial Intelligence</i>	<i>Business Intelligence</i>
Definition	AI refers to the processes including designing techniques and methods that replicate the human brain's abilities of learning and reasoning. Marketing, healthcare and risk management are some of the sectors in which it is used to bring efficiency and automation to certain tasks (Majeed, 2024).	Business intelligence (BI) involves collecting and presenting information pertinent to commercial operations and conducting business analyses accordingly. It aids organizations in their decision-making processes by facilitating the examination of market trends and corporate performance (Vineetha et al., 2024).
Application	Artificial intelligence is utilized in predictive and prescriptive analysis, which means that an organization can foresee trends happening in the future and take appropriate action early enough. It minimizes the use of raw data in decision processes because they are mostly executed and managed by the artificial intelligence system (Badmus et al., 2024).	Due to combination of AI into BI systems, superior appliances have been adopted that help in performing procedures, forecasting the future and ushering customized interfaces. It also opens up questions about data accuracy and data protection (Goswami et al., 2024).

(Continued)

Table 1.1 (Continued)		
	Artificial Intelligence	Business Intelligence
Impact	AI transforms data management and decision-making as it builds up a high-speed decision support system coupled with improved predictive accuracy (Goswami et al., 2024).	Therefore, the advancement of BI has evolved from conventional methods towards AI predictive analytic methods where data analytics has played its role in expanding BI beyond traditional tools (Eboigbe et al., 2023).

Source: Created by author.

1.1.1 Why AI Must Be Incorporated into SBI

It enhances data quality and reduces costs, which are essential for sustainability performance measurements (Adelakun, 2024). Predictive analytics enhanced by AI can predict sustainability risks and opportunities, as suggested by Kumar R. et al. (2024). AI helps to constantly monitor the environmental and social consequences, allowing interventions to be made immediately (Adelakun, 2024). AI stands for decision-making for preservation of organizational resources with the aim of achieving sustainability initiatives that help in the minimization of wasting resources (Nwaimo et al., 2024). When incorporating AI into sustainable BI, there are many advantages, but there are also some disadvantages, including data privacy, algorithm data transparency, and moral issues. Such challenges indicate that there should be better governance of AI’s implementation and effective cooperation between different industries to unleash the potential of AI in supporting more justifiable business models.

1.2 Objectives

- To explore the development of AI and sustainability
- To investigate AI’s contribution to sustainable business intelligence
- To recognize the obstacles faced by AI in sustainable business intelligence

1.3 Sustainable Business Intelligence

Sustainable BI is an existing but still emerging concept pointing to the use of advanced tools and methods to improve organizational activities; support organizational growth and development; and foster economic, social, and environmental sustainability in business. By adopting this approach, the firm incorporates technology features like AI, analytics, and IoT to enhance the use of resources, cut wastage, and enhance sustainability performance. Through integrating sustainability measures in BI systems, it becomes easier for most organizations to make the right decisions towards sustainable development and business growth. The subsequent sections in the chapter provide detailed descriptions of the focus areas of sustainable BI, including its integration with AI, as well as the prospects and risks associated with it (Balcioglu et al., 2024).

AI is instrumental in the concept of sustainable business development by contributing to improving organizational productivity and the environment, using renewable energy, and minimizing emissions (Balcioglu et al., 2024). AI enables the incorporation of environmental, social, and governance (ESG) benchmarks into BI models effectively as means of sustainable value generation and risk management of social and environmental issues (Karthik, 2024). BI as a sustainable technology engages sophisticated instruments, such as predictive analytics, machine learning, and blockchain technology in capturing, processing, and visualizing a variety of data emanating from different sources subsuming environmental imprint, social responsibility, and economic outcomes. These tools can help one seek rational organizational solutions to issues affecting resource usage and the performance of the sustainability agenda, as illustrated in different case studies (Nwaimo et al., 2024). Some of the known problems of sustainable BI are costs, the complexity levels of BI, concerns with data privacy, and scalability of BI solutions (Jain & Mitra, 2024). Regarding adoption, there are best practices such as leadership commitment, cross-functionality, and ethical parameters, which are required for better implementation (Nwaimo et al., 2024).

1.3.1 Artificial Intelligence and Sustainable Business Intelligence

AI is rapidly emerging as a major approach for enhancing business sustainable intelligence and is applicable in all domains. The case studies show that by incorporating AI into sustainability initiatives, companies can improve performance while contributing to environmental quality and supporting

the UN sustainable development goals (Giovannoni & Fabietti, 2013). This synthesis is centered on how AI can be used to enhance sustainable business intelligence through literature across various fields. AI plays a significant role in the successful application of the United Nations Sustainable Development Goals, as it helps minimize resource utilization and wastage while maximizing energy utilization. This approach enables industries to devise and implement strategies that effectively address current requirements while safeguarding the ability of future generations to meet their own needs. Substantial volumes of data can be processed along with complex decision-making tasks that rely on extensive datasets for sustainable development. This functionality is particularly beneficial in sectors such as energy, agriculture, and transportation, as these industries are primarily concerned with optimizing productivity and minimizing environmental impact (Ruggerio, 2021).

1.3.1.1 Sustainable Development Business Model

The United Nations World Commission for Environment and Development made the first sustainability definition through its Brundtland Report (Marx & Ahmed, 2014). In 1987, the United Nations (1987) provided their report which plainly described sustainable development as “Humanity can make development sustainable to ensure that it meets the needs of the present without compromising the ability of future generations to meet their own needs.” Long after the event, the European Union has maintained its position on sustainability because it serves as an “interlinking policy element that runs across everything we undertake” (European Commission [EC], 2018, p. 9). Global leaders have prioritized sustainable development throughout the years through agreements starting with the Kyoto Protocol in 1997 followed by the Copenhagen Conference in 2009 and the Paris Agreement in 2015 (Alrazi et al., 2016). The SDG 2015 stands as new sustainable development targets of the European Union that require business sector participation in the Global Sustainability Agenda 2030 (EC, 2017). Sustainable development receives acceptance from the European Union as part of the United Nations Agenda 2030 for Sustainable Development. In addition, the European Parliament and Council’s decision-making regarding sustainable investments has been influenced by the ESG aspects that are included in investment performance reports. According to EC (2018, p. 10), the widely recognized ESG dimensions encompass three main categories: Environmental (E) aspects, which relate to the state and operation of natural systems and environments;

Social (S) aspects, which address the rights, welfare, and concerns of individuals and communities; and Governance (G) aspects, which focus on the management practices of corporations and other entities in which investments are made. The actions lead to sustainable economic pursuits while society confronts rising international concerns about proper economic sustainability (Beltramello et al., 2013) and simultaneously fights social and environmental consequences from climate change and global warming (Alrazi et al., 2016). Transiting a sustainable business framework means an entity should be ready to get rid of old habits, innovate, and often collaborate in successfully addressing environmental, social, and governance issues. Companies can achieve sustainability integration by innovating their business model, which leads to “re-conceptualizing the purpose of the firm and the value-creating logic and rethinking perceptions of value” (Bocken et al., 2014, p. 43). The business model should create competitive benefits so that customers remain loyal to the organization while also supporting sustainable development for the company and society (Lüdeke-Freund, 2010, p. 23). Competition-based companies need to expand their stakeholder range beyond monetary gain towards society and environmental involvement (Bocken et al., 2013, 2014). In the disclosure (Directive 2014/95/EU), companies need to organize material issues that reflect their core business operations (EC, 2018) (Figure 1.1).

1.3.1.1.1 Environmental Sustainability

The United Nations Sustainable Development Goals, with their 17 points, include six objectives that address environmental management alongside



Figure 1.1 Sustainable business model

human influence (Waughray (Ed.), 2011). Companies can achieve green criteria through the employment of AI tools that help them develop business models compatible with environmental sustainability. Smart grid technology has recently been adopted by organizations to use AI for immediate demand response capabilities, which stabilize energy flow. The integration of sustainable business models with artificial intelligence presents significant opportunities. The combination of various energy sources from non-renewable and renewable types makes the power grid system easier to manage through AI processing of big data sets, thereby achieving better stability and autonomy. Energy efficiency proves to be the primary concern (Ashford, 2000) as the predicted eco-cigarette trend likely drives industrial adoption of clean technology. Supply chain optimization models generate energy consumption concerns regarding worldwide manufacturing levels. Artificial intelligence offers dual capabilities to enhance the development of decision support systems, which help organizations reduce energy costs combined with frontier technologies that decrease energy utilization and environmental effects (Ashford, 2000). Moreover AI serves as a tool for environmental aspects ranging from air pollution to waste management systems. This chapter examines the fundamental reasons behind losses and wastage of harvested products during agricultural supply chain logistics and food industry delivery networks. Access to smart food logistics and supply chain systems demands artificial intelligence support in sensor and communication technology systems. Through supply chain management, automation enables precise perishability tracking of items being shipped within smart containers by using GIS with sensory smart devices for data gathering. Supply chain professionals employ smart measurement equipment signals, according to Kumar and Gopal (2015) for deciding pricing changes, rerouting strategies and final usage decisions. Such processing methods decrease both travel expenses and delivery management expenses.

1.3.1.1.2 Social Sustainability

Companies that care about social responsibility contribute to the differentiation process among companies. Their reputation is boosted by social compliance, while the market share is further popularized by it. Intellectual hegemony over the competition is established by their greater adaptability to the changing environment (Luna-Nemecio et al., 2020). There is a great number of social problems that AI can provide assistance with, for example, the development of the labor workforce, gender inclusion, employee safety, and working conditions (Thomas et al., 2009). It is a common belief that

the advent of artificial intelligence will revolutionize by replacing numerous jobs: at least 30% of jobs are under future automation between the early and late twenty-first centuries. Yet, the number of future jobs that will be taken over by robots directly corresponds to the level of skills one will need to handle the remaining work be handled by a workforce that is already well counter-balanced and re-deployed. The fact is that displacing humans with automated systems will allow companies to relieve humans from doing repetitive, monotonous, and labor-intensive activities, thus keeping their skills in place and moving them to use more complicated and meaningful jobs (Nicholls (Ed.), 2008).

1.3.1.1.3 Governance Sustainability

The general definition of corporate governance describes both the systems and organizational relationships along with all control functions that guide business operations (Elkington, 2006). This research investigates corporate governance through the evaluation of insolvency and money laundering along with corruption and bribery in addition to board gender diversity and audit systems and decision-making processes. Artificial intelligence algorithms, which include statistical and machine learning techniques, enable the creation of bankruptcy prediction methods, providing financial institutions with the ability to select better lending approaches. Billi, Mascareño, and Edwards (2021) developed an assessment model through artificial neural networks' learning capabilities combined with evolution strategies optimization for evaluating a company's true corporate value by using non-accounting and accounting information, which benefits firms and investors.

The use of AI systems will introduce gender representation into boards of directors while leading to cultural transformation; however, male executives continue to outnumber women in boardrooms. In practice, AI technology advances hidden corporate issues, making difficult data accessible and thus facilitating better candidate identification during recruitment processes (Adger, 2009). AI technology promotes advanced decision systems for board leadership while supplying powerful analytical tools for fundraising and the tracking of ongoing activities, which strengthens organizational performance across corporate governance and regulatory standards and safety protocols (Naciti et al., 2022).

1.3.1.2 AI-Enhancing ESG Strategies

AI and its interconnection with environmental, social, and governance (ESG) methods are changing the business analytics landscape by offering new,

complex methods for threat identification and possibilities assessment. AI improves the use of resources optimizing the overall environmental impact, which in turn works with ethical, sustainable investment goals introduced in business (Rane et al., 2024). The due diligence of ESG is on the rise as AI becomes increasingly functional in the analysis of the consequences of environmental impact and corporate social and governance performance. The combination of the evaluation of the existence of a win-win situation between profitability and ecological management (Nwaimo et al., 2024).

1.3.2 The Role of AI in Sustainable Business Intelligence

There is a rising recognition of the importance of AI in improving business intelligence sustainability through revolutionary opportunities across all industries. It is hypothesized that the integration of artificial intelligence into sustainable business processes leads to increased productivity and reduced environmental impact, hence meeting global sustainability goals. This investigation uses a range of research situations to investigate AI's varied role in creating long-term business intelligence. The next section provides a few case studies to show how, as early as 1987, sustainable development received focus within the Brundtland Report issued by the United Nations, which identified technology as an essential part in promoting and advancing sustainable strategies. The World Economic Forum recognized AI as the dominant technological force that would define upcoming years during their 2015 report (Espinel et al., 2015). It underlined the significance of AI as “the most critical general-purpose technology of our time” and stated that “in the realm of commerce, AI is set to have a revolutionary impact, comparable to earlier general-purpose technologies.” It is a new, disruptive technology that has swiftly expanded. Business executives must have a mindset that not only adapts to new techniques but also translates them into economic value for clients, associates, and the community as a whole.

1.3.2.1 Xcel Energy

Xcel Energy Inc. operates as a subsidiary under the ownership of the company. The company operates from Minnesota to produce electricity through Texas-based coal plants. Operations at Xcel Energy Inc. result in the emissions of nitrogen oxide, which functions as a greenhouse gas leading to increased global warming effects. The company has already started exploring multiple artificial intelligence technologies towards achieving

sustainability. The startup employs artificial neural network technology similar to human brain functioning to evaluate coal combustion data for minimizing nitrogen oxide emissions from coal-fired plants. The system then generates specific operational change recommendations that decrease emissions while maximizing production levels of the plant. Xcel set a national precedent when it became the first utility company in America to deploy drones with automatic systems for conducting procedural checks of its physical assets. The company has developed an agreement with the National Centre for Atmospheric Research to enhance wind prediction capability through machine learning algorithms. Improved accuracy becomes possible through the data obtained from hundreds of wind turbine sensors. A new solution addresses both intermittency problems and predictive inaccuracies that have hindered forecasting since its early days. Xcel Energy has achieved a \$60 million reduction in costs along with lowering CO₂ emissions from fossil-reserve energy generation beyond 250,000 tons through the implementation of AI technology (Schiermeier, 2016).

1.3.2.2 *Telefónica*

Telefónica³ stands as a Spanish multinational telecommunications corporation which operates among the top telephone network providers and mobile operators worldwide. Telefónica Ingeniera de Seguridad initiated its partnership with AnyVision, the world leader in artificial intelligence development and recognition platforms, to enhance workplace security worldwide during January 2018 (Telefónica, 2018). The technology enabled integration between the company and AnyVision's advanced AI systems for physical object and body and facial recognition capabilities for multiple security sectors that include homeland security, transportation, critical infrastructure, and smart cities. Telefónica, alongside Atos, has jointly designed major initiatives which include airport development, smart city expansions, stadiums, and financial institutions. The places that deliver authentication solutions together with onboard management also maintain smooth access control. The company applies both AI approaches and IoT and big data technology to build smart city initiatives.

Internet-connected traffic movement sensors help determine vehicle density in cities as well as adjustable parking fees and responsive traffic direction signage that guides citizens during their daily travel. The decision about implementing speed limits on motorways relies on combined monitoring stations alongside weather data to avoid hazardous pollution levels in specific

locations. Real-time sensors operated by Telefónica in Valencia support the implementation of parking charges that both boost parking distribution equality and minimize fuel usage and CO₂ emissions (Marr, 2017). Telefónica implements its Valencia Smart City project based on AI and IoT and big data technology to enhance the quality of life for residents in the city. The examples show how their supporting resources serve to explain to the reader (Massaro et al., 2018b). Each scenario describes the effects of AI adoption on a specific ESG dimension. The authors show that AI startup partnerships with multinational corporations enabled these corporations to implement AI-based approaches which brought improvements to their sustainable business operations. These examples demonstrate how sustainability business models can develop their ESG dimensions along with showing historical insights and sustainability model development capabilities. The research demonstrates how AI technologies enable sustainable business model development from a complete ESG standpoint, producing practical outcomes for industry practitioners. The chapter includes illustrative examples that assist managers who wish to deploy AI systems. The best method to fulfill technical manager requirements for sustainable business model creation rests in AI company and startup partnerships, according to the illustrative examples presented.

1.3.3 The Challenges of AI in Sustainable Business Intelligence

Incorporating artificial intelligence into business intelligence presents numerous hurdles across technological, economic, ethical, and operational spheres. While AI is poised to transform sustainable business practices by enhancing resource efficiency and decision-making processes, AI's deployment is fraught with intricacies. AI's potential is currently untapped and has the potential to be a sustainable alternative to human AI for sustainability (Table 1.2).

There is evidence that AI can be used in sustainable business intelligence, thus enabling sustainable business intelligence. It can improve efficiency in operations, use of resources and support sustainable goals, for example, the United Nations Sustainable Development Goals. However, addressing the ethical, technological, and operational challenges and their solutions will unlock these benefits much more successfully. By promoting responsible AI development and integrating ethical considerations into AI strategies, businesses can realize the benefits of AI while upholding ethical standards and societal values.

Table 1.2 The Challenges of AI in Sustainable Business Intelligence

<i>Technological and Economic Barriers</i>	<i>Ethical and Regulatory Challenges</i>	<i>Environmental and Operational Impacts</i>	<i>Strategic and Cultural Resistance</i>
Infrastructure costs: Developing AI infrastructure is not free and has a pretty huge cost to it that SMEs would find almost unaffordable (Rane et al., 2024).	Data privacy and security: AI systems handle sensitive data. This raises privacy and security concerns. Data protection while using AI is a significant challenge (Rane et al., 2024).	Operational burden: AI technologies being dynamic in nature, continuous updates and maintenance are needed, which increase operational burdens and costs (Rane et al., 2024).	Organizational resistance: AI incorporation in business practices is faced with resistance based on the culture and organization, requiring a strategic change management effort (Rane et al., 2024).
Skill shortfalls: Demand for technical competence in the workforce involved in AI and data science is immense; however, the global supply is a bottleneck for the adoption of AI (Rane et al., 2024).	Algorithmic bias and transparency: AI systems can perpetuate biases present in training data, leading to ethical concerns about fairness and transparency in decision-making processes	Resource optimization: Although AI helps improve resource utilization and lessen environmental degradation, its application does increase energy consumption and carbon emissions, which creates a paradox for sustainability efforts (Tiwari et al., 2024).	Cultural acceptance: This is very much dependent on employee training and engagement for the cultural acceptance of AI-driven changes (Khandbahale & Pachorkar, 2024).

1.4 Future Direction

Business intelligence development through sustainable measures will experience major advancements from artificial intelligence technology in the near future. Companies employ AI systems to improve their decisions about combining financial gains with social sustainability targets as well

as environmental sustainability targets. AI will manifest its use primarily through three domains, including social media involvement and other areas.

1. Predictive analytics: AI will better predict the impacts of activities, energy consumption and usage of resources for the efficient optimization of supply chains and operational efficiencies (Judijanto et al., 2023).
2. Integration with IoT: AI-driven BI systems will increasingly integrate with IoT devices to monitor and analyze real-time data on energy, water, and waste management, thus promoting transparency and responsiveness (Nazarian-Jashnabadi et al., 2024).
3. Circular economy models: AI can analyze product lifecycles to support circular economy initiatives, such as recycling, remanufacturing, and waste reduction, driving more sustainable production and consumption patterns (Ahmad et al., 2024).
4. Ethical AI systems: Development of AI models aligned with ethical principles will ensure that sustainable BI prioritizes not only efficiency but also social equity and inclusion.
5. Better decision support: AI will enable actionable insights through the integration of ESG data into strategic decision-making processes, thus helping organizations meet regulatory and stakeholder expectations (Dhamija & Bag, 2020).

With such directions, AI is likely to redefine sustainable BI and help to bring the world's economy in tandem with ecological preservation. Data privacy, algorithmic biases, and the environmental cost of AI itself must be overcome to unlock the full potential of these advances.

1.5 Conclusion

Artificial intelligence (AI) is rapidly becoming a crucial element in the revolution of business intelligence in the global economy. It equips organizations with the means to process vast amounts of data efficiently, anticipate future patterns, and make well-informed decisions that harmonize financial, environmental, and social sustainability objectives. As more technologies embrace AI technology, their capacity to revolutionize business methods, enhance resource use, and lessen environmental consequences becomes increasingly apparent. Another key contribution of AI to sustainable business intelligence is the enhancement of predictive analytics. This is achieved

through the application of machine learning algorithms, enabling companies to anticipate environmental risks of resource distribution and modify their supply chains in response to escalating circumstances. This predictive capability not only improves business operations but also minimizes waste and reduces carbon emissions. The combination of AI and the Internet of Things (IoT) enhances AI's effectiveness in gathering and analyzing data on energy consumption and resource utilization. Moreover, AI promotes the circular economy model by allowing companies to evaluate product lifecycles and spot opportunities for recycling, remanufacturing and waste reduction. This is a global move towards sustainable production and consumption patterns. Ethical AI systems created to emphasize fairness and inclusion ensure that technological innovation is responsibly deployed, incorporating social equity along with environmental concerns. Although AI has potential, its deployment in sustainable BI comes with several challenges. Among these are data privacy issues, algorithmic biases, and the environmental costs of the infrastructure that supports AI. The energy-intensive nature of AI, especially in the training of large models, creates a paradox in efforts to reduce the environmental impact of organizations. Such factors can be overcome if companies and policymakers take measures seriously for developing energy-efficient AI technologies and make their usage in data and algorithms more transparent.

In the coming decades, the scope of application of AI in sustainable BI will increase significantly. This is because emerging novel AI algorithms, along with developing IoT and blockchain technology, would allow the management of sustainable data in a highly efficient and secure manner. Organizations will increasingly use AI-driven insights to integrate environmental, social, and governance (ESG) metrics into their decision-making processes. Moreover, collaboration between AI developers, businesses, and regulatory bodies will be key in developing the ethical frameworks and standards to guide the responsible use of AI.

AI is a transformative opportunity to advance sustainable business intelligence. It poses a difficult challenge to achieve harmony between profitability and sustainability. The potential possibilities of being intelligent are infinite, as AI can help boost decision-making with data, better use resources and engage in circular economy activities while maintaining a harmonious ratio between profitability and sustainability through business means. As the world begins to focus on sustainability, artificial intelligence plays an important role in creating a culture that promotes commercial success as well as societal and environmental prosperity. Companies that adopt these ideas and

technologies will not only gain a competitive advantage but will also have the ability to contribute significantly to the world's betterment. This implies that applying AI approaches to construct sustainable business models has far-reaching implications for practitioners throughout government, society and the environment. The chapter delivers concrete use cases that managers need to employ AI technology. Managers have access to images which illustrate how they can team up with AI organizations to optimize business requirements and learn technical expertise that enhances sustainable business models. The academic community needs to conduct extensive literature examinations which both develop existing understanding and research potential future research of available resources.

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Chapter 2

Evolution of Sustainable Intelligence Business Practices

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Novelty

With the focuses on their role in accomplishing environmental, social, and governance (ESG) objectives, this chapter examines in a novel way how innovative technologies like artificial intelligence (AI), the Internet of Things (IoT), blockchain, and digital twins might be incorporated into sustainable business operations. It emphasizes how these technologies promote innovation in transparent supply chain management, real-time monitoring, and resource optimization, promoting alignment with worldwide sustainability programs such as the sustainable development goals (SDGs) of the UN. In addition, the chapter discusses important obstacles such as moral dilemmas, legal difficulties, and organizational opposition, offering a thorough analysis of how to get past them. It offers forward-thinking tactics for promoting circular economy principles and empowering small- and medium-sized businesses to embrace sustainable intelligence by concentrating on cutting-edge technology like green AI.

2.1 Introduction

The implementation of global sustainability principles puts in high gear the speed of change in the digital environment of a business. Using technologies

such as big data and artificial intelligence (AI) analytics, blockchain, and the Internet of Things enables organizations to adopt the right data-driven approach and achieve operational excellence with an environmentally friendly nature. These innovations optimize resource usage with zero waste and greater transparency (Brendel et al., 2021). With the result, there will be efficiency along with sustainability. Artificial intelligence (AI) and machine learning (ML) enable businesses to handle complicated data sets that automatically result in actionable insights related to environmental, social, and governance (ESG) metrics, making it easier for a company to know trends or impending risks; thus, the firm can address sustainability concerns head-on. For instance, predictive analytics supports the consumption of energy by anticipating use, minimizing emissions, and optimizing supply chains. Thus, artificial systems facilitate operations by minimizing waste, improving energy efficiency, and streamlining processes aimed toward fitting the sustainable development goals (SDGs) of the United Nations (Sjödín et al., 2021).

Internet of things (IoT) technologies contribute significantly by offering real-time tracking of environmental factor performance and energy usage. IoT-enabled devices identify areas of inefficiency and enable timely interventions, thereby reducing resource wastage and minimizing negative impacts on the environment. In agriculture, IoT sensors maximize irrigation and pest control measures. Such applications support adaptive operations, reducing ecological footprints of production processes (Santa-Maria et al., 2022).

Blockchain technology contributes to more openness and responsibility in supply chains of supply due to the unalterable records of all transactions. The technology has allowed companies to verify proper sourcing, avoid inefficiency, and detect fraud. Blockchains can support circular economies by tracing material lifetimes to provide the most effective recycling and reuse. This process allows for the efficient use of resources with lesser environmental footprints in production processes. Digital twin technology will make it possible for organizations to simulate and optimize operations before applying them. As businesses look at virtual environments, they can detect inefficiencies, minimize resource usage and costs, and reduce their ecological footprints. This is how digital twins improve workflows and energy efficiency while meeting new market requirements in manufacturing and construction (Omol, 2024).

These technologies collectively enable organizations to become agile in response to changes in regulatory conditions and shifts in the market environment, securing competitive advantages in a rapidly changing context. Advanced analytics help predict trends, while blockchain and IoT systems

ensure compliance with environmental standards and sustainable sourcing requirements. By integrating these tools, businesses foster innovation and develop long-term strategies for sustainable growth (Arora et al., 2025). Digital tools also encourage collaboration among stakeholders, allowing for shared insights and collective progress. They create value for stakeholders while building trust with customers and investors by promoting circular economy principles and regulatory compliance. Predictive maintenance and IoT-enabled monitoring further improve operational efficiency, lowering expenses and the impact on the environment (Lee et al., 2021).

By using artificial intelligence (AI), blockchain technologies, Internet of Things (IoT), big data, and digital twins, organizations become aligned with global sustainability goals through decision-making processes. It brings them closer to operational excellence through efficiency and resource optimization while reducing waste, hence achieving transparency. As they implement these technologies, companies create themselves as sustainable leaders toward an innovative future of efficiency and environmental stewardship (Nazarian-Jashnabadi et al., 2024).

2.1.1 Overview of Sustainable Intelligence in Business

The business sustainable intelligence develops from combining social, environmental, and governance frameworks with artificial intelligence technologies. It allows business organizations to enhance decision-making, optimize resource utilization, and drive long-run effects. With the help of artificial intelligence (AI), businesses can monitor environmental social and governance (ESG) metrics, keeping their operations transparent and accountable. Minz et al. (2024) discuss how AI-driven strategic innovations empower SMEs with sustainable business models. Artificial intelligence facilitates technological and strategic innovation, empowering SMEs to achieve carbon neutrality with reduced environmental impacts. Thus, these innovations contribute toward operational efficiency, in addition to positioning a firm at the forefront of contributions to global sustainability goals.

Sustainability is only achievable when integrated with intelligence-driven practices. Artificial intelligence in practice has become a key technology for the optimization of processes and resource consumption in the attempt to align business performance with the goal of sustainability. This means that, with artificial intelligence (AI), an organization is able to deal with the environment while being more efficient, innovative, and effective (Chen et al., 2024). Smart technologies and smart processes play a vital role in the

Table 2.1 Definition and Key Components

<i>Concept</i>	<i>Meaning</i>	<i>Author</i>
Sustainable intelligence	The long-run capability of businesses to undertake operations without depleting resources or harming societal wellbeing, integrating intelligent systems to drive sustainability.	Su and Wu (2024)
Intelligence	The capability to gather, process, and apply information effectively.	Su and Wu (2024)
Management control systems	Systems that track and direct organizational performance, aiding sustainable development by aligning business strategies with sustainability goals.	Tu Le et al. (2024)
Data-driven adaptability	Necessary for controlling and measuring sustainability activities with continuous improvement and adherence to international sustainability standards.	Tu Le et al. (2024)

Source: Author.

development of sustainable business practices. Such technologies allow for real-time analysis of data, predictive capacities, and efficient resource distribution, which are drivers of sustainability. Smart processes ensure that businesses can adapt to the demands of the market and reduce environmental impact while promoting long-term growth (Vaseei et al., 2024). Table 2.1 presents the meaning of key components with the author source.

2.1.2 Traditional Business Practices vs. Sustainable Practices

The rapid speed of digital transformation has emerged as a pivotal force in aligning businesses with global sustainability principles. By combining cutting-edge technology such as big data analytics, block chain, artificial intelligence (AI), and internet of things (IoT) into decision-support systems, organizations can leverage data-driven strategies for operational excellence and sustainability. These technologies promote resource optimization, waste minimization, and transparency in business processes, thereby improving both efficiency and sustainability outcomes (Madanaguli et al., 2024).

Artificial intelligence (AI) and machine learning (ML) algorithms allow firms to scan complex datasets, generating actionable insights to monitor environmental, social, and governance metrics. The insights enable businesses to make informed decisions toward sustainable development goals. For example, systems with internet of things (IoT) can monitor operations in real-time; it would mean that all operations are energy-efficient, which would lower the impacts on the environment. It allows businesses to have all the tools to react very fast to changing environmental and operating conditions. Such a culture enables a climate of innovation and long-term development.

Blockchain technology is essential for increasing the transparency of the supply chain and accountability. By providing immutable records, blockchain ensures ethical sourcing and reduces risks associated with fraud or inefficiencies. Similarly, digital twins allow organizations to simulate and optimize processes before implementation. This capability lowers operating expenses while simultaneously minimizing ecological footprints by identifying potential inefficiencies beforehand (Setyawan et al., 2024).

Digital transformation also enables businesses to be proactive in adapting to changing market demands and changing regulatory environments. Agility allows for competitive advantage in ever-changing markets, thus placing firms ahead of others in the market. Further, these digital tools aid in the attainment of sustainability by ensuring compliance with environmental regulations, optimum usage of resources, and a circular economy (Fosso Wamba et al., 2024).

Advanced technologies such as artificial intelligence and machine learning are playing an increasingly important role in achieving sustainable development goals (SDGs). These technologies enable industries to implement sustainable practices, increase operational efficiency, and reduce environmental impacts, thereby filling the gap between traditional business models and sustainable practices (Rane et al., 2024). Table 2.2 depicts the differences between traditional and sustainable practices of the businesses.

2.1.3 Key Milestones in the Creation of Sustainable Intelligence

The development of sustainable intelligence, especially through the integration of artificial intelligence (AI) into circular business models, is a big leap toward fostering sustainability. AI-capability development allows businesses to adopt circular economy principles, shifting from the conventional linear model of “take, make, dispose” to a method of regeneration in which

Table 2.2 Traditional Business Practices vs. Sustainable Practices

<i>S. No.</i>	<i>Aspect</i>	<i>Traditional Business Practices</i>	<i>Sustainable Practices</i>
1	Focus	Prioritize profit maximization and short-term goals	Balance profit, people, and the planet for long-term benefits
2	Resource utilization	Rely heavily on non-renewable resources, often leading to depletion	Promote efficient use of renewable resources and minimize environmental impacts
3	Environmental impact	Often ignore or minimally address environmental consequences	Actively reduce carbon footprint and adopt eco-friendly operations
4	Social responsibility	Limited focus on social welfare and community engagement	Integrate social responsibility into core business strategies, emphasizing community development and equity
5	Governance	Governance systems may lack transparency and accountability	ESG frameworks ensure transparent, accountable, and ethical governance
6	Innovation	Focus on cost-cutting and conventional technologies	Invest in sustainable technologies and AI-driven innovations for operational efficiency and environmental benefits
7	Stakeholder approach	Emphasize shareholder value	Prioritize a wider variety of stakeholders, like as workers, clients, local communities, and the environment
8	Regulatory compliance	Minimal adherence to regulations, often as a reactive measure	Proactively align with international sustainability standards and practices
9	Waste management	Generate significant waste with limited recycling initiatives	Adopt circular economy concepts, with a focus on recycling, reuse, and waste reduction
10	Adaptability	Resistant to change, focusing on traditional models	Embrace adaptability and innovation to meet evolving sustainability challenges and market demands

Source: Author.

resources are preserved, waste is reduced and recycled, and products are designed for longevity. Artificial intelligence (AI) plays a crucial role in this process by optimizing resource usage, improving recycling techniques, and ensuring effective product lifecycles. Sjödin et al.'s (2023) artificial intelligence (AI) techniques like machine learning, predictive analytics, and smart sensors allow businesses to monitor resources in real time, helping to reduce waste and save on resources. For instance, artificial intelligence AI-based systems would predict equipment failure, decrease the downtime, and therefore prolong the lifespan of such machinery. Similarly, AI can optimize supply chains to find opportunities in reusing materials, reusing parts, and consuming less energy. In that way, companies not only reduce their footprint on the environment but also save hundreds of millions of dollars through cost-cutting (Su et al., 2024).

Additionally, AI helps businesses design products that align better with the circular economy principles. Through data analysis and design optimization, AI can help create products that are easier to disassemble, recycle, or refurbish, thereby keeping valuable materials in circulation for longer periods. This is an important step toward recognizing the importance of sustainable business practices by introducing AI into circular business models. It shows that smart systems can drive change toward more sustainable and resource-efficient models, allowing businesses not only to meet regulations but also to make positive contributions to environmental preservation. It will allow businesses to adopt innovation in a way that promotes global sustainability (Madanaguli et al., 2024).

This research focuses on the innovative strategies for sustainable organizational growth, which involve advanced technologies for fostering long-term development. It identifies critical strategies that are used in business to integrate sustainability into its business operations, emphasizing the significance of innovation and adaptability to achieve sustainable success. Such milestones underscore the convergence of technology, sustainability, and intelligence-driven practices to create future business models (Setyawan et al., 2024).

2.1.4 Drivers for Adopting Sustainability in Business Intelligence

Some of the primary motivators to adopt sustainability in business intelligence include increasing pressure on responsible production and consumption practices. In this regard, as the pressures of environmental sustainability

increase, businesses have turned to AI to ensure that they utilize resources to their maximum capacity, minimize waste, and improve their decision-making. Data-driven insights are provided through AI technologies to ensure that organizations can adapt sustainable practices for better environmental and financial performance (Hasan & Ojala, 2024).

This further emphasizes the core role of AI in present-day business management, which is how it can make operations simple, improve decision-making capacity, and promote sustainability. The marriage of AI with emotional intelligence can help deal with sustainability issues while infusing a sense of accountability and ethical leadership in organizations. The integration of both AI and emotional intelligence boosts business growth while aligning with the larger sustainability objectives (Thakur, 2024).

2.1.5 Role of Technology and Innovation in Shaping Sustainable Intelligence

The role of technology and innovation in shaping sustainable intelligence lies in how digital technologies can integrate into business models at their core. They emphasize that businesses that utilize digital tools are far better placed to innovate, optimize resources, and advance sustainability, ultimately leading to long-term competitive advantage (Böttcher et al., 2024).

Sustainability branding is changing business strategies through the power of technological innovations. It maps emerging trends in sustainability branding, showing how companies can better communicate their efforts toward the environment through technological means, which shapes perceptions and drives sustainable behavior by consumers (Nascimento et al., 2024).

2.1.6 Chapter Objectives

- To analyze the shift from traditional business practices to sustainable practices and identify key milestones in sustainable intelligence development.
- To investigate the function of artificial Intelligence (AI) and machine learning (ML) applications in enabling business practices and advancing sustainable intelligence.
- To investigate the difficulties that firms encounter implementing sustainable intelligence and the drivers influencing its adoption.

2.2 Role of Technology in Sustainable Intelligence

Technology is a part of sustainable customer relationship management (CRM) because it provides businesses with digital tools and data analytics that help in creating long-term relationships with customers in an environmentally and socially responsible manner. Technology supports the creation of value-driven, sustainable strategies aligned with customer expectations and organizational goals (Ferrer-Estévez et al., 2023). Figure 2.1 shows the role of technology in sustainable intelligence.

2.2.1 Machine Learning (ML) and Artificial Intelligence (AI) Applications

The usage of artificial intelligence (AI) and machine learning (ML) in designing circular economy e-business models is crucial. Here, the author talks about how AI and ML can make e-business applications more efficient through optimized processes, better resource utilization, and sustainability-related purposes. These technologies have a significant influence on improving ESG performance to add value to sustainability results (Fatimah et al., 2023).

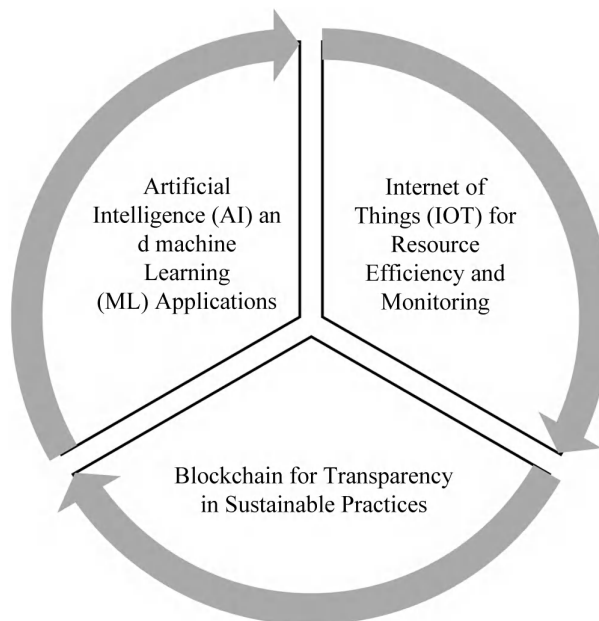


Figure 2.1 Role of technology in sustainable intelligence Source: Author

Innovation in business and sustainability merge in the context of the sustainable development goals (SDGs), with AI and ML as essential factors in achieving the said goals. They claim that AI and ML help bring innovative business strategies into conjunction with sustainability, thereby making organizations work toward a sustainable future. The integration of these technologies with business practices creates new avenues for environmental and social sustainability (Azmat et al., 2023).

2.2.2 Internet of Things (IoT) for Resource Efficiency and Monitoring

The Internet of Things (IoT) contributes to improving resource efficiency and monitoring in sustainable development processes. They emphasize that it makes possible real-time data collection, which enables the development of better decision-making resources on how to manage the use of available resources. This implies that, with digitalization and artificial intelligence (AI), IoT integration enhances organizational performance in operational efficiency and minimizes waste and ensures effective environmental monitoring for sustainability (Menzies et al., 2024).

The combination of AI and IoT contributes to sustainable decision-making. AI algorithms can analyze volumes of data generated by devices, thus helping businesses take more informed decisions about choices that are sustainable in respect to energy consumption and minimizing waste (Zhao et al., 2023). These are key technologies for the forward movement of sustainability in modern operations.

2.2.3 Blockchain for Transparency in Sustainable Practices

The application of blockchain technology plays a vital role in enhancing transparency in sustainable business activities. They state that blockchain promotes tamper-proof, decentralized record-keeping of transaction data, which makes it possible to trace supply chain operations and business processes more comprehensively. This is of immense importance for ethical and sustainable business activities, as it enhances verification and reduces environmental consequences among stakeholders (Perifanis et al., 2023).

Digital transformation, through the incorporation of blockchain, changes the game in sustainable manufacturing and business operations. Blockchain has facilitated efficient supply chain management and reduction of waste while increasing sustainability through sourcing, all because data is shared

in real time and fraud is diminished. This technological change in turn enables more sustainable business models since accountability and transparency prevail in operations to match the set standards environmentally and ethically (Moghrabi et al., 2023).

2.3 Business Practices Enabled by Sustainable Intelligence

Artificial intelligence (AI) supports business models aligned with the sustainable development goals (SDGs). They emphasize that AI-driven strategies enable businesses to optimize processes, enhance sustainability performance, and contribute to achieving environmental, social, and economic goals by integrating sustainable intelligence into business practices (Di Vaio et al., 2020). The business practices enabled by sustainable intelligence are depicted in Figure 2.2.

2.3.1 Circular Economy Initiatives

The effects of artificial intelligence (AI) regarding the circular economy initiatives are highlighted. AI can optimize resource efficiency, improve waste management, and support product lifecycle management—a critical feature of a circular economy. Artificial intelligence-based predictive analytics and machine learning optimize material use, reduce waste, and extend product lifecycles, all aimed at the sustainability goals that businesses should pursue (Goralski et al., 2020).

The scope and challenges of using artificial intelligence for sustainability, including circular economy practices, were mentioned. It can be applied to supply chain optimization, monitor resource consumption, and enable sustainable manufacturing processes. However, data privacy and ethical concerns, along with a skilled workforce, are obstacles to fully realizing AI in

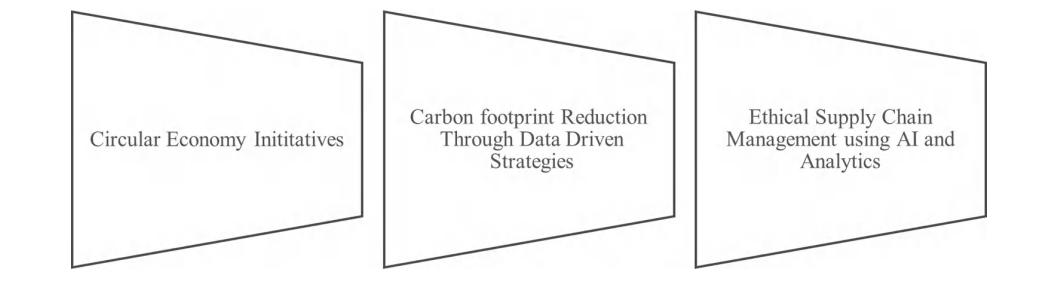


Figure 2.2 Business practices enabled by sustainable intelligence Source: Author

sustainability. Their research agenda places much emphasis on the need to overcome these barriers to successfully driving the adoption of AI in sustainability initiatives (Nishant et al., 2020).

2.3.2 Carbon Footprint Reduction through Data-Driven Strategies

Artificial intelligence AI-driven strategies have also contributed to carbon footprint reduction. They indicate that artificial intelligence is the pathway where energy consumption can be optimized, efficiency improved, and waste reduced based on data. Machine learning, predictive analytics, and automation are some of the AI technologies that can be useful in reducing the environmental footprint of organizations as they continue to strive for sustainability. It would allow businesses to monitor operations and then optimize those operations, thereby giving a view of where they must reduce carbon emissions and, consequently, save on resources (Kulkov et al., 2024). The digital transition promotes sustainability. They explain how digital technologies, especially AI, play a crucial role in carbon footprint reduction through efficient management of resources, increased energy efficiency, and minimized waste. Digital transition allows companies to gather, process, and respond to environmental information, which makes them more sustainable and decreases the carbon footprint by industries (Rosário et al., 2022).

2.3.3 Ethical Management of Supply Chain Using AI and Analytics

The topic of ethical supply chain management discusses the possibilities of using artificial intelligence and analytics to improve ethical supply chain management. The authors believe that with AI technologies, it has become easier to track supply chains and even optimize these chains for better sustainability along with the accomplishment of appropriate ethical standards as required by businesses. Predictive analytics and blockchain, as some AI-driven solutions, aid in monitoring labor practices, environmental impacts, and sourcing to promote transparency, thereby making supply chains more ethical and sustainable (Mio et al., 2020).

Al Aina et al. (2020) discuss how talent management practices contribute to sustainable organizational performance. They propose that the implementation of AI-based systems for talent management allows companies to align their human resource strategies with sustainability goals. Talent

management, integrated with ethical AI practices, can create a more sustainable and ethically responsible workplace (Al Aina et al., 2020).

2.4 Challenges in Implementing Sustainable Intelligence

The implementation of sustainable intelligence, especially through AI-driven solutions, is hindered by several significant challenges identified above. Among the primary challenges are technological barriers: it can be very difficult to implement advanced AI systems in small business or firms that lack technical infrastructure. Furthermore, the lack of data integration poses a critical challenge. For AI to be effective in driving sustainability, it needs access to the most accurate, high-quality data from a variety of sources. Many organizations are also facing siloed data systems, which prevents them from leveraging AI effectively for sustainable innovation (Tu Le et al., 2024).

Another challenge is the resistance to change within organizations. Employees and stakeholders will resist the adoption of new technologies, especially when they are uncertain about their implications or fear that their jobs may be replaced. This resistance slows down the adoption of AI systems, which are essential in developing sustainability, as individuals will not see the benefits right away or do not have the skills to use the tools driven by AI. To overcome these challenges, the authors stress organizational alignment. Companies need to make sure that AI adoption is aligned with their sustainability goals and overall business strategies. Furthermore, the authors argue that strong frameworks should be developed in order to guide the integration of AI into current operations. These frameworks must engage technological and human perspectives. They should implement the solutions offered by AI such that their potential is fully tapped into for sustainable innovation and resisted by technological barriers as low as possible (Mariani et al., 2023). Figure 2.3 shows challenges in implementing sustainable intelligence.

2.4.1 Technological, Organizational, and Financial Barriers

The adoption of sustainable intelligence, particularly through AI, faces several barriers that hinder the widespread integration of AI-driven solutions for sustainability. One significant technological challenge is the high implementation costs associated with AI systems. Integrating advanced AI into existing

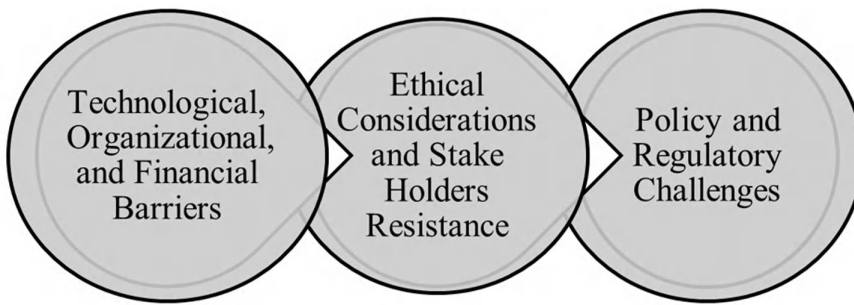


Figure 2.3 Challenges in implementing sustainable intelligence Source: Author

infrastructures requires substantial investments in hardware, software, and data management systems, which can be a considerable obstacle for businesses with limited financial resources. Additionally, the need for highly skilled professionals is another barrier. AI-driven sustainability initiatives require expertise in AI, machine learning, and data science, which most organizations struggle to find or afford, especially in industries where this kind of specialized knowledge is scarce (Al Aina et al., 2020).

Organizational challenges also contribute to the slow adoption of sustainable intelligence. Organizations tend to be resistant to change, especially when it involves adopting new technologies. It may be due to apprehension over the disruption caused to established processes, the loss of jobs, or a lack of understanding of the long-term benefits of AI-driven sustainability initiatives. Therefore, the organization may be reluctant to invest in AI, thus delaying or hindering the adoption of innovative solutions that can drive sustainability. The integration of AI into existing infrastructures is also challenging. Legacy systems may not be compatible with new AI technologies, making it difficult to seamlessly incorporate AI-driven solutions into current operations. To overcome these barriers, organizations must focus on building a strong foundation for AI adoption, investing in technology as well as human capital, and creating a culture of innovation and change (Di Vaio et al., 2020).

Mhlanga makes similar points for emerging economies. Again, he argues that poverty can be reduced through the effect of AI and Industry 4.0 technologies, along with innovation and infrastructure. As such, he points out financial as well as technological disparities between regions as significant hurdles against the effective use of AI in achieving sustainable development objectives in these regions (Mhlanga, 2021).

2.4.2 Ethical Considerations and Stakeholder Resistance

Jamwal et al. (2021) highlighted ethical concerns and stakeholder resistance to the implementation of Industry 4.0 technologies for sustaining manufacturing. They argue that these technologies provide significant benefits but with huge ethical challenges, such as ensuring data privacy, avoiding worker replacement, and addressing environmental impacts. Added to this is the element of stakeholder resistance by change, including job displacement and a lack of belief in AI-driven operation (Jamwal et al., 2021).

Ali et al. (2023) highlight that ethical issues associated with AI and innovation are concerns over biases in decision-making processes, lack of transparency, and even unintended consequences for workers and communities. The integration of ethical frameworks into AI research and development may mitigate these risks. Stakeholder resistance to adopting AI, especially from employees and communities, means that there is a need to communicate clearly and make the decision-making process inclusive (Ali et al., 2023).

2.4.3 Policy and Regulatory Challenges

AI capabilities, above all through co-evolutionary processes, play a very important role in business model innovation. Co-evolutionary processes refer to the mutual adaptation of AI systems and business models, both evolving together toward optimizing performance, creating feedback loops that allow for continuous improvement (Leal Filho et al., 2023). The more sophisticated AI applications become, the finer-tuned businesses can be in terms of their products, services, and interactions with customers based on real-time data, knowing what previous actions have accomplished and making adjustments accordingly. These feedback loops allow for a dynamic innovation process and enable companies to adapt their models better to changing market demands and consumer preferences. However, with growing AI applications within businesses, so too do policy and regulatory challenges. Current regulatory frameworks often lag behind AI development, which may result in the unintended consequences of new applications that have adverse ethical or societal effects. For instance, AI-based decisions can perpetuate biases or infringe on data privacy in unintended ways, yet the regulations are not well equipped to respond to such issues. Companies trying to scale AI-based innovation will be hindered by vague or obsolete policies, which can slow down growth and innovation (Lyulyov et al., 2024).

Businesses will hesitate to deploy AI in its full potential due to fear of regulatory pushback or ambiguity. Clear, proactive policies are important to make sure that AI technologies are developed and applied responsibly. There is a need for regulations to evolve with changes in technology so that business can incorporate AI in ways that do not harm public trust and that ethical standards are being met. Moreover, guidelines that enhance coordination between industry and policymakers might be developed to support further adaptive, forward-looking regulation so that AI could also continue to bring beneficial changes with fewer risks (Sjödín et al., 2021).

It involves investigating the ethical management of artificial intelligence (AI) and arguing that the development of AI should align with sustainability goals. Since the authors believe that business and societal systems are integrating more AI technologies, it makes it imperative to address the data privacy, bias, and accountability concerns. They further emphasize that responsible AI practice by the organizations must include the fact that AI systems are designed and deployed with transparency, fairness, and equity. This means being free of bias in their design of AI models; such processes in decision-making be made explainable; and priority to be given for users' data protection. Regulating frameworks also emphasize this aspect on managing the AI ethical implications. They claim that the present rules are often inadequate and that policies should be devised in keeping with technological advancement. Such policies should promote ethical practices, yet simultaneously support innovation, as it is only through AI that society will benefit without getting harmed (Perifanis et al., 2023).

The study also suggests that businesses should proactively engage in ethical considerations as part of the AI lifecycle, from design and development to deployment and monitoring. The authors conclude that the ethical management of AI is important for fostering trust and ensuring that AI contributes positively to both business success and societal well-being. In this regard, adopting sustainable AI practices will enable organizations to align their operations with broader ESG goals and drive long-term value, thus fostering a responsible AI-driven future (Brendel et al., 2021).

2.5 Future Trends and Directions

The revolution of Industry 4.0 is revolutionizing consumer behavior and the development of human capital. Modern technologies, including artificial Intelligence (AI), automation, and the Internet of Things (IoT), are

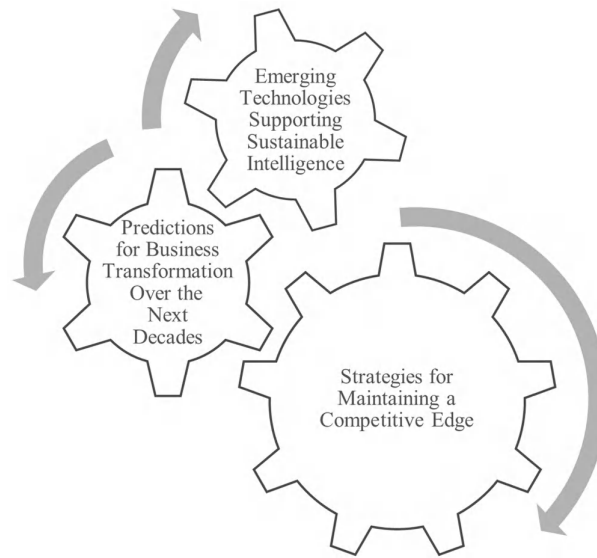


Figure 2.4 Future trends and directions Source: Author

reconfiguring workforce skills and transforming consumer expectations, thereby forcing business strategies and sustainability trends to change significantly. AI and automation redefine the nature of jobs; thus, employees have to adjust to new skill sets like data analysis, problem-solving, and digital literacy. Continuous learning and upskilling have become indispensable for organizations to maintain competitiveness. On the other hand, automation streamlines repetitive tasks so that human resources may focus more on value-driven, innovative, and strategic endeavors. On the consumption side, technology has been driving greater expectations for customized experiences, real-time interaction, and sustainable products. Businesses have used AI and IoT in analyzing consumer data to predict preferences and personalize offerings, which increases satisfaction and loyalty among customers and fosters sustainability through optimal use of resources and the minimization of waste. This duality of the impact of Industry 4.0 on workforce and consumer dynamics requires proactive action that is adaptive. Organizations need to adopt technology-driven strategies that align human capital development with the ever-changing demands of the market. In this way, businesses can foster innovation, drive sustainability, and achieve long-term competitiveness in an ever-evolving global landscape (Sima et al., 2020). Figure 2.4 depicts future trends and directions.

2.5.1 Emerging Technologies Supporting Sustainable Intelligence (e.g., Green AI, Quantum Computing)

In a more recent study, discuss how incumbents innovate business models embracing the circular economy, taking up the discussion of micro-foundations of dynamic capabilities. The authors further explicate that firms need to change their strategy to make sustainability integral to core business models and to exploit technological advancements through AI and quantum computing to push for sustainability innovations (Jamwal et al., 2021). The convergence of Industry 4.0 with the concept of sustainable development has been researched by mapping the perspectives of sustainable business strategies, the circular economy, and the triple bottom line. Green AI is one such emerging technology that is revolutionizing how businesses use resources, cut waste, and make more sustainable operations for enhancing efficiency in operations. It will allow organizations to maintain long-term sustainable operations by integrating their operations to gain economic and environmental benefits. This has been enabled through the fusion of Green AI with Big Data Analytics, Blockchain, and IoT. Firms can use data-driven strategies that ensure maximum resource utilization while having minimal ecological footprints. AI-based algorithms will look into very complex datasets and generate insights that will aid in improving decision-making. These will help in tracking ESG metrics, forecasting energy consumption, and determining inefficiencies, hence enabling sustainable practices in any industry (Khan et al., 2021).

IoT is an enabler by allowing real-time monitoring and control of the operations. Sensors and other connected devices can collect information about energy consumption, the performance of equipment, and environmental conditions to enable a business to adopt energy-saving measures. Such systems will also ensure adherence to environmental regulations and facilitate a circular economy through improved waste management and resource recycling (Khan et al., 2021). The use of blockchain will increase transparency and accountability in the supply chain, as transaction records cannot be altered once they are entered. This ensures ethical sourcing and sustainability standards while maintaining stakeholder trust through these practices. Digital twin technology also supports this as it will simulate business processes prior to implementation, identify areas that are inefficient, and allow for workflow optimization. All these cut down the cost and environmental degradation associated with the processes. All of these technologies are employed toward achieving operational excellence, adaptability, and

innovation which can foster a culture of sustainability. Such advanced tool integration enables them to sustain competitiveness while ensuring their commitment to global goals of sustainability (Santa-Maria et al., 2022).

2.5.2 Predictions for Business Transformation over the Next Decade

The progress and trends in the application of AI and ML in smart production highlight the impact on business transformation. They also claim that within the forthcoming decade, there will be drastic changes in production methods by AI and ML that are directed toward more productivity, waste minimization, and sustainability. These systems will assist companies in reducing operational processes, predicting consumer behavior, and resource optimization, improving productivity and sustainability. In their paper, Cioffi et al. (2020) outline how sustainable intelligence can inform pro-environmental behavior, applied to the field of ecotourism. This has created a platform where destination social responsibility, fostered by sustainable intelligence, can lead to visitor behavior that is environmentally friendly, thus setting examples for businesses looking to increase sustainability through informed decision-making. Collectively, these studies show that AI and sustainable intelligence are key enablers of business transformation through innovation and sustainability.

2.5.3 Strategies for Maintaining a Competitive Edge

The application of artificial intelligence (AI) in human resource management redefines how organizations achieve the competitive edge. An AI capability framework will unlock extraordinary potential in recruitment, engagement, and performance management capabilities within HRM. Such AI-based solutions enhance decision-making, improve operations, and align HRM strategies accordingly with the organization's major business objectives. Recruitment uses AI to optimize sourcing, screening, and matching candidates, analyzing vast data sets that ensure the discovery of the best talent more efficiently. Automated tools are used to minimize biases in processes and enhance candidate experience, further strengthening employer branding. Employee engagement is also improved through the use of sentiment analysis and personalized feedback mechanisms by AI. Monitoring how employees are interacting and where they have issues can further allow targeted interventions to improve positive work culture and retention rates within organizations (Brendel et al., 2021).

In performance management, with AI-powered analytics, actual employee contributions can be highly accurately evaluated to identify knowledge gaps and suggest customized training interventions. This is a process of continuous development in complete alignment with the organizational strategy. The framework optimizes human capital, making businesses achieve significant competitive advantage. AI supports better decision-making and ensures that the business can adapt with speed to a changing environment. It also helps free up routine HR tasks and thus focus on strategic activities to promote innovation and growth. As organizations increasingly adopt AI in HRM, they position themselves to thrive in a rapidly evolving business landscape. Integration of AI technologies ensures not only operational excellence but also long-term sustainability and success. This transformation underscores the critical role of AI in achieving competitive advantage and driving organizational excellence in the modern era (Chowdhury et al., 2023).

2.6 Findings

By fusing cutting-edge technologies like artificial intelligence (AI), the internet of things (IoT) and blockchain with environmental, social, and governance (ESG) principles, the chapter emphasizes how sustainable intelligence is revolutionizing business models. These technologies improve operating efficiency, optimize resource consumption, and facilitate environmentally decision making. Businesses that use AI solutions see improvements in supply chain transparency and ESG metric monitoring. Additionally, sustainable intelligence aligns companies with the sustainable development goals (ADGs) of the UN by promoting innovation in product design efficiency, and responsible sourcing.

2.6.1 Limitations

Accessibility for smaller businesses is limited by the study's short comings, which include expensive implementation costs and insufficient technical infrastructure. Adoption is further hampered by organizational change aversion and a shortage of qualified personnel. Other obstacles are brought about by antiquated legal frameworks and ethical issues, such as data privacy and AI biases. There is no actual data on the scalability of sustainable intelligence across industries, and combining cutting-edge technologies with existing systems presents further difficulties.

2.6.2 Future Directions

Future studies should look into ways to remove organizational, financial, and technological obstacles so that smaller businesses can use AI-driven sustainable practices. New technologies like digital twins and green artificial intelligence (AI) have the potential to improve resource efficiency and circular economy principles even more. To prompt sustainability globally and ensure long-term societal benefits, cooperation between businesses, governments, and communities is crucial.

2.7 Conclusion

The evolution of sustainable intelligence into business represents a transformative shift in integrating sustainability into core business practices. The emergence of artificial intelligence and data analytics has critically facilitated businesses to make informed eco-friendly decisions, optimize the use of resources, and enhance operational efficiency. The rise in demands for sustainable products and governmental pressures leads to an increasing number of companies adapting their strategies and aligning with environmental, social, and governance factors—a new form of reshaping the corporate governance and long-term objectives. Sustainable intelligence also induces innovation by encouraging the innovations in product design, energy efficiency, and responsible sourcing. Future trends will, therefore, require even closer interaction between industries, governments, and communities for the achievement of a sustainable global economy. By embracing sustainable intelligence, businesses will create value for both shareholders and society at large as well as for the environment, hence securing future success.

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Chapter 3

AI-Driven Disruption: Driving Business Innovation and Excellence

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3.1 Introduction

The use of disruptive technologies in business has important implications for organizational growth (Malini et al., 2023). Artificial intelligence (AI) is not a very new technology, but it has garnered more attention in the digital era (Ransbotham et al., 2018). AI is one of the important reasons for digital disruption in different sectors worldwide (Davenport & Ronanki, 2018). AI is an innovative technology that fosters the growth of not only businesses but also the economy (Fornahl & Kopka, 2024). AI is seen as a key technology for future economic growth. Business models developed using AI are important for business transformation (Perifanis & Kitsios, 2023). Companies using AI get more benefits in terms of cost reduction, leading to increased profitability and high business growth (Alsheibani et al., 2020). More research and detailed reports are required to understand how AI will be useful for business growth (Templier & Paré, 2015). To understand AI, it is important to differentiate intelligence from artificial. Intelligence involves learning, understanding, and reasoning (Lichtenthaler, 2019). Artificial pertains to something created by human beings, not

occurring naturally (Mikalef & Gupta, 2021). If we combine both terms, artificial intelligence means intelligence generated by machines (Wamba Taguimdje et al., 2020). By using AI, computers can mimic human intelligence, which involves reasoning, problem-solving, understanding, and decision-making (Mikalef & Gupta, 2021). AI plays a role like the human brain by processing data and information as input (Eriksson et al., 2020). AI creates human thoughts by using information from the environment. It can perform tasks similarly to, sometimes even better than, the average human being (Bytniewski et al., 2020). Some researchers explained that AI doesn't need high-level programming, but it does require proper interpretation (Kolbjornsrud et al., 2017; Wang et al., 2019). The objective of an organization must be accomplished using AI (Makarius et al., 2020). Without following any predefined pattern, AI should be capable of providing information after processing the data (Demlehner & Laumer, 2020). AI is a tool that solves problems that are either unsolvable by humans or even if solved it will be very time-consuming (Makarius et al., 2020). Some of the researchers explained that AI can exactly work like a human being (Kolbjornsrud et al., 2017; Wang et al., 2019), whereas another group of researchers explained that AI cannot perform all the work like a human being (Wamba-Taguimdje et al., 2020). There is also a need for a center of excellence for disruptive technology (Sewpersadh, 2023). Some researcher says AI as a scientific analysis (Schmidt et al., 2020), while other group of researchers explain AI as the capacity of a machine for application (Lee et al., 2019; Afiouni, 2019). Machine learning can be categorized as reinforcement learning, unsupervised, semi-supervised, or supervised (Schmidt et al., 2020). Computers can create their own patterns to analyze the data for getting the result (Afiouni, 2019). The computer must understand the structure of data to analyze and resolve the problem (Afiouni, 2019). The system must identify hidden patterns in unsupervised learning for association mining and automatic clustering (Schmidt et al., 2020). Labeled and unlabeled information is used in semi-supervised learning (Quinio et al., 2017). But past data is not used in reinforcement learning (Afiouni, 2019). Somewhat, it yields results by interacting with the external environment (Quinio et al., 2017). In AI, the computer is provided with the objective by humans to find out the best solution to a problem (Afiouni, 2019). In this regard, this chapter aims to present a holistic approach to understanding the use of AI in transforming business (Arora et al., 2025). It will also identify how AI impacts business growth and explore the challenges associated with its implementation in business.

3.2 Methodology

This study utilizes a mixed-methods approach to examine the impact of AI on corporate transformation. The methodology incorporates multiple elements to deliver an extensive comprehension of AI's influence and practical uses. The research commences with a comprehensive literature assessment, utilizing peer-reviewed journals, industry reports, and conference proceedings (Arora et al., 2025). This review assesses current research on the impact of AI on company creativity and operational efficiency, providing a robust theoretical framework for the topic. In addition to the literature review, empirical case studies are examined. These case studies analyze the application of AI across many sectors, highlighting its transformative capacity to enhance decision-making, consumer segmentation, and resource allocation. The research delineates optimal practices and the concrete advantages of AI adoption through the examination of specific situations. Qualitative interviews with industry experts and scholars enhance the study. These interviews offer significant insights into the actual obstacles and opportunities related to the use of AI technology, highlighting the necessity of collaboration between technical teams and management. Quantitative data analysis is utilized to evaluate the quantifiable effects of AI on organizational performance. Metrics including return on investment, profitability, and market response are examined to assess AI's impact on financial and operational results. The report establishes a strategic framework to assist firms in the efficient adoption of AI. This methodology tackles essential obstacles, including data bias, governance constraints, and staff preparedness, enabling firms to surmount difficulties and fully leverage AI's capabilities. The integration of various methodologies provides actionable knowledge, allowing firms to innovate and thrive in a competitive environment.

3.3 Machine Learning and Deep Learning

Machine learning (ML) is a disruptive technology that is widely used nowadays for business transformation. Machine learning can process large sets of data for future prediction and decision-making (Afiouni, 2019). ML analyzes data and gives information for decision-making in organizations (Wang et al., 2019). It is very helpful for deciding decision rules by using several statistical techniques (Schmidt et al., 2020). The architecture of shallow-structured learning is very traditional, which learns data from the features

that are predefined (LeCun et al., 2015). But in the case of deep learning, the structure is derived from the data in a multi-layered method (Wang et al., 2019). The main difference between shallow-structured learning and deep learning is that artificial neural network architecture is used for deep learning (Wamba-Taguimdje et al., 2020). Neural network architecture mimics the functionality of the human brain (Jelonek et al., 2019), which replicates the neurons of humans (Schmidt et al., 2020). In deep learning, both higher-level and upper-level layers create deep neural networks (Quinio et al., 2017). It defines different concepts, where each concept is divided into more direct concepts (Borges et al., 2020). In the digital world, AI is gaining more attention, as it is used for many use cases and provides accurate results in many disciplines. Although machine learning is used extensively, other AI technologies are also employed in organizations (Devi et al., 2024). Many of the companies are now using machine learning in collaboration with deep learning to achieve optimal solutions to the problem. For chatbots, both machine learning and natural language processing (NLP) are used (Baby et al., 2017). Machine learning supports chatbots to improve as they get more data and information (Castillo et al., 2020).

3.4 Influence of Top Management

Top management support is essential in the adoption of AI technology in any organization (Alsheibani et al., 2018; Demlehner & Laumer, 2020). Top management should support the technical team in exploring new technology for the business. They should not leave it solely to the technical team (Alsheibani et al., 2020). There is a major role in creating innovative culture within their organization (Lee et al., 2019). Also, top management should allocate resources and capital expenditure for the adoption of AI. The dedication and support of top management are crucial factors for the use of AI in the organization, as they will supply resources for AI adoption (Alsheibani et al., 2020). Innovation and AI adoption require financial resources, for which a proper budget is required in the company (Pumplun et al., 2019). Employees must be knowledgeable in the relevant domain and skilled enough to use the AI (Pumplun et al., 2019). The employees not only need to understand the technical skills, but they also need to know in which functional area they should use it (Mikalef & Gupta, 2021). Collaboration between employees and AI is required, and employees must trust in AI, the way AI is working and giving the result (Makarius et al., 2020). It is more

concerned about the organization, regarding its structure and how organizations can adopt AI quickly and successfully (Mikalef & Gupta, 2021). AI is one of the technology that can change business models and support in the transformation of business (Lee et al., 2019). So, the companies and their employees of the companies must accept change to embrace innovative technology (Pumplun et al., 2019). Innovative companies and individuals are always ready to adopt new technology like AI, which will make them competitive in the digital world (Mikalef & Gupta, 2021). Transformation and development of companies are possible only if the employees are willing to accept innovative technology (Lee et al., 2019). Organizations with an open and innovative mindset are ready to use AI in their various functional activities (Mikalef & Gupta, 2021).

3.5 Market Effectiveness Metrics

With the introduction of AI, some studies have been performed to measure performances related to finance like gross profit margin, return on investment, and profitability (Kumar et al., 2023a). AI segments customers as per their needs and segments them. For different segments of customers, AI uses customized marketing and promotional strategies, which in the long term provides multiple benefits for the segmented customers with a more focused approach. Thus, AI can be used by organizations for marketing and promotional purposes. Data plays an important role; AI uses the existing customer data and then segments customers according to their liking and lifestyle. AI analyzes in more detail all customer requirements and segments them accordingly in a more precise manner (Mishra & Pani, 2020). So, organizations can be more customer centric and can focus on customers individually for a more personalized experience. Thus, they can improve and strategize marketing techniques for individual customers (Mishra & Pani, 2020). In case there is a change in consumer behavior, AI analyzes the data and re-segments the customers accordingly. So, the effectiveness of the organization increases over time to time as per customer behaviors and requirement (Afiouni, 2019). With the use of AI, organizations can focus more on customers, thus eliminating any unpleasant experiences. Customers are satisfied with the company's way of service and offerings (Kumar et al., 2023b). Customers are believed to be loyal and retained for a long time with good service and products, furthermore with a good buying experience. This is where AI plays an important role in categorizing customers and taking

care of their needs to retain them forever (Riikkinen et al., 2018). Providing a more customized experience, customers will be more loyal, and attrition rates can be decreased. With AI interaction, customers will get better-customized information for their choices and needs, which in turn will lead to more customer satisfaction and retention (Schmidt et al., 2020). On the contrary, in some cases, customers can also get irritated with AI interaction, such as chatbots, which leads to dissatisfaction. As customer problems do not get resolved and the same repetitive messages leave the customers feeling irritated and unattended, the company needs to give special attention to this. So, instead of chatbots, direct interaction with customers is preferred, and accordingly, AI can be designed considering customer feelings and requirements (Castillo et al., 2020). AI can be a game changer as well as a potential innovation. It can suggest organizations innovative solutions catering to social and environmental issues. It can contribute to society and organizational benefits, leading to long-term sustainable development. It can give holistic solutions, keeping in mind organizational as well as environmental benefits (Toniolo et al., 2020).

3.6 Recourse Optimization

AI can help optimize energy in organizations and give the utmost sustainable results. It will help to build a greener planet by reducing wastage and pollution (Borges et al., 2020; Toniolo et al., 2020). Research studies are ongoing, validating the impact of AI on economic strategies, such as AI helping organizations suggest strategies for recycling of materials and reusing materials and lesser emissions. Organizations contributing to the environment and being socially responsible improve their competitive advantage in the market, thus increasing their brand image and positioning (Toniolo et al., 2020). AI works on data. Social responsibilities can be fulfilled by adopting AI. Companies can participate in new challenges to maximize their efficiency and fulfill social responsibility. However, organizations must maintain the privacy and security of the data used as input to get the result (Lee et al., 2019). Data can be repetitive, and it can make AI give discriminatory outputs. Organizations must ensure that the actions are valid and non-discriminative. AI systems function purely on data; they neither understand the inputs nor the outputs. The results are mechanical and purely dependent on data (Keding, 2020). AI interprets data and patterns to predict outcomes based on data it receives. However, the results can sometimes be suspicious or even racist (Keding, 2020). A great example of recruitment can be taken,

based on previous data; if the AI system explores the recruitment process and the process does not account for gender and ethnicity, the result will be discrimination (Afiouni, 2019). On the contrary, AI can give fair judgments by removing bias in the process, if it is objective, in cases like recruitment and customer segmentation (Toniolo et al., 2020).

3.7 Transformative Power of AI

Talking about the positive impacts of AI, it can enhance working conditions and employee safety. Human interventions can be reduced in the manufacturing process, avoiding human causality situations (Toniolo et al., 2020). Employees can focus on creative tasks, enhancing their capabilities, whereas through AI, the daily repetitive tasks can be automated (Toniolo et al., 2020). Thus, organizations can get to know employees' perceptions of their working environment after the implementation of AI automation. Businesses that have adopted and used AI in an organized manner and built organizational capacity around the new technologies have seen performance improvements. Key accounting and financial performance metrics, including growth in total financial performance, are positively impacted by AI capabilities (Mikalef & Gupta, 2021). AI enhances decision-making (Wang et al., 2019). With the help of AI, decision-makers and managers receive more information, increasing their thinking capability and challenging their limitations (Finch et al., 2017; Keding, 2020). They can make quality decisions in less time (Keding, 2020). By getting information from AI, companies can leverage their performance. They can position themselves more effectively and can respond to market needs more quickly (Wamba Taguimdje et al., 2020). Agility is how organizations make decisions, respond, and sense new opportunities. Organizations can be more agile with the help of AI (Wang et al., 2019). Humans sometimes miss the underlying messages, whereas AI can be very useful in recognizing patterns and underlying messages (Eriksson et al., 2020) and AI can recognize and respond to signals fast and with accuracy. (Wang et al., 2019). AI can transform inputs into valuable outputs; results and outputs are what matters most in any organizational process (Mishra & Pani, 2020). AI is creative and can develop and modify corporate working styles and operations and SOPs. AI facilitates and creates new products and services (Wamba-Taguimdje et al., 2020). Processes can be changed with new technology to get valuable outputs (Mishra & Pani, 2020). For example, businesses can recognize new opportunities by noticing changes in customer preferences, which can add to their revenue and explore new niche markets.

Companies can innovate by launching new goods and services. AI can recommend new products for development, which require creative designs. Launches of new goods and services can encourage innovation in company models (Mikalef & Gupta, 2021). Companies will get to create products and services incorporating features based on AI. It can be used in business to increase the customer confidence and experience (Alsheibani et al., 2020). AI is used to increase the quality of the product (Davenport & Ronanki, 2018). Business can be transformed by increasing the quality of the product (Lee et al., 2019).

3.8 Challenges in AI Implementation

In many cases, it is found that if there is a lack of appropriate rules and regulations in AI governance, unexpected and negative consequences can occur. Data algorithms can be biased; they can give partial and unfavorable results to certain ethnic groups, populations, and genders. Some reports are also there regarding gender bias related to AI (Dastin, 2018; Vigdor, 2019) and cultural perception (Zuiderveen Borgesius, 2020). Sometimes these kinds of biased results from AI can hamper the image of the organization, leading to fines and financial losses (Engler, 2021). Since the beginning organizations should take caution while developing AI applications. Special precautions need to be taken to reduce biases. The data and algorithms should be checked at all stages of deployment to reduce biases. Government organizations, such as European Commission, are now suggesting deploying fixed rules and regulations to measure how AI applications are used and developed in an organization. AI's negative impacts are not only limited to biased outcomes but also include security concerns, can be harmful to society and the environment, lack of transparency, accountability, and the black box algorithm (Loyola Gonzalez, 2019). If practices cannot be explained and transparency is low, there may not be adoption of AI in the system (Samek & Müller, 2019). Such effects now force organizations to explain the AI algorithms (Arrieta et al., 2020). Cases are there, where customers are frustrated interacting with chatbots, hampering corporate image (Marcondes et al., 2019).

3.9 AI Adoption and Diffusion

A very small number of companies are using AI for their functions and the growth of business. Organizations can deploy AI as per the business value,

which can be significant for all business operations (Anon, 2020). Deep understanding is required for different dynamics to allow organizations to adopt AI. Employees from different functional areas must work together to create AI applications (Holton & Boyd, 2019). Adopting and implementing AI in any organization is difficult (Alsheibani et al., 2018). Many factors are responsible for the implementation of AI, such as environmental, organizational, and technological readiness (Alsheibani et al., 2018). Other costs are also related to infrastructure, capable employees, and dependency on external partners.

3.10 Growth in Recent Years

AI can be mostly used to enhance human capacity instead of replacing them. Some complex tasks done by AI are far better than humans (Jarrahi, 2018). A combination of AI and human expertise can enhance the growth of businesses (Schmidt et al., 2020). Organizations can use AI to overcome the limitations of human cognition. AI can process enormous amounts of data more quickly than humans, outpacing human cognitive abilities (Jarrahi, 2018). Managers can use AI to gain insights from simplified data. As in many cases the data is too complex to analyze and evaluate by managers and decision-makers. With the help of AI and data, managers can make suitable conclusions (Borges et al., 2020). The forecast can be more accurate by using the predictive analytics of AI (Makarius et al., 2020). Such analysis can also be used for sales and when companies introduce new product (Bytniewski et al., 2020). Even feelings, opinions, and attitudes towards specific good and service can also be examined using AI (Jelonek et al., 2019). As it provides them insights into how their customers perceive their products, this is becoming more and more crucial for organizations (Bytniewski et al., 2020; Davenport & Ronanki, 2018). Surgical robots can be developed with the help of AI to support doctors during complex procedures (Makarius et al., 2020) or identify patterns in cancer (Jarrahi, 2018). AI can be used in the medical field (Jarrahi, 2018), marketing and sales (Mishra & Pani, 2020), and also in the fashion industry (Wamba-Taguimdje et al., 2020).

3.11 Scope of Future Research

The scope of future research in AI is very vast. More research can be done in specific areas like genetics, climate science, astronomy, healthcare,

manufacturing, and customer care. Research can also be done on the challenging areas related to AI such as the regulation of AI, data privacy, and job losses due to the adoption of AI. Sustainability, supply chain transformation, and AI can also be future scope of research for researchers.

3.12 Conclusion

As a disruptive technology, AI is used in various industries, such as production optimization, marketing, customer service, and business management. Many important reforms can be taken in our lives through AI technologies and it can also be implemented in an organization's value chain. Firms should be aware of the potential consequences of adopting AI, which might help them better prepare to integrate AI into their operations. AI is required where customer interaction is significant to sustain in the digital world. The impact of AI on business transformation is very high, though certain problems exist. Adoption of AI requires resources like finance, skilled employees, the trust of the employees in the use of AI, and overall top management support. AI is essential for companies nowadays to gain profit and achieve high growth in the competitive world. For internal operations as well, companies are using AI continuously. By using AI, the quality of the products and services of the companies can also be increased. Businesses can preserve their market position by utilizing creative business strategies. Understanding how AI can be employed in organizations involves making better judgments and choosing where to use AI solutions in their value chain for optimum benefit. AI can perform tasks where human intelligence is required or which were previously done manually. The tasks for which humans are now responsible now can be done by AI, and the role of employees in the new system can be redesigned. Therefore, employees must understand what role the AI is going to play and what is the role and responsibilities of the employees in the organization to adopt the disruptive technology.

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Chapter 4

Green Supply Chain Management with AI and Its Implications

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4.1 Introduction

All the upstream and downstream processes associated with the manufacturing and distribution of a company's products and services need to be supervised and optimized via supply chain management (SCM). The main objective of SCM is higher efficiency in all processes that range from adding value to raw materials and components and converting them into goods to ensuring that they reach the end consumer (Radivojevic, Mitrovic, & Popovic, 2022). The degree to which various processes can be made simple, waste can be minimized, customers can be satisfied, and finally a noteworthy competitive edge can be gained, all depends on how efficient and effective a firm's SCM is. Hence SCM is a vital component of all businesses (Khedr, 2024). Environmental challenges, including the widespread use of non-eco-friendly materials, ozone layer depletion, and global warming, are increasingly endangering our planet. Among the sectors in urgent need of reform, supply chain management stands out as a critical area within manufacturing requiring significant changes. Adopting sustainable procurement practices enables organizations to embrace resource recycling, streamline production, optimize distribution channels, and minimize the environmental impact of end consumption. Green supply chain management (GSCM) refers

to sustainable SCM, which involves incorporating eco-friendly practices and principles into the various stages of supply chain operations (Nozari, Fallah, & Szmelter-Jarosz, 2021). This type of SCM evaluates every stage such as designing of products, sourcing of raw materials and components, production, transportation, distribution, and even the waste management of products in the final lifecycle stage and makes adaptations based on the influence on the environment.

There is hardly any place on the globe that is not feeling the burden of global warming, climatic deviations, and ultimately bearing their socio-economic costs. On the one hand, while certain places grapple with excessive rainfall, while, on the other, there are places that suffer from a lack of rainfall. Such wide disparities affect day to day commercial operations in the form of the destruction of real estate, low employee output, and high insurance expenses. To ensure survival in the long run, businesses irrespective of their scale need to take instant steps to decrease the threat of global warming and its repercussions. GSCM has become more significant as business success is being more closely associated with the welfare of consumers and communities. The environmental impact of supply chain processes across various industries is gaining visibility and public scrutiny. The growing awareness of such concerns among consumers and communities has negatively impacted the image of several firms. Incorporating GSCM enables the marketing team to showcase that they are environment-friendly as an organization. This improves the image of the brand(s) offered, enables product differentiation w.r.t. competition and thus increases the survivability of the business. GSCM improves the supply and operational process efficiency by bringing down waste. Resources required in the various supply chain processes are optimally utilized since motivating all stakeholders to reuse and recycle is a key GSCM objective. All these achievements improve the bottom line and other measurable financial parameters, making GSCM vital to businesses of all sizes.

Artificial intelligence (AI) is a business game changer (Devi et al., 2025; Kumar et al., 2023b). It is transforming the way FMCG companies market their products, banks remember their customers' transactions and preferences, and healthcare firms treat their patients. The advent of various AI technologies has changed the way that firms are making their supply chains more environment-friendly. Machine learning (ML), natural language processing (NLP), robotics, blockchain, and predictive analytics are the popular and diverse AI-related technologies that offer tremendous scope in terms of optimization, automation, and decision-making ability. For

example, predictive demand forecasting can be used to analyze vast datasets to make very intelligent estimates of the future demand for resources as well as finished goods, thus enabling businesses to optimize procurement processes and minimize wastage. Further, in the sourcing of resources and distribution of the finished goods, AI can reduce costs via intelligent routing and logistics by identifying the most efficient transportation routes and schedules. Such a high level of optimization will not only reduce non-renewable energy consumption and lower CO₂ emissions but also cut down operational costs. AI can also make a difference in terms of business ethics. Supply chain transparency can be vastly improved by leveraging technologies such as blockchain to track materials and products throughout the supply chain, to ensure sustainable and ethical sourcing of raw materials. Hence AI can revolutionize traditional supply chain operations and a shift towards GSCM can enable organizations to pursue sustainability goals with unimaginable efficiency and effectiveness (Panwar & Koushik, 2024). The goals of GSCM differ from sector to sector and company to company. These goals could include increasing the adoption of biodegradable materials, reducing the carbon footprint, minimizing waste in upstream and downstream processes, emphasizing on green sourcing, complying with environment protection policies, and making every process more answerable. Hence, the application of AI to GSCM has numerous practical implications and several social and financial advantages, across various diverse industries.

In the years to come, AI systems will be used to optimize the integration and management of renewable energy sources, such as solar or wind power, across supply chain operations (Velrani et al., 2025). Predictive analytics will also help align energy consumption with renewable energy availability, enhancing sustainability in logistics and manufacturing.

4.1.1 Objectives of the Study

This chapter explores a new understanding of how AI and related technologies such as IoT, blockchain, and machine learning can be applied in achieving GSCM. The awareness and need for adoption of artificial intelligence (AI) in supply chain management and sustainability is growing; however, there is a notable gap in the literature exploring the association of these two vital aspects, i.e. AI and green supply chain management. Current studies predominantly either examine AI applications in traditional supply chain optimization context or investigate green supply chain management

with technology in general, as an enabler. This chapter has the following objectives:

- To study how by integrating green energy into GSCM and leveraging AI's potential, organizations can simultaneously lower operational emissions and build more resilient, sustainable supply chains.
- To understand the potential synergy between AI and GSCM, the resulting benefits, and the implications across various industries.
- To explore the transformative impact of AI on GSCM, in terms of its challenges, and future trends.

This chapter is structured as follows: To start with, pertinent literature is reviewed to gain a preliminary understanding of the subject and the methodology of the study is briefly explained. Thereafter, the key themes that emerged, which include the role of advanced technologies in GSCM and the implications for different sectors, have been discussed. Lastly, the barriers and future trends have been discussed.

4.2 Literature Review

Supply chain management (SCM) involves the strategic alignment of organizational functions to streamline procurement processes, boost overall efficiency, and enhance customer satisfaction. It plays a critical role in the success of business operations, where even small data errors or inaccuracies can result in substantial challenges for end-users (Radivojevic, Mitrovic, & Popovic, 2022). Business success depends on strong relationships with various stakeholders such as suppliers, employees, etc., and SCM enables sustained relationships (Khedr, 2024). Green supply chain management (GSCM) is all about ensuring that each supply chain process is environment-friendly (Nozari, Fallah, & Szmelter-Jarosz, 2021). For example, Peter England uniquely marketed its Oxygeans line of jeans by highlighting that each pair conserves 80 liters of water during its production (Halan et al., 2013).

Application of artificial intelligence (AI) in GSCM across diverse industries from manufacturing industry to those offering services such as banking and healthcare is proving to be effective in meeting operational efficiency as well as environmental governance goals (Panwar & Koushik, 2024). Deep learning (DL) and machine learning (ML), which are integral elements of AI, are being widely used to make supply chains more resilient,

transparent, and green (Khedr, 2024). In the healthcare industry, Balan and Conlon (2018) argue that hospitals should embrace a computerized approach leveraging practical big data to enhance the visibility of their GSCM. This shift would provide significant benefits by enabling hospitals to understand how BDA concepts and methods can be applied to advance environmental practices. Enhancing GSCM collaboration boosts environmental performance, thereby contributing to a company's long-term sustainability (Rashid, Baloch, Rasheed, & Ngah, 2024). The effective application of modern technologies offers supply chains significant potential to build and sustain a greener future. By integrating technologies such as IoT, AI, and blockchain, businesses can minimize greenhouse gas emissions, optimize transportation routes, eliminate waste, facilitate seamless supplier transactions, enhance worker safety, and mitigate risks (Padmavathi & Saminathan, 2023). Governments targeting to develop green economies need to provide an environment that encourages green production and marketing (Halan, Aashish, & Thaichon, 2024).

While many environmentally conscious companies are genuinely contributing to sustainability, some companies misleadingly claim that their products are eco-friendly. This practice is known as “greenwashing,” where businesses only pretend to be environment-friendly. Such companies often invest more in creating their “green” image than in implementing actual sustainable practices. This is a major concern area. Integrating multimodal AI into the green supply chain presents several technical hurdles, with data integration and convergence being the primary obstacles. Data from various sources often differ in formats and structures, necessitating the development of specialized algorithms and techniques for efficient data fusion. Furthermore, considerable power and memory is required to analyze the data from diverse sources (Ruan, 2024). If we consider the energy industry, forecasting the energy requirement is possible only by converging the information from various devices monitoring the dynamic energy usage, the climatic conditions, and the past consumption trends (Khedr, 2024).

The future offers tremendous scope in terms of GSCM with AI since the Fourth Industrial Revolution offers high potential of utilizing AI and other related technologies such as blockchain (Ahmed et al., 2022). Resource optimization and higher transparency are likely to be achieved by developing smart supply chains that are connected with each other. With advancements in blockchain technology, supply of raw materials can take place in a more ethical manner (Arora et al., 2025). The environmental guidelines will be more strictly followed, and the environmental impact will be more

measurable (Zejjari & Benhayoun, 2024), thus making global supply chains more responsible. Sustainable resources will be evaluated more stringently by AI tools in terms of their contribution to the triple bottom line (Velrani et al., 2025). Advanced technologies will lead to smarter sourcing, choice, and processes. We can hope to see a considerable reduction in CO₂ emissions, with more drones and electric vehicles being used for transportation in a highly efficient manner (Nikseresht, Golmohammadi, & Zandieh, 2024; Kumar et al., 2023a). Disaster management will improve with AI and other emerging technologies predicting extreme events such as floods and hurricanes more accurately (Singh & Goyal, 2023). Futuristic research is expected to lead to quantum-powered AI systems that can result in tremendous improvements in basic areas such as logistics, energy, and inventory management (Whig et al., 2024). These developments will also result in a demand for more people who understand SCM as well as are highly skilled in using AI tools (Kong & Yuen, 2024).

4.3 Methodology

This study is based on a comprehensive review of several research papers, news articles, and reports. Content analysis of all relevant text revealed various insights on the what, where, which, why, and how AI can be used to achieve GSCM. This study is designed as a thematic literature review that focuses on critically evaluating a specific domain, i.e. achieving GSCM with AI. A thematic review highlights key themes and subthemes, enhancing the depth and scope of the insights obtained for a specific domain (Lim et al., 2022). For locating the journal papers, well-known databases like Emerald Insight, Elsevier, and Taylor and Francis were searched to source articles from high-ranked journals indexed in Scopus and Web of Science. *Journal of Cleaner Production*, *International Journal of Research in Industrial Engineering*, and *International Journal of Intelligent Systems* are some of the journals from where papers have been cited. Only papers in the management domain were included, while those in the engineering, environmental science, materials science, and computer science were excluded. Only full-text articles in English were included, and non-peer-reviewed publications were excluded. A total of 38 research papers, articles, reports, and books yielded diverse and rich insights for this study. The key themes that emerged were as follows: (i) role of advanced technologies in GSCM, (ii) integrating green energy into GSCM, (iii) role of green energy in achieving GSCM with

AI technologies, (iv) dual-channel green supply chain impact and contribution to GSCM, (v) implications of GSCM with AI, and (vi) barriers and concerns in GSCM with AI.

4.4 Role of Advanced Technologies in GSCM

4.4.1 *Artificial Intelligence (AI) and Machine Learning (ML)*

AI and ML are enablers for global supply chain management, from predictive analytics to process optimization to decision-making. Machine learning algorithms use historical and real-time data to predict demand, identify fragility, and optimize resource allocation (Floridi & Cowls, 2019). The algorithms help the AI systems gain transparency and consistency, and enterprises can use them to create sustainable, efficient, and innovative supply chain operations while ensuring equity and regulatory compliance. Here are some global supply chain management AI applications.

4.4.1.1 *Predictive Analytics*

With AI-driven predictive analytics, organizations can predict demand accurately, optimize inventory, and reduce waste. To this end, machine learning models utilize historical and real-time data from the supply chain to enable better predictions of consumer behaviors and market trends. The predictions are then used to adjust supply with demand while minimizing the environmental footprint (Kritzinger, Karner, Traar, & Henjes, 2018).

4.4.1.2 *Process Optimization*

AI revolutionizes supply chains by detecting pain points and recommending effective solutions. Atmospheric and terrestrial ecosystems are the other fields that use data in different capacities. AI is used here to analyze the number of natural resources used and to reduce them by minimizing the energy and materials usage through smart factories (Tao, Qi, Liu, & Kusiak, 2018).

4.4.1.3 *Enhanced Decision-Making*

AI can process complex datasets and deliver actionable insights to supply chain managers when embedded in tools. Such insights allow for better

resource allocation, a smaller carbon footprint, and improved supply chain performance overall (Swan, 2015).

4.4.1.4 Autonomous Systems

AI-based self-driving logistics vehicles and drones enhance efficiency and reduce fuel consumption and carbon footprint. The system can thus minimize lags in the supply chain processes and choose the best route for delivery (Crosby, Pattanayak, Verma, & Kalyanaraman, 2016).

4.4.2 Internet of Things (IoT)

GSCM evolution is fueled by several advanced technologies, of which IoT is the most promising. IoT sensors offer near real-time data on inventories, shipments, and production efficiency across the supply chain, improving traceability and adherence to sustainability measures. This makes it possible to become resource-efficient, predict maintenance, prevent breakdowns, and reduce resources and waste, thereby improving sustainability and operational resilience. IoT value propositions include reducing energy use, preventing overproduction, and outfitting waste with actionable insights. By enabling collaboration between stakeholders, it enables interoperability in communications and operations coordination. IoT world-wide usage demonstrates several benefits. Stocks and conditions can be supervised and monitored in intelligent warehousing using IoT sensors; in the transportation industry IoT implemented devices can keep track of the routes and also lower fuel figures, build up fleet efficacy, and mitigate discharges. The internet of things enhances circular economy efforts by monitoring products and ensuring they are collected at the end of their lifecycle for recycling or refurbishment, thereby reducing resource consumption. Finally, the adoption of IoT in GSCM enhances efficiency, sustainability, and resilience across the supply chain, emphasizing its critical significance in aiming at eco-efficient and resource-saving activities.

4.4.3 Blockchain Technology

Blockchain technology enhances transparency, traceability, and trustworthiness in global supply chain management. With all the supply chain participants gaining access to a single source of truth, decentralized ledger technology, also known as blockchain, ensures that information transfer is

trustworthy and consistent. It calls for verifying the sources of raw materials, responsible sourcing, and following up on carbon footprints to drive adherence to environmental regulations and boost stakeholder trust (Saber, Kouhizadeh, Sarkis, & Shen, 2019). Everything we hear about blockchain's trustworthy systems is the key value proposition of this technology—the ability to generate trust, improve process efficiency, and protect data confidentiality. According to Tapscott and Tapscott (2016), blockchain reduces data manipulation and fraud risk: “In blockchain, the evidence of transaction is secured in a tamper-proof, distributed ledger.” Blockchain's real-world value is evident from several examples. It retains traceability in critical applications, such as food and drugs, and provides an auditable trail for compliance and safety (Saber, Kouhizadeh, Sarkis, & Shen, 2019). Blockchain enables low-cost international payments owing to the large number of intermediaries and faster transacting (Narayanan, Bonneau, Felten, Miller, & Goldfeder, 2016) and facilitates automated inventory management through smart contracts (Swan, 2015). There are various challenges encountered throughout the supply chain, and blockchain covers various risks of security, transaction speed, and confirmation time with minimal regulatory inexplicitness. This is bringing about a revolution to the field of compact supply chain management (SCM) even with the appending costs related to the implementation (Crosby, Pattanayak, Verma, & Kalyanaraman, 2016).

4.4.4 Big Data Analytics

The decision-making process and supply chain optimization are being significantly improved by big data analytics (BDA). BDA can offer enriching insights based on trends determined through the scrutiny of vast amounts of data from different sources, enabling them to predict and make data-driven decisions supporting sustainability. Accurate forecasting of the demand based on historical data in bulk avoids overproduction while meeting the supply in a balanced manner. Studies on customer behavior and market growth ensure that inventory planning is tailored to accurate levels and that supply and demand can match them. In logistics, big data is helping to pinpoint inefficiencies in transportation routes, fuel consumption, and delivery timelines. Actual data from IoTs is enhancing the routing effectiveness, equilibrating the workloads and shortening the overall trip distance to mitigate emissions (Swan, 2015). Cloud computing, the concealed facilitator of global supply chain management, provides scalable and cost-effective data manipulation and analysis solutions. It enables businesses to expand infrastructure

when demand increases, enabling companies to utilize resources efficiently while permitting seamless connections to emerging technologies such as IoT and AI. Cloud systems accomplish instantaneous cooperation, improve transparency within supply chains, and allow for enhanced sustainability.

4.5 Integrating Green Energy into Green Supply Chain Management (GSCM)

Integration of renewable energy with blockchain in a supply chain begins with a wide-scale energy assessment and supply chain audit to find high-energy use and emissions areas. Energy management systems (EMS) are essential tools that measure the energy used and monitor the performance over time. The transition to renewable energy (solar, wind, and hydropower) is at the integration's core. Fossil fuels are displaced by installing renewable energy systems, such as rooftop solar panels and wind turbines, at production and distribution facilities. This process is part of ongoing energy-efficient practices, such as retrofitting all the equipment and lighting systems with energy-efficient alternatives and establishing smart grids in warehouses and factories. IoT, AI, and other emerging technologies enable and drive customer transformation. Many sensors used in IoT facilitate the monitoring of energy usage in real-time basis. At the same time, AI-based algorithms play a role in predictive maintenance and optimization, resulting in high-energy efficiency. The procurement of green energy also facilitates the shift through power purchase agreements (PPAs) and carbon offset programs. In terms of logistics, the use of electric or hydrogen-powered vehicles and AI-optimized delivery routes helps reduce fuel consumption and emissions (Tschorsch & Scheuermann, 2016).

The integration of green energy into GSCM has many benefits. The action dramatically reduces carbon footprints and greenhouse gas emissions and creates permanent cost savings through energy efficiencies. It also builds corporate reputations on wanting to be green and enhances consumer trust in the organization. Through adherence to the existing regulation frameworks, such as ISO 50001, and increased energy resilience, supply chains are better insulated from shocks to the market. The integration is aligned with the United Nations' Sustainable Development Goals (SDGs), in particular, SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action) as well as the global movement towards sustainability. This domain is growing,

and large volumes of data analyzed illustrate this approach's economic and operational benefits. Research by institutions such as the International Energy Agency and McKinsey has identified it as a fundamental piece of the puzzle acting against climate change and supply chain disruption. Thus, implementing various green supply chain management (GSCM) practices has valuable implications for environmentalists and businesses. A significant final consequence is a lowered carbon footprint, achievable throughout the provision chain with diminished greenhouse gasoline emissions. Along with this come cost savings from long-term gains in energy efficiency and waste-reduction strategies. In addition, the organizations engaged in GSCM necessarily improve their reputation and consequently their brand image ranging from environmentalist consumers. Environmental compliance is one area that most organizations invariably discover not only promotes an attitude of environmental stewardship within their organization but also tends to provide them with significant regulatory benefits ranging from the avoidance of potential sanctions to the ability to leverage incentives.

Finally, good GSCM fosters customers' loyalty, providing value for customers who care and trust brands that look after their environment and social sustainability. Combined, these findings highlight the strategic aspect of GSCM in balancing memorabilia with sustainable production practices over time. The components of green supply chain management (GSCM) and their resulting outcomes are outlined in Figure 4.1.



Figure 4.1 Components of GSCM and its outcome Source: Author

4.6 Role of Green Energy in Achieving GSCM with AI Technologies

There are some essential practices that aid and catalyze GSCM. One of these is sustainable procurement, which emphasizes procurement from suppliers with environmentally sustainable practices. It is supplemented by green manufacturing, which seeks to reduce environmental impact by maximizing the use of sustainable materials and processes during manufacturing. This is integrated with green logistics, which minimizes emissions and optimizes the transport and storage of goods. Similarly, reverse logistics is an underlying process related to recycling, reusing, and refurbishing products that are part of the circular economy. GSCM is the compliance with regulations to comply with environmental laws and standards. Also, stakeholder collaboration—i.e., engaging suppliers, customers, and, where appropriate, NGOs—to ensure that sustainability goals align up and down the supply chain is critical.

Emerging technologies such as the internet of things (IoT), artificial intelligence (AI), and blockchain hold the promise of transparency, efficiency, and accountability in establishing GSCM. The evolution of GSCM is attributed to artificial intelligence and related emerging technologies such as IoT, blockchain, and machine learning. Machine learning techniques can perform predictive analytics that can also help mitigate challenges encountered in green supply chain management, thereby helping to optimize resource allocation and recognize waste. IoT devices also provide instant data on energy usage and emissions, which allow for just-in-time interventions to minimize waste and energy usage. Such processes are valuable when empowered by blockchain as they guarantee the transparency of these activities and the proven positive impact on the environment that leverages stakeholders' trust (Sabeti, Kouhizadeh, Sarkis, & Shen, 2019). This integration establishes a strong foundation for operational excellence and sustainability, empowering companies to tackle current global environmental challenges while advancing their strategic objectives.

Renewable energy source development is inevitable if we are serious about tackling the climate change crisis and decreasing our reliance on non-renewable energy sources like crude oil and coal. Therefore, green energy is positioned as a key solution to fight the climate change crisis and build renewable energy sources—something which every country in this world desires. By making green energy an integral part of GSCM and

further utilizing the vast scope offered by AI, it is possible for businesses to not only lower operational emissions but also develop more resilient, sustainable supply chains. The incorporation of green energy in green supply chain management (GSCM) and the application of artificial intelligence can reduce emissions and make sustainable supply chains more resilient. This will align businesses with the United Nations' 2030 Agenda and Sustainable Development Goals (UN, 2015). The integration of blockchain within GSCM has resulted in an improvement in traceability and transparency across the supply chain. In addition, IoT and AI technologies were integrated and resulted in a reduction in energy consumption during logistics processes, which in turn reduced overall energy consumption. As part of the GSCM frameworks, the tangible benefits suggested by these findings logically demonstrate the role of modern technologies in enabling a degree of efficiency and sustainability (Saberli, Kouhizadeh, Sarkis, & Shen, 2019).

4.7 Dual-Channel Green Supply Chain (DGSC) Impact and Contribution to GSCM

The dual-channel green supply chain (DGSC) integrates traditional and e-commerce sales channels, advancing a more energy-efficient and sustainable supply chain. It can meet the increased demand for sustainability-responsible products and make more effective use of resources. E-commerce platforms have one of the highest degrees of freedom to create accessibility for all stakeholders and reduce pollution by turning retail into an online service due to the energy saved and reduced CO₂ emissions. By incorporating advanced data analytics into inventory management, DGSC can ensure that healthy stock is on hand while maximizing supply turnover and re-running stock lists and stock levels multiple times a week. It improves the efficiency of logistics by merging deliveries and optimizing transportation routes (Tao, Qi, Liu, & Kusiak, 2018), with IoT tracking and blockchain being used to ensure transparency.

4.8 Implications of GSCM with AI

GSCM has numerous implications and several social and financial advantages. Green supply chain management aims to ensure an environmentally

friendly workplace, which would decrease greenhouse gas (GHG) emissions, prevent waste, and help to save natural resources. Most sustainable supply chains tend to generate cost savings by maximizing efficiency, minimizing waste, and optimizing resource use, providing organizations an edge in the marketplace, particularly with environmentally aware consumers. Furthermore, companies need to abide by rigorous environmental regulations, and hence compliance also plays a significant role. GSCM assists businesses in fulfilling these requirements to steer clear of penalties evident in their market representation. GSCM builds trust among the key stakeholders (i.e. consumers, employees, and investors) by employing ethical sourcing and sustainable processes. It also encourages the adoption of innovative technologies to enable the flexibility of supply chains towards disruptions for business continuity. Hence, GSCM with AI aids in developing a sustainable, ethical, and efficient corporate space.

Strategies for GSCM differ across industries, reflecting each sector's unique characteristics and challenges. It is important to understand the applications and implications of GSCM across key sectors:

4.8.1 Manufacturing

Green supply chain management focuses on waste reduction, resource optimization, and emission control in production. Artificial intelligence and the internet of things allow predictive maintenance, whereby machines can be repaired based on forecasts as to when they are likely to need human intervention to function harmoniously and sustainably. To improve quality control, big data analytics can be adopted to determine whether there are any faults and inefficiencies within the production processes. Besides providing data integrity through an immutable blockchain, it allows for resource traceability to ensure recycling and move towards a circular economy. Cloud computing facilitates remote and real-time monitoring and evaluation of production control parameters and continuous improvement opportunities (Tao, Qi, Liu, & Kusiak, 2018). Implementation of cloud computing in production monitoring helps in improving operational efficiency, while IoT predictive maintenance features help reduce the downtimes. Blockchain integration enables precise traceability of resources, while transparency is improved by the facilitation of circular economy principles. This exhibits the disruptive effect of novel technologies as potential drivers for sustainability and efficiency in GSCM.

4.8.2 Retail

As customers increasingly look for green products along their supply chains, retail companies adopt green supply chain management to drive their sustainability practices. Demand forecasting optimizes inventory management and reduces excess inventory and waste. IoT sensors monitor energy use for effective operation in retail and storage facilities. Blockchain allows the transparent traceability of the source, which is a step towards ethical production as an end goal. With the help of such analytics, the merchants can analyze the purchase patterns, and supply chain processes can be optimized to meet the business's sustainability aims. Personalized marketing, which is possible due to cloud solutions, significantly improves the consumer experience (Saber, Kouhizadeh, Sarkis, & Shen, 2019). The implementation of blockchain in retail supply chains leads to traceability and transparency. Internet of things sensors on retail facilities saves energy use, and demand forecasting tools bring down waste. Ultimately it leads to an increase in customer engagement and an increase in sales conversion. This indicates that the adoption of GSCM technologies can be a self-sufficient option in order to comply with sustainability goal without damaging the business objectives. Real-time access to stock changes is another big benefit.

4.8.3 Healthcare

GSCM is a framework within the healthcare industry that can address environmental concerns associated with managing medical supply chains. Supply chains in healthcare utilize AI and IoT to optimize the logistics of temperature-sensitive products (e.g. vaccines) while improving the efficiency of supply and decreasing energy consumption and waste. Therefore, blockchain makes the procurement and disposal of medical products transparent, thus proving that it leads to higher sustainability. Utilization of big data analytics allows hospitals and suppliers to forecast the requirements for medical products, thus eliminating waste and ensuring that the requisite supplies reach on time (Cachin, 2016).

4.8.4 Agriculture and Food

Food loss mitigation and, at the same time, efficiency improvements in agriculture and food-related industries are being achieved through GSCM advancements. AI is helping manage irrigation systems more efficiently and

forecast demand precisely. Blockchain is enabling an immutable ledger of documented data, demonstrating sustainability practices and traceability. Big data analytics is helping in monitoring the weather, temperature, and crops. Lessons learned by applying complex analytics to climate and agricultural crop information result in enhancing the yield (Kouhizadeh & Sarkis, 2018). This advanced technology addresses food security problems and food production's environmental consequences worldwide.

4.8.5 Energy

In the energy sector, artificial intelligence is revolutionizing the integration of renewable energy sources and enhancing grid efficiency. IoT smart grids are facilitating this division of energy and its fair share, which keeps a constant record of energy flowing in and out to balance the system. Renewable energy certificates traced on blockchain verify the source of clean power. In response to the increasing volume of data related to energy consumption, big data analytics is determining the growth of energy to be produced, forecasting future energy requirements, and aiding waste reduction and sustainability (IEA, 2021). AI and related technologies help the smart grid become more efficient, while blockchain-empowered renewable energy certificates increase traceability. Moreover, utilization of big data analytics results in reduction in energy losses by improving the accuracy of demand forecasting and optimizing production planning.

4.9 Barriers and Concerns in GSCM with AI

Greenhouse gas emissions and global warming are pressing global issues, prompting governments worldwide to establish regulations and set ambitious targets to address them. As a result, businesses are increasingly compelled to adopt sustainability principles. Studies show that supply chains account for approximately 80% of the CO₂ emissions in consumer companies, making the development of green supply chains a critical priority. However, organizations aiming to implement GSCM face numerous challenges. A major challenge in adopting green initiatives is the high cost associated with implementing them. Most businesses lack adequate knowledge about green supply chain management (GSCM) practices or are unaware of their potential benefits. This lack of awareness hinders the development and implementation of meaningful sustainable strategies. Organizations operating in multiple

jurisdictions face varying regulations and standards. Ensuring compliance with these diverse regulations can also hinder the consistent implementation of green practices. Often technological access and limited availability of appropriate technologies can also be an issue. There is a likelihood that business culture and employee conduct may make GSCM objectives very difficult to achieve. Overcoming these barriers often requires significant cultural shifts and mindset changes. A lack of support from the business owners or CXOs can also lower the prioritization and investment in GSCM initiatives, thus hindering progress.

There are some specific AI technological barriers that need to be overcome. Inadequate technology readiness includes insufficient IT infrastructure, inadequate access to AI tools and techniques, and a deficit of employees who are skilled enough to install and monitor AI technologies effectively. These aspects impede seamless integration into supply chain operations. A lack of clarity regarding the tangible benefits of AI, such as efficiency gains, cost savings, and performance improvements, can deter decision-makers from adopting these technologies. Clear communication of AI's advantages is vital for encouraging its adoption. The absence of compatible facilities for testing AI technologies makes it difficult to evaluate their scalability, compatibility, and performance. Establishing appropriate testing environments is essential to build confidence and facilitate adoption. Insufficient measures towards privacy and security concerns can lead to data breaches and non-compliance, which can make AI adoption difficult. A lack of alignment between overarching goals and actionable strategies can create inefficiencies and hampers AI implementation. Defining a clear pathway from vision to strategy is crucial for success. Without strong backing from top leadership, resource allocation, decision-making, and momentum for AI adoption will be hindered. Leadership commitment is essential to drive AI initiatives. A lack of initiatives to manage behavioral changes among employees and stakeholders can lead to resistance against AI adoption. Change management programs are necessary to address these concerns and promote acceptance. Limited financial and human resources, along with inadequate skillsets, can slow AI development, deployment, and maintenance. Hence, building capacity in these areas is fundamental for progress. An organizational culture that discourages knowledge sharing can inhibit effective AI implementation. Therefore, promoting an environment conducive to collaboration and information exchange is essential. The lack of proper training for staff and end-users' results in inadequate understanding and suboptimal utilization of AI technologies. Comprehensive training initiatives are key to

enhancing adoption and effectiveness. Ethical issues in data collection can cause distrust in AI usage. Compliance with ethical guidelines is critical to maintaining integrity and trust. The absence of clear regulatory frameworks can create uncertainty and resistance to AI adoption. Hence, establishing robust compliance requirements is crucial for safe and responsible AI integration. Aggressive competition can prompt hasty AI adoption without proper planning, leading to inefficiencies. A balanced and strategic approach is necessary to align AI implementation with business needs. Fluctuations in demand can disrupt AI systems, resulting in inefficiencies like overproduction or underproduction. Adaptive AI solutions are critical to address these challenges effectively. Skepticism about institutional capabilities in handling AI systems and data can hinder adoption. Building trust through transparency and reliability is essential for stakeholder confidence.

Embedding sustainability into supply chains with AI support is crucial for protecting the planet and ensuring business relevance in future markets. Recognizing the obstacles that impede implementation is key to minimizing negative impacts and achieving successful execution. Early identification of risks enables organizations to prepare effectively with the appropriate tools and strategies. A clear vision and well-thought-out planning can guide a company towards sustainability, providing a competitive edge in the market.

4.10 Conclusion and Future Scope

Future developments in the AI domain, such as, for example merging it with edge computing, will substantially enhance prediction and decision-making speed and accuracy throughout the supply chain. As organizations band together to tackle sustainability issues, we will see collaborative AI platforms enabling organizations to safely and securely share their data and insights. Furthermore, the evolution of AI ethics and governance will encompass fairness, justice, and transparency issues and ensure that the use of AI in GSCM confirms to social norms (Floridi & Cowls, 2019). AI, along with green energy, has the potential to revolutionize GSCM, which is truly groundbreaking. Organizations can foster sustainability and residual resilience in their supply chains. AI contributes to moving them to push the broader agendas of solving climate change and meeting the sustainable development goals (SDGs) by adopting state-of-the art, cutting edge technology tools ranging from IoT to blockchain to machine learning. Yet the challenges notwithstanding, the payback in a flourishing AI-enabled GSCM and its

upswing in businesses looking to balance their economic performance and environmental sustainability, depict a promising situation. A limitation of this study is the certain search words that were used to locate papers, articles, and reports on AI and GSCM. Future research could broaden the scope by using different terminologies and analyzing additional databases and data sources.

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Chapter 5

Firm Performance, Innovation, and Government Support in Agriculture SMEs

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5.1 Introduction

The goal of achieving Zero Hunger and ensuring food security by 2030, as outlined in the sustainable development goals, highlights substantial global challenges associated with food production, distribution, and consumption. These challenges give rise to behavioral, procedural, or technological solutions, or a combination of these approaches. More often, technological solutions are more effective and efficient. Technological interventions in agriculture are often known as smart agriculture. The literature indicates that technologies such as the internet of things (IoT), artificial intelligence, blockchain, and machine learning are used in land registration data, resource management, prediction of food grain production (Nesarani et al., 2020), and agriculture supply chain (Ahmed et al., 2022; Chen et al., 2023). “Technology is the future of agriculture” captures the vast potential of technology to transform agriculture (King, 2017).

The development, adoption, and use of technology in agriculture is associated with various challenges. Technology development typically requires substantial resources and is carried out by large research organizations (Arora, 2025). However, adoption and use largely depend on small and medium enterprises within the agriculture supply chain and farmers,

who often have limited resources and technical knowledge. Furthermore, agriculture is associated with traditional practices. As a result, governments frequently provide support to offset the cost of technology, training, and implementation.

Government support for agriculture is a sensitive issue in India. The agriculture sector is the largest employer. Economically vulnerable small farmers, low agricultural productivity, a large number of intermediaries in the supply chain, dependency on rainfall, and price volatility of agri-products are some of the major challenges, among others. Given this context, the government tries to support farmers in multiple ways such as providing training, input subsidies, helping agri-producers in marketing their products, subsidizing production equipment, encouraging farmers to use technology, and giving tax subsidies.

The state and the central governments are also encouraging farmers and associated individuals to take up entrepreneurship in agriculture through mentoring and incubation centers. Agriculture is the primary responsibility of the state governments, but the central government also actively supports and facilitates the policies. Over the years, the government has tried to promote agricultural entrepreneurship through farmer producer organizations (FPOs) and their subsequent conversion to producer companies (Ministry of Agriculture, 2013) and also through the Mission Shakti (Government of Odisha, n.d.-b; Ministry of Women & Child Development, 2022) program. Additional schemes include National Agricultural Insurance Scheme, Agriculture Entrepreneurship Promotion Scheme-2018 of the government of Odisha (APICOL, n.d.), and Agri Clinic and Agribusiness Centres Scheme (NABARD, n.d.). Various state governments have their state-specific policies for the promotion of agriculture and allied industries.

Government policies cover almost every aspect of agriculture and allied sectors. Seed funding, credit guarantees, tax exemptions, innovation, mentorship, and investor meetings are some important schemes by the government (Government of India, n.d.). The market access is extended through the National Agriculture Market, sustainability is attempted through the National Mission for Sustainable Agriculture, and insurance is assured through the Prime Minister's Agricultural Insurance Scheme. These schemes or policies are from various ministries such as science and technology, finance, food processing, public sector enterprises, agriculture, commerce, and micro, small, and medium enterprises (MSME).

However, there are concerns that such support results in adequate favorable outcomes for the organizations. At a broad level, India overcame food

shortages in the 1960s through technology intervention programs such as the Green Revolution, the White Revolution, and other revolutions in different sub-sectors of agriculture. Substantial progress has been registered at a macrolevel. At the same time, distress selling and persistent poverty remain for agri-producers. Thus, the broad question of how small and medium agri-entrepreneurs and producers attempt innovation to overcome challenges is worth investigating. The policy intention to double farmers' income in India is also relevant in this context.

5.2 Literature Review

The modification to the design, production, or recycling of commodities and services, practices, norms, markets, or institutional environments and arrangements by people, communities, or organizations that can change the existing network of production, processing, delivery, and consumption is defined as agricultural innovation. Objectives of agricultural innovation are to increase effectiveness, competitiveness, resilience, and environmental sustainability for food security and nutrition, economic development, and managing natural resources in a specific context. Innovation brings farmers out of poverty, reduces unemployment, and helps in achieving food security and the sustainable development goals. Organizations, communities, businesses, and individuals and their interactions that create the change are known as innovation systems. Innovation platforms are projects or efforts that unite diverse stakeholders and create space for co-learning and collective action for transitions toward sustainable agricultural systems for food security and nutrition (FAO, 2019; Devi et al., 2024). Innovation platforms are practices to integrate scientific and local knowledge to result in innovations that can have larger impacts. Very few platform-related innovation impacts have been observed thus, questioning the technology dissemination and scaling mechanism. Innovation should be demand-driven, participatory, based on collective investment and action, and have committed stakeholders whose outcomes should be technically sound, locally adapted, economically feasible, and socially, culturally, and politically appropriate (Schut et al., 2018; Kumar et al., 2023a).

A Rwanda-based study indicated the following factors for the robust functioning of the agricultural innovation system: evidence-based policy-making, stakeholder interactions and policies, institutional capacity, allocation of resources and platforms, and interest, commitment, and collaboration

(Yongabo & Göktepe-Hultén, 2021; Kumar et al., 2023b). A Croatian study applied the concept of Regional Innovation Systems and observed regional heterogeneity in knowledge creation and dissemination, systems' performance, and firm innovation activities, indicating the diffusion of innovation, distinct value chain, external R&D, public financing, entrepreneurial and technological infrastructure, and scientific and innovation capacities to be the root causes of regional differences (Katarina & Zoran, 2016). A concept of Sectoral Systems of Innovation was invoked to understand productivity differences between two agricultural sectors in India, indicating differences in the diffusion of new technologies, articulated regulatory policy, and a lack of cohesion between multiple actors as significant factors (Mani & Santhakumar, 2011). The Organizational Innovation Systems framework was used to explain how the Agricultural Knowledge and Innovation System (AKIS) is formed by institutions. Multi-actor co-innovation partnerships mobilize complementary knowledge, while outreach programs foster dialogue in an enabling environment (Fieldsend et al., 2020; Mahalle & Dongre, 2024). The systemic perspective of AKIS indicates the usefulness of networking and social capital in strengthening the adoption of sustainable innovation, where ambidexterity acts as a mediator. Researchers have claimed that ambidextrous relations improve performance, stimulate innovation, and farms' competitiveness (Vecchio et al., 2021). Knowledge and innovation management (KIM) emerged to address the dual challenge of boosting productivity while minimizing environmental impact. It's closely associated with employee creativity, responsible green innovation, and improved performance in agribusiness. There is also a need to redefine the meaning of firm performance (Ureña-Espallat et al., 2023). The positive spatial overflow effects of rural innovation and entrepreneurship are also established in the literature (Pan et al., 2024).

5.3 Government Policy and Agriculture Performance

Governments employ subsidy policies, programs, regulations, and financial assistance to support sustainable initiatives in agriculture, encourage rural development, employment, organic production, and industry growth (Barbosa, 2024). Subsidies can boost short-term performance but often impede long-term progress, whereas tax credits promote both immediate and lasting innovation performance. Financial flexibility enhances the positive relationship between incentives and innovation, while excess human

resources have a dampening effect on this relationship (Zhang & Guan, 2018).

Globally, the agricultural environment is changing rapidly. In the Netherlands, the agriculture market has turned from shortage to surplus and from a government-led to a private-led market where competition within the industry has increased, and only niche products command good prices (Diederer et al., 2002). Not all policies by different governments of different countries have been successful. The Kenyan government's Strategy for Revitalizing Agriculture showed almost no progress (Poulton & Kanyinga, 2014). A decrease in agricultural productivity was observed across South and Southeast Asian nations during 2002–2016 (Liu et al., 2020). Effective industrialization strategies, advanced informal service sector, and participation of the market, government, and private sectors were critical for expediting agricultural productivity growth in Africa (Badiane & Makombe, 2014). Agricultural profitability without subsidy was observed to be zero or negative in the majority of regions in Russia. The improper use of the increased amount of subsidies decreased production efficiency in agriculture (Kontsevaya et al., 2017). However, in Slovakia, a strong correlation was observed between agricultural production and the quantum of subsidies granted (Vojarova & Kotulic, 2016).

Tax incentives and subsidies or a mix do not affect innovation similarly. Tax incentives alone encourage experimentation with new production processes but reduce social welfare. Conversely, subsidies alone create the highest social welfare compared to a mix of incentives (Akkaya et al., 2021). Heterogeneity was observed in the impact of government subsidies on technological innovation within agricultural enterprises across various industries, between state and non-state enterprises, and among large corporations versus small and medium enterprises (SMEs) (Wu et al., 2022).

Some blame the exclusive focus on smallholders in government policies as the problem (Collier & Dercon, 2014). In contrast, public agricultural research programs mostly benefit technological leaders, reducing the productivity among average producers. Support in credit, education, and infrastructure can reduce the productivity gap (Rada & Buccola, 2012). The effectiveness of rural financial assistance and the degree of regional economic advancement significantly and positively influence rural agricultural efficiency. However, the increased intensity of rural financial services and the scale of agricultural production and operations have been found to adversely affect agricultural efficiency (Song et al., 2022).

Increasing government spending on agriculture boosts sector performance and significantly raises rural income, measured by value added per capita (Anriquez et al., 2016). The achievement of food self-sufficiency in India was through a combination of technology-policy-institution framework. However, the distribution, specifically ensuring the forward and backward linkages to non-agricultural sectors, has lagged suggesting a policy reorientation, rural industrialization, and skill improvement of the rural labor force (Sekhar, 2014).

5.3.1 Innovation and Agriculture Performance

Undoubtedly, agriculture has recorded performance gains. Higher performance was recorded in countries with higher investment in R&D and education of entrepreneurs. Innovation positively influenced the performance of agriculture, but economic performance negatively influenced environmental performance. Measures to minimize the consumption of inputs did not ensure economic performance (Coca et al., 2017). The technical efficiency varies considerably across regions and over time and substantially depends on irrigation intensification (Pilo, 2019). Technical change has been the primary driver of total factor productivity (technical change, technical efficiency change, and scale change) growth, although its pace has slowed down. The decline in the change of scale and technical efficiency has contributed to the decline in productivity over time. Technological progress has predominantly shaped productivity performances. Additionally, factors such as human capital, urbanization level, and development flow positively influenced productivity growth, while economic development level and agricultural imports reduced the growth in total factor productivity (Liu et al., 2020).

Along with agricultural technology, research, and development (R&D), the distribution of technology substantially explains productivity growth. Mostly the public sector carries out agricultural research, but the private sector pioneers in food research, indicating a need for partnership (Poapongsakorn, 2011). The performance of agricultural innovation systems and reasons for failure in Europe were analyzed using the innovation system failure matrix tool (Hermans et al., 2015). The use of the innovation performance matrix for the fruit supply chain indicated organization, product, process, and market as critical success factors for innovation, whereas quality, efficiency, responsiveness, and flexibility were performance factors (Trienekens et al., 2008).

Largely, the effects of research and innovation in agriculture are understood through expenditure and productivity (Viaggi, 2015). The relationship

between performance and innovation is complex to measure primarily because of a lack of appropriate evaluation criteria. Specifically, the lack of funds, horizontal and vertical differences in innovation, and collaborative innovation networks contribute to the complexity (Hermans et al., 2015). Innovation has to include cooperation and interactive learning, specifically in agriculture and related sectors. Collaborative innovations are necessary to influence total factor productivity (Liu et al., 2020).

Global economic crises also affect firm's innovation inputs and performance, specifically for SMEs, since they carry out less internal R&D and cooperation for innovation (Zouaghi & Sánchez, 2016). So, in the case of SMEs, government support programs have a significant effect (Kim et al., 2016).

Interestingly, a study based on the Vietnamese agriculture and allied industries sector indicated that (a) innovation and intangible assets (IA) diminished firms' performance, (b) age, size, and financial robustness positively influenced the formation of IAs, but investments in land, labor, and R&D showed mixed effects, and (c) regional characteristics also significantly influenced innovation and intangible assets (Nguyen-Anh et al., 2022). The use of blockchain technology increased profit, return on investment, information access, availability, and sharing in the agri-food supply chain, but the cost, flexibility, and responsiveness of operations were not influenced (Stranieri et al., 2021).

5.3.2 Innovation and Government

Promoting national innovation capacity is key to creating an innovation environment that depends on the attitude of the government, where the innovation performance should give feedback to policy. A top-down approach directed the government research fund and resources to develop target industries in Taiwan, but a bottom-up approach was used by the Irish government to create an innovation environment to encourage firm-level R&D; both approaches had different degrees of success (Lin et al., 2010). Government orientation also influences innovation. A leftist ruling party inhibited the growth of technical innovation, whereas a right-wing ruling party promoted it. Thus, the effect of government ideology on innovation was not conclusive (Wang et al., 2019).

A comparative study between Singapore and Hong Kong indicated that large multinational companies lead in the innovation output. Industry innovation is largely self-financed and less directed by the government in Hong Kong, but Singapore has more innovation output. Government support to local companies improved their innovation performance due to the concentration of resources among selected sectors and players (Wang, 2018).

Ethiopian context research has identified associated factors such as (a) adoption and adaptation of incremental innovation, (b) impact innovation to influence broad segments of the economy, (c) demand-oriented innovation focusing on market needs instead of technology push only, (d) spatial innovation focusing on the concentrated dispersal, and (e) government coordination to strengthen capability through mutual learning in the innovation community (Shkabatur et al., 2022). The evolution of mission-oriented innovation systems in agriculture was led by the Green Revolution, which involved technology development and diffusion for the practice to be successful (Anand et al., 2023).

5.4 India-Based Studies

Admittedly, there are fewer India-specific studies. A positive and lagged effect on the growth of firms due to investments in innovations was observed in the Indian agricultural inputs industry (Manogna, 2020).

Communication channels such as news, media, and social networking positively influenced sustainable agricultural practices but institutional factors like loans, subsidies, and credit facilities contributed negatively (Swami & Parthasarathy, 2024). Product innovation varies by enterprise size. Product innovation in SMEs is more important for diversification but is more likely influenced by internal, collaborative, and external factors (Ali et al., 2021).

Knowledge production can occur through the interaction of formal and informal means; thus, they have to be connected. Traditional knowledge must be collated and cultivated in the agricultural sector to enrich formal knowledge and innovation (Alaie, 2020).

Agriculture innovation systems are complex, multi-staged, and involve multiple stakeholders. While the use of technology innovation enhances agriculture performance, its impact is not uniform. Government policies influence innovation; however, their ultimate effect on agriculture performance remains debatable, especially for agricultural SMEs. Studies indicate that outcomes vary depending on the context.

5.4.1 Context of Research

The Odisha Department of Agriculture and Farmer's Empowerment outlines several key goals, including enhancing the agricultural sector through the adoption of advanced technologies, empowering extension workers

and farmers through capacity-building initiatives, boosting agricultural output and efficiency, fostering the overall economic advancement of farmers, creating awareness about developmental schemes, imparting training, ensuring quality production, ensuring farm mechanization, creating irrigation potential, monitoring soil status, and providing fertilizer recommendations leading to crop management, distributing subsidies, promoting Agri-entrepreneurship, and providing incentives/subsidies to farmers among others (Government of Odisha, n.d.-a).

Odisha has 4.7 percent of the total land and 3.5 percent of the total population of India. Around 50 percent of the population is engaged in agriculture and related sectors. The state has ten agro-climatic zones. It is the first state in India to have a separate budget for agriculture. The agricultural productivity has been increasing over a period (Hoda et al., 2021).

Along with the literature review, this context supports the need for research.

5.4.2 Research Gaps

The literature has not yet provided a thorough analysis of government support mechanisms in the agricultural sector and their potential influence on the adoption of sustainable practices (Barbosa, 2024). Also, insufficient attention has been given to researching innovation and managing intangible assets in labor-intensive sectors like agriculture (Nguyen-Anh et al., 2022). The existing literature lacks consensus on various government approaches and orientations, which have diverse impacts on innovation (Wang et al., 2019). There is measurement complexity in the relationship between performance and innovation (Hermans et al., 2015). India is known for frugal innovation, but its influence on agriculture has received limited attention, suggesting a possibility of traditional and frugal innovation influencing agricultural performance (Hossain, 2017).

Food-related consumption practices have cultural stickiness, indicating a possible lack of product innovation practices. Agriculture, being the oldest practice influenced by culture, tradition, weather, and other geographic endowments, is also likely to be less responsive to innovation practices. However, the need to increase production, profitability, and sustainability demands innovation in agriculture and allied sectors. Government support is usually on a social basis or a populist basis. The diverse nature of innovation, the multiplicity of government support practices, and heterogeneous performance measures require adequate understanding. Prior research

considered isolated impacts of either government policy or innovation on agricultural performance.

This study adopts the organizational innovation systems framework, which views innovation as the result of collaborations among firms, institutions, and organizations within the broader context of culture, history, society, and economics. It investigates the interaction of government policies and firms' performance as innovation drivers.

The following are specific objectives to be tested in the agriculture sector: (a) innovation leads to better performance, (b) better performance leads to higher innovation, and (c) government incentives lead to higher innovation.

5.4.3 Methodology

The scale for business performance (Cronbach's $\alpha = 0.808$, no. of items = 6, Likert scale value from 1 – very dissatisfied to 5 – very satisfied) included profit growth last year, sales growth, asset growth, employee growth, customer satisfaction, and quality of product or service. The test indicated the measure is reliable. Innovation was measured through 6 items: newness in product, process, market, services, technology, or sources of supply, with the Likert value from 1 – strongly disagree to 5 – strongly agree. Cronbach's $\alpha = 0.856$ indicated adequate reliability. For the government support items such as training, subsidy, marketing support, production support, technology, tax subsidy, incubation support, and mentoring, respondents were asked to indicate yes if they have received such support or else no. A final confirmation was if no support was received by the respondent.

Sample: The sample of respondents was selected from (a) agri-entrepreneurs who attended different entrepreneurship development programs sponsored by the government and (b) from the industrial directory containing firm details in the broad sector of agriculture and allied industries. About 1000 respondents were identified in the process. The link to a structured online questionnaire was shared among respondents. A maximum of three reminders was sent. The data collection was from 1 June 2023 to 25 February 2024, within which 635 responses were collected, indicating a response rate of 64 percent. After rejecting incomplete responses, 599 were considered for final data analysis.

Ethics: Ethical principles of informed consent, anonymity, and voluntary participation were adhered to for this online survey. Respondents could refuse or withdraw at any time before submitting their responses, and no identifiable personal data was required.

5.5 Results

Table 5.1 gives the distribution of respondents indicating different government support received by them.

Put together, 64 percent agreed to some form or other form of government support. The highest was subsidy (41 percent), 33 percent received mentoring support, and the third highest was tax benefits.

Table 5.2 indicates the response distribution for performance and innovation items. On the Likert scale, 1 indicates the lowest and 5 indicates the highest score. Higher scores indicate better scores on the scale.

The response distribution indicates a better score by the entrepreneurs for most items, indicating better firm performance and a higher level of innovation.

5.5.1 Association between Government Support, Performance Parameters, and Innovation Types

A chi-square test was performed to understand the association between government support status, performance parameters, and innovation types. Most of the values indicated an association in the anticipated direction, that is, with government support, a higher percentage showed better results in

Table 5.1 Distribution of Availing of Government Support

	<i>Availed Support: No</i>		<i>Availed Support: Yes</i>		<i>Total</i>	
	n	%	n	%	n	%
Training	513	85.6	86	14.4	599	100.0
Subsidy	354	59.1	245	40.9	599	100.0
Marketing	553	92.3	46	7.7	599	100.0
Production	558	93.2	41	6.8	599	100.0
Technology	557	93.0	42	7.0	599	100.0
Tax	479	80.0	120	20.0	599	100.0
Incubation	570	95.2	29	4.8	599	100.0
Mentoring	402	67.1	197	32.9	599	100.0
Any govt. support	217	36.2	382	63.8	599	100.0

Source: Authors' own data and analysis.

Table 5.2 Frequency Distribution of Performance and Innovation

	N (%)					Mean	Median	Mode	SD	Skew	Total
	1	2	3	4	5						
Profit (last year)	4 (0.7)	9 (1.5)	68 (11.4)	444 (74.1)	74 (12.4)	3.96	4.00	4.00	0.60	-1.17	599 (100)
Sales growth	5 (0.8)	6 (1.0)	73 (12.2)	387 (64.6)	128 (21.4)	4.05	4.00	4.00	0.67	-0.92	599 (100)
Asset growth	4 (0.7)	12 (2.0)	87 (14.5)	377 (62.9)	119 (19.9)	3.99	4.00	4.00	0.70	-0.83	599 (100)
Employee growth	5 (0.8)	12 (2.0)	79 (13.2)	389 (64.9)	114 (19)	3.99	4.00	4.00	0.69	-0.97	599 (100)
Customer satisfaction	3 (0.5)	3 (0.5)	38 (6.3)	375 (62.6)	180 (30.1)	4.21	4.00	4.00	0.62	-0.81	599 (100)
Product/ service quality	3 (0.5)	4 (0.7)	65 (10.9)	374 (62.4)	153 (25.5)	4.12	4.00	4.00	0.65	-0.71	599 (100)
New product	-	3 (0.5)	15 (2.5)	427 (71.3)	154 (25.7)	4.22	4.00	4.00	0.50	0.10	599 (100)
New process	-	3 (0.5)	46 (7.7)	321 (53.6)	229 (38.2)	4.30	4.00	4.00	0.63	-0.44	599 (100)
New market	-	6 (1.0)	65 (10.9)	330 (55.1)	198 (33.1)	4.20	4.00	4.00	0.66	-0.46	599 (100)
New service	-	4 (0.7)	62 (10.4)	350 (58.4)	183 (30.6)	4.19	4.00	4.00	0.63	-0.34	599 (100)
New technology	1 (0.2)	5 (0.8)	73 (12.2)	322 (53.8)	198 (33.1)	4.19	4.00	4.00	0.68	-0.54	599 (100)
New supply	1 (0.2)	5 (0.8)	73 (12.2)	322 (53.8)	198 (33.1)	4.17	4.00	4.00	0.71	-0.62	599 (100)

Source: Authors' own data and analysis.

performance and innovation types. For the sake of brevity, this section mentions non-significant associations or atypical results.

Training and sales growth did not show any significant relationship ($\chi^2(2) = 3.55, p = .170$), government subsidy and sales growth ($\chi^2(2) = .862, p = .650$), subsidy and asset growth ($\chi^2(2) = .498, p = .780$), subsidy and customer satisfaction ($\chi^2(2) = .131, p = .936$), subsidy and quality of product or service ($\chi^2(2) = 3.88, p = .144$), and subsidy and new product ($\chi^2(2) = 2.67, p = .263$). The subsidy and newness of the process was against expectation. About 96 percent of those who did not get any subsidy agreed or strongly agreed to have done some process innovation, compared to only 86 percent of those who received subsidy ($\chi^2(2) = 19.824, p = .000$). Subsidy and newness of the market was similar, with 93 percent of respondents without subsidy agreeing or strongly agreeing with market innovation compared to about 81 percent of those who received subsidy ($\chi^2(2) = 16.838, p = .000$). A similar observation was made for newness of service: 93 percent without subsidy but 83 percent with subsidy agreed on the newness of service ($\chi^2(2) = 16.978, p = .000$). Subsidy and newness of technology indicated 92 percent without subsidy and 80 percent with subsidy agreed to some technology innovation ($\chi^2(2) = 23.936, p = .000$); 88 percent without subsidy but 81 percent with subsidy agreed on some newness in supply ($\chi^2(2) = 11.874, p = .003$). Government support for production did not show a significant association with employee growth ($\chi^2(2) = 5.022, p = .081$), the newness of the process ($\chi^2(2) = .600, p = .741$), or the newness of supply ($\chi^2(2) = 5.485, p = .064$). Government support for technology did not show a significant association with process innovation ($\chi^2(2) = 1.987, p = .370$). Tax subsidy was not significantly associated with sales growth ($\chi^2(2) = 4.037, p = .133$), asset growth ($\chi^2(2) = 5.538, p = .063$), employee growth ($\chi^2(2) = 4.066, p = .131$), customer satisfaction ($\chi^2(2) = .864, p = .649$), product/service quality ($\chi^2(2) = 1.343, p = .511$), newness of service ($\chi^2(2) = 2.900, p = .235$), new technology ($\chi^2(2) = 5.50, p = .064$), or newness of supply ($\chi^2(2) = 2.638, p = .267$). Incubation did not show a significant association with the new process ($\chi^2(2) = 2.722, p = .256$). Mentoring did not show a significant association with customer satisfaction ($\chi^2(2) = 1.788, p = .409$), product/service quality ($\chi^2(2) = 2.352, p = .309$), new product development ($\chi^2(2) = .377, p = .828$), new market ($\chi^2(2) = 1.241, p = .538$), newness of service ($\chi^2(2) = 1.800, p = .407$), new technology ($\chi^2(2) = 1.304, p = .521$), or supply newness ($\chi^2(2) = .937, p = .615$).

5.5.2 Correlations with the Total Number of Supports

Since different firms received different types of support, the total number of supports received was calculated and the correlation was calculated with firm performance measures. The following correlation coefficient values (r) were observed: last year profit $r = 0.146$ ($p \leq 0.01$), sales growth $r = 0.089$ ($p \leq 0.05$), asset growth $r = 0.095$ ($p \leq 0.05$), employee growth $r = 0.115$ ($p \leq 0.01$), customer satisfaction $r = 0.098$ ($p \leq 0.05$), and product/service quality $r = 0.163$ ($p \leq 0.01$). Interestingly, the total amount of government support did not show any significant correlation with any innovation factors.

5.5.3 The Mean Difference of Total Performance and Innovation by Government Support

The total scores for performance and innovation were evaluated for their significant differences (Table 5.3) by the status of availing different government support.

The total performance score did not significantly differ by subsidy, tax, mentoring, or any government support. The total innovation score did not significantly differ by mentoring support.

5.5.4 Correlations

A correlation analysis was done for each item of performance measures and innovation types (Table 5.4). The analysis indicated that each item of performance measures and innovation types has stronger and more significant correlations between themselves, indicating the convergent validity of constructs. Employee growth did not significantly relate to any item of innovation measure. Profit for the last year was negatively correlated with most innovation types; it was significantly negative for service innovation. It indicated that a higher last year's profit would mean lower innovation of any kind. Though not significant, employee and asset growth showed a negative and low correlation with service and technology innovation. Overall, the correlations were low ($r < 0.3$). The correlation and t -test analysis results suggested a need for regression analysis to understand the combined effect of factors (Table 5.4).

Table 5.3 Mean Difference in Performance and Innovation by Government Support

		<i>Govt. Support = No</i>			<i>Govt. Support = Yes</i>				
	<i>Support type</i>	N	<i>Mean</i>	<i>SD</i>	N	<i>Mean</i>	<i>SD</i>	T	p
Total performance	Training	513	24.23	2.67	86	25.05	3.45	−2.59	.010
	Subsidy	354	24.14	2.99	245	24.59	2.50	−1.92	.056
	Marketing	553	24.18	2.75	46	26.11	2.95	−4.56	.000
	Production	558	24.23	2.76	41	25.59	3.19	−3.00	.003
	Technology	557	24.19	2.76	42	26.12	2.83	−4.36	.000
	Tax	479	24.22	2.84	120	24.75	2.63	−1.86	.063
	Incubation	570	24.21	2.74	29	26.59	3.18	−4.52	.000
	Mentoring	402	24.21	2.96	197	24.55	2.47	−1.37	.171
	Any govt. support	217	24.11	3.37	382	24.45	2.43	1.43	.152
Total newness	Training	513	24.87	2.78	86	27.60	2.64	−8.49	.000
	Subsidy	354	25.70	2.73	245	24.63	3.08	4.48	.000
	Marketing	553	25.10	2.87	46	27.22	2.87	−4.81	.000
	Production	558	25.15	2.88	41	26.76	3.13	−3.42	.001
	Technology	557	25.13	2.89	42	27.05	2.81	−4.16	.000
	Tax	479	25.45	2.77	120	24.51	3.37	3.18	.002
	Incubation	570	25.16	2.89	29	27.21	2.94	−3.71	.000
	Mentoring	402	25.37	2.74	197	25.05	3.26	1.27	.205
	Any govt. support	217	25.94	2.63	382	24.88	3.01	−4.34	.000

Source: Authors own data and analysis.

Note: df = 597.

5.5.5 Innovation as a Predictor of Performance

Various innovation types such as product, process, service, technology, supply, and a new market were considered as independent variables to predict total performance measures. The F statistic $F(6, 592) = 5.394$, $p = 0.000$,

Table 5.4 Correlation between Performance Factors and Innovation Types

	Performance						Newness					
	1	2	3	4	5	6	7	8	9	10	11	12
1. Last year profit	1	.544**	.583**	.449**	.326**	.353**	-.071	-.009	.004	-.091*	-.027	-.079
2. Sales growth	.544**	1	.520**	.434**	.342**	.402**	-.021	.178**	.084*	.078	.050	.054
3. Asset growth	.583**	.520**	1	.545**	.282**	.297**	-.063	.100*	.032	-.031	-.008	.016
4. Employee growth	.449**	.434**	.545**	1	.272**	.270**	-.053	.051	.018	-.012	-.004	.057
5. Customer satisfaction	.326**	.342**	.282**	.272**	1	.576**	.192**	.252**	.274**	.256**	.242**	.194**
6. Product/service quality	.353**	.402**	.297**	.270**	.576**	1	.252**	.271**	.294**	.271**	.327**	.215**
7. Product	-.071	-.021	-.063	-.053	.192**	.252**	1	.455**	.532**	.477**	.487**	.469**
8. Process	-.009	.178**	.100*	.051	.252**	.271**	.455**	1	.472**	.517**	.531**	.492**
9. Market	.004	.084*	.032	.018	.274**	.294**	.532**	.472**	1	.575**	.556**	.470**
10. Service	-.091*	.078	-.031	-.012	.256**	.271**	.477**	.517**	.575**	1	.502**	.475**
11. Technology	-.027	.050	-.008	-.004	.242**	.327**	.487**	.531**	.556**	.502**	1	.520**
12. Supply	-.079	.054	.016	.057	.194**	.215**	.469**	.492**	.470**	.475**	.520**	1

Source: Authors own data and analysis.

**Significance at the 0.01 level (two-tailed).

*Significance at the 0.05 level (two-tailed).

indicated the model to be significant. The adjusted $R^2 = 0.042$ indicated a low prediction level. The unstandardized β coefficients and p values were as follows: product innovation = -0.557 ($p = 0.052$), process = $.802$ ($p = 0.001$), new market = $.549$ ($p = 0.019$), new service = $-.116$ ($p = .628$), new technology = $.103$ ($p = .646$), and new supply = $.015$ ($p = .942$). Thus, the new process and new market were significant predictors at $p \leq .05$, and the product innovation was a negative but significant predictor at $p \leq 0.1$ level. Overall, innovation types were not significant predictors of performance.

5.5.6 Performance as a Predictor of Innovation

Alternatively, this research tested if the performance parameters substantially predict innovation in an agricultural firm (Table 5.5). The total score for innovation was the dependent variable, and performance parameters were considered independent variables. The specific type of government support was considered as moderators.

Following are some important observations from the regression analysis (Table 5.5): Firm performance parameters explain about 18.4 percent of the variance in innovation. With marketing support, the explanation goes up to 32.2 percent; with subsidy the innovation explanation goes up to 29.6 percent; with production-related support or incubation assistance, the innovation is explained up to 57 percent; and technology or technical assistance increases the innovation explanation up to 52 percent. Overall, with government support, innovation is better explained compared to no innovation or an average situation, except in the case of training programs where the innovation reduces to 10 percent. In this case, no performance parameter significantly predicts innovation, but the model is significant.

Interestingly, last year's profit negatively influences innovation in all scenarios. This can be considered as the profit inhibiting innovation. The maximum inhibition to profit ($\beta = -1.58$) when the entrepreneur has not received any training. Without any support from the government, the inhibition to innovate is slightly lower ($\beta = -0.99$); with government support, the inhibition reduces to $\beta = -0.67$. This inhibition is not significant when training, subsidy, marketing, production, technology, tax, and incubation support are received by entrepreneurs. Mentoring support does not significantly reduce this inhibition. Furthermore, mentors and businesspeople are likely to have different perceptions of business (Kar & Sarangi, 2020).

Under different conditions, four factors such as last year's profit, sales growth, customer satisfaction, and product or service quality are significant

Table 5.5 Performance Parameters as Predictor of Innovation

	Model values					Unstandardized β , p-value						
	Adj. R ²	F Change	df1	df2	p	Const.	Last Year Profit	Sales Growth	Asset Growth	Employee Growth	Customer Satisfaction	Product/ Service Quality
Support												
Sample = All	.184	23.42	6	592	.000	19.95, .000	-1.20, .000	0.21, .312	0.00, .989	-0.14, .453	0.93, .000	1.43, .000
Training = 0	.165	17.85	6	506	.000	20.76, .000	-1.58, .000	0.18, .418	0.15, .517	0.05, .806	0.96, .000	1.18, .000
Training = 1	.101	2.59	6	79	.024	21.83, .000	-0.44, .415	0.18, .764	-0.14, .774	-0.10, .816	0.38, .612	1.36, .072
Subsidy = 0	.172	13.20	6	347	.000	23.74, .000	-1.30, .000	-0.06, .812	-0.38, .145	0.03, .908	0.69, .008	1.41, .000
Subsidy = 1	.296	18.11	6	238	.000	10.56, .000	-0.47, .193	0.46, .169	0.32, .344	0.39, .246	1.42, .000	1.26, .000
Marketing = 0	.168	19.56	6	546	.000	21.16, .000	-1.29, .000	0.11, .604	-0.08, .709	-0.16, .441	0.97, .000	1.34, .000
Marketing = 1	.322	4.56	6	39	.001	13.74, .000	-0.43, .588	0.99, .302	0.02, .976	0.25, .683	-1.24, .348	3.39, .009
Production = 0	.162	18.93	6	551	.000	21.25, .000	-1.29, .000	0.10, .667	-0.09, .691	-0.10, .628	0.93, .000	1.33, .000
Production = 1	.570	9.85	6	34	.000	8.89, .006	-0.02, .976	0.66, .358	0.23, .791	0.42, .486	0.44, .738	2.33, .045
Technical = 0	.169	19.84	6	550	.000	21.17, .000	-1.37, .000	0.14, .532	-0.06, .775	-0.13, .527	0.99, .000	1.33, .000
Technical = 1	.519	8.36	6	35	.000	9.37, .003	-0.29, .645	1.59, .069	-0.31, .721	0.46, .464	-0.56, .520	3.06, .001
Tax = 0	.182	18.75	6	472	.000	21.75, .000	-1.17, .000	0.12, .583	-0.15, .501	-0.17, .397	0.75, .001	1.45, .000
Tax = 1	.269	8.32	6	113	.000	9.84, .000	-0.89, .222	0.74, .300	0.52, .449	0.53, .332	1.53, .013	1.07, .068
Incubation = 0	.170	20.38	6	563	.000	20.93, .000	-1.27, .000	0.08, .703	-0.09, .684	-0.10, .626	0.96, .000	1.38, .000
Incubation = 1	.568	7.14	6	22	.000	11.85, .002	-1.15, .193	2.01, .066	0.02, .985	0.21, .783	-1.40, .447	3.66, .029
Mentoring = 0	.158	13.50	6	395	.000	22.49, .000	-1.21, .000	0.07, .743	0.09, .710	-0.27, .205	0.58, .019	1.36, .000
Mentoring = 1	.272	13.19	6	190	.000	12.91, .000	-1.08, .043	1.13, .032	-0.31, .497	0.03, .947	1.66, .000	1.48, .001
Support = 1	.278	25.45	6	375	.000	12.93, .000	-0.67, .022	0.54, .049	0.06, .814	-0.01, .976	1.40, .000	1.55, .000
Support = 0	.132	6.49	6	210	.000	26.37, .000	-0.99, .017	-0.28, .347	-0.51, .141	0.12, .676	0.34, .282	1.12, .000

Source: Authors own data and analysis.

predictors of innovation. Employee growth and asset growth are not significant predictors under any scenario. In 17 of 19 scenarios, product or service quality as a performance parameter is a significant innovation driver. With training support and tax incentives, product or service quality becomes a non-significant predictor of innovation.

With mentoring and some government support, sales growth becomes a significant predictor of innovation. Employee growth and asset growth are non-significant and negative predictors under most conditions of no support from the government.

5.6 Discussion

Technologies such as AI, ML, and IoT, among others, are being used to push data-driven decision-making in agriculture. Large organizations have developed decision-making platforms such as IBM-Watson and Microsoft-FarmBeats to support AI-enabled decision-making. Innovation is the key to achieving agricultural sustainability. However, concerns remain about the adoption of these technology innovations, their impact on SME performance, and the level of government support required for effectiveness.

This research, within the scope of the organizational innovation systems framework, aimed to investigate three specific questions: whether innovation leads to better performance, whether better firm performance leads to higher innovation, and whether government incentives act as moderators in the relationship between innovation and performance. These hypotheses were tested in the context of agriculture in Odisha, a state in India with lower agricultural productivity compared to many other states.

Even though responses indicated better performance and higher innovation, we find that (a) the ability of innovation to explain performance is not substantial even though significant, (b) performance explains innovation to a higher degree, and (c) government incentives act as a moderator to improve the link between performance and innovation.

A good performance does not necessarily imply innovation. A higher current performance creates an inhibition for innovation. Entrepreneurs may not like to change or innovate if performance is up to the level of satisfaction. At the same time, attempting innovation at a poor performance level is difficult due to the demand for resources. The significance of product or service quality and customer satisfaction in explaining innovation indicates that innovation becomes an externally imposed requirement. It is a competitive

compulsion, more so when quality is a comparative and evolving standard or requirement.

These research findings also partially agree with prior observations that innovation diminished firms' performance, financial robustness influences innovation positively, fixed asset and employee growth showed mixed effects, and external factors significantly influenced innovation (Nguyen-Anh et al., 2022). Focus on sectors and small players improves innovation output (Wang, 2018). Also, small farmers are unlikely to influence the level of technology as a moderator to improve performance (Umar et al., 2020). Innovation measurement should also be rigorous, accurate, and continuous and should include "what works" and its cost-benefit analysis (Schut et al., 2018). Elsewhere, it is indicated that a drastic change to push "mega-farms" with government support is an unlikely answer (Collier & Dercon, 2014). This research finding also corroborates earlier findings that Indian agriculture depends on public innovation and interacts closely with society, and innovation systems adapt to external pressures (Kompella, 2021).

5.7 Limitation and Future Scope of Research

Several limitations in this research require attention in future studies. First, this research considered firm performance and innovation as subjective assessments of owners. Firm-level objective data on performance and innovation is difficult to access in the Indian context. Second, both the scales on performance and innovation were reliable, but they arguably left out many dynamic aspects that should be included in future research. As prior research argues, the performance matrix for agricultural innovations has continued to expand, encompassing sustainable intensification goals such as environment, productivity, economic, human, and social conditions (Spiegel et al., 2022). This research considered performance and innovation as a snapshot, thus indicating limited process dynamics. Innovation decisions take time and evolve over a period, suggesting a qualitative study for better explication.

5.8 Conclusion

Practices related to agriculture and allied sectors are rooted in the history, culture, and traditions of a region. Innovation is likely to be riskier in a

culturally sticky context. This explains why innovation does not explain performance substantially, but performance explains innovation significantly and substantially. Government policies act as a moderator between performance and innovation. Performance and external context are more likely to push innovation and ensure sustainability.

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Chapter 6

An Empirical Study on Role of Green Banking and Technology in Sustainable Development

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6.1 Introduction

Environmental degradation has adversely affected human life. Industrial growth in the last few decades has enormously increased the carbon emission in the atmosphere which has ultimately resulted in global warming. The fossil fuels have adversely affected the clean environment and its high time to look for alternative energy sources for the existence of humanity. In countries like India the energy requirement is high due to over population and unsustainable consumption pattern (Chang et al., 2019). Thus, ecological balance is really a concern for the industry, where green banking can provide effective solution for sustainable environmental growth. Banking operations are also having a great impact on the environment. Today's banks are focusing on green banking technology to reduce their operational cost and to provide their customers with IT-enabled services. In order to safeguard the environment, the polluting industries are facing resistance and some of the industries are forced to close down. The major source of carbon emission Industries is steel, oil and gas, cement, fertilizers, etc. In the global banking

sector, green banking has assumed great importance, and it is essential for banks to adopt green banking for its survival and growth. With increased competition among the banks in the country, a bank has been instrumental in the carbon emission in the atmosphere. The activities of the banks related to carbon emission is in terms of extensive use of paper for various reports and documents, high electricity consumption in bank branches, extensive use of electronic equipment, air-conditioning, electric bulbs, lighting, and office stationery by banking staffs in bank branches. The management of Uttarakhand Gramin Bank has realized the relevance of sustainable development not only for the conservation of energy in its operational activities but also in creating pollution-free environment in the area of its operations.

The IT and system use in business models have been effective in reducing carbon footprint and thus banking sector should encourage investment in green sustainable IT/IS for environmental sustainability (Danish et al., 2019). Uttarakhand Gramin Bank has emphasized the importance and relevance of green banking for sustainable development. Uttarakhand bank encourages environmentally friendly investment to industries which is focusing on green projects to restore the environment. Technology has enabled the banking sector to maximize its green financial products and reduce carbon footprints in its activities (Prabhu & Aithal, 2021a). Thus, RBI should strengthen green practices by creating more satisfied customers for sustainability of green banking policies adopted by banks. Green banking initiatives by Indian banks have played significant role in the restoration of customer trust in building green brand image and green trust (Sharma & Choubey, 2022). Green product success, green process innovation, and green product competitiveness has influenced green innovation performance. Thus, the organization needs to enhance its investment in green product innovation (Nuryakin & Maryati, 2020).

The challenges of climate change is faced not only by manufacturing industries but also by banking industry (Park & Kim, 2020). The role of RBI and financial regulators is significant to promote green banking activities in order to change dynamics of banking activities and implement environmental and social safeguard standards. The institutional barrier and sectorial barrier have to be examined for environmental development. The bank needs to finance climate resilient projects and increase the use of renewable energy for enhancing energy efficiency in the banking sector. The implementation of green banking depends on the commitment of top management and the bank's environmental ethical practices for sustainable development. The top-level management role in the adoption of green

banking has been able to enhance branch image and operational efficiency (Syed & Fathyah, 2022).

Environmentally friendly initiatives of banks such as ATMs and other automated services had a positive impact on the bank's performance and in the protection of environment (Kala et al., 2020). Green services will yield fruitful results against environmental threats resulting from global warming, soil erosion, deforestation, ozone depletion, water pollution, and carbon emission in the air. Thus, green projects, energy-efficient practices, and environmental awareness represent the future of sustainable banking services. Bank's regulations can be effective in facilitating climate change and in the generation of low carbon global economy through its web services and customer friendly banking practices (Bowman, 2010). The banking model of business, activities, and strategies has changed over the decades in order to protect natural resources and offers environmentally friendly services for their clients. Thus, laws and regulations for energy conservation are vital for the sustainable development of the economy. Climate change has laid emphasis on green infrastructure through the mechanism of public-private partnership and green investment banks to enhance low carbon investments (David & Venkatachalam, 2019). Banks for sustainable development are promoting industries going green. The performance of such banks has also enhanced that focuses on environmental development through corporate entrepreneurship awards and incentives (Bradwaj et al., 2013).

The green banking initiatives on customer satisfaction is influenced by variables like data security, bank trust, convenience, customer friendly users, and environmental and social issues (Herath & Herath, 2019). Indian banks have undergone economic renovation by focusing on sustainable energy for the growth of banks though its green investment policies (Rajput et al., 2013). The corporate social responsibility (CSR) laid emphasis on the green marketing strategies aimed at enhancing the green image of the banks in the economy (Lymperopoulos et al., 2012). Green banking has significantly reduced the operating cost of banks through paperless work, power, and energy. Maintaining natural resources without harming the ecological environment for banks has been a great challenge for environment sustainability (Gupta, 2015). BRIC countries such as Brazil and China have performed better than India and Russia in sustainability by transition of green products for environmental protection (Shershneva & Kondyukova, 2020). India for sustainable green banking and energy needs to make huge investment along with international agencies and corporates for ecological balance after COVID-19 crisis. Green financial policy is vital for environmental sustainability enhancing the growth of green technology (Rout & Sahoo, 2021).

GB regulations have significantly enhanced the banking environment by increasing the operational efficiency of banks but not bank's staff and customer-oriented GB practices (Chen et al., 2022). The impact of CO₂ emission on the expansion of banking sector development and financial inclusion is evaluated. Hence, policies of investment on GB services for the renewable energy consumption are crucial for ecological balance in the economy (Khan & Rehan, 2022). Turkey's CO₂ emission from 1980 to 2014 suggests that policymakers for banking sector development have to ensure reduction in environmental degradation by promoting energy investment in the banking sector using renewable resources (Samour et al., 2019). Investment in long-term green projects is at risk as investment in renewable energy has reduced to 1% from 3% so public financial Institutions & NBFC (insurance companies and pension funds) should encourage investment by giving high returns on green projects and green credit card schemes.

In order to meet the increasing demand of energy and in the reduction of carbon dioxide emission in the atmosphere, the banking sector can play a very essential part by enhancing investment in renewable energy. High-income countries banking performance had a positive impact on renewable energy consumption along with its asset's quality as well as market capitalization and managerial efficiency). The firm's performance is affected by carbon emission and ineffective implementation of green project's return on equity (ROE) (Hart & Ahuja, 1996). There is a positive relationship between carbon emission reduction and the firm's performance. The data of 920 firms during the period of 2014–18 reveals that renewable energy use is not relevant in maximization of profit (Hulshof & Mulder, 2020). Thus, firm strategy to counter climate change via renewable energy is not aimed at profit maximization. The author examined environmental issues and bank risks in substantial development (Suborna Barua, 2020). Thus, sustainable growth can only be effectively managed by financial sector and banks through strict policies and regularity measures only. Environmental consciousness is an important determinant in the purchase of environmentally sustainable products and services (Joshi & Rahman, 2019). Thus, bank investment in green projects will play a very significant role in safeguarding the environment. The objective of the study are as follows:

- To identify the initiatives taken by Uttarakhand Gramin Bank to make it a green bank for rural customers.
- To assess customers' perception on the role of green banking in sustainable development of Uttarakhand.

6.2 Green Banking Initiatives of Uttarakhand Gramin Bank for Sustainable Development

- **Green Banking Financial Products:** Uttarakhand Gramin Bank laid focus on insta banking, vehicle finance, carbon footprint calculators, solar ATMs, green home loan schemes, energy-saving projects of MSME, green insurance, mutual funds, etc. for sustainable development. All the IT-enabled banking services were used for enhancing growth and reducing operational cost. The traditional energy resources (solar, wind, wave, and biomass) provides energy with less environmental damages, but industrial electronics needs to create a new form of energy into existing grids for sustainable development (Lisserre et al., n.d.).
- **Renewable Energy (Solar and Wind Energy):** In India, it was State Bank of India which adopted efficiently solar and wind energy by make huge investment in plants using solar and wind energy. Moreover, it laid emphasis on solar ATM's and green building for sustainable banking across the country. The barrier to renewable energy can be overcome by investment in renewable energy by bank. The barriers are usually due to market, finance, technology, institution, and policies of banks for green investment in the country and abroad (Painuly, 2001).
- **Paperless Banking:** The bank encouraged and promoted its online banking services and insurance services for its customers. All efforts of the bank were to have an environmentally friendly service for its client. A number of initiatives were taken to create awareness among the general masses about the services offered by UGB. The U.S. banks are more customer-oriented, and IT-enabled services have ensured for operational accuracy and green services accepted by the population (Tallon, 2010).
- **Less Energy Consumption:** Apart from it, Uttarakhand Gramin banks were promoting green loans to Industries engaged in renewable energy. The bank was saving energy by restructuring its lighting and by using the latest LED bulbs and promoting green electricity in the banking premises. Thus, the management needs transformation of green hardware, effective wastage management, and energy-efficient technology products for sustainable growth. The penetration of renewable energy in the power sector has enhanced and the bank needs to focus on financing both power grid-connected and solar/wind system in power generation (Badwawi et al., 2015).

- **Green Efficient Practices:** Go Green initiatives empowered or encouraged banks in launching solar-powered ATMs across the country, financing creation, or generation of wind farm projects for electricity and promoting firms manufacturing incandescent bulbs or LED bulbs. This inventiveness of banking will not only benefit the bank but will also promote sustainable banking. Green banking practices have enhanced customer loyalty, reduced operating cost, data security, and the efficiency of banks adopting it. These practices have a significant impact on the banking environment (Kumari & Dat, 2021).
- **LPG/Electric Vehicles:** Uttarakhand Gramin Bank encouraged industries engaged in promoting LPG cylinder motor car manufacturers and distributors across the state for sustainable development. The bank helped in getting automobile loans to individuals who approached the bank for vehicle loans. All LPG gases automobiles, electronic vehicles loans were given priorities by Uttarakhand Gramin Bank for sustainable development. Through sustainable finance, banks can promote coal power plants rather than financing fossil fuel projects for sustainability (Chan et al., 2022).
- **Green Buildings:** Uttarakhand Gramin Bank placed emphasis on green housing loans and solar panels for residential homes in the state for sustainable development. Moreover, it aims at having solar ATMs across the state for sustainable development. All these efforts were direct towards the protection of the environment. Banks should also focus on reducing energy consumption through the promotion of green building practices and implement green vegetated envelops for green residential buildings to increase cooling and electricity loads (Azis, 2021). Financial incentives to green buildings by banks can add to the reduction of carbon emission and promote sustainable development as in Canada (Rana et al., 2021).
- **Cost Efficiency:** Energy and fuel conservation of banks has contributed towards low carbon economy and in the economic transformation of operating and financing risk. Due to the green banking products like ATM, e-banking, mobile banking, UPI, e-wallet, e-loan, e-statement to customers, etc., the transaction cost of banks has drastically reduced and have enhanced accuracy in the maintenance of accounts. Bank strategy for enhancing renewable energy in the global banking sector is to focus on green investment, green securities, green infrastructure bond, green insurance, green credit cards, climate finance, and carbon

finance (financial products) for sustainable development (Akomea-Frimpong et al., 2022).

- **Plantation by Banks:** Corporate social responsibility of the bank identified the importance of plantation near the bank premises. It promoted plantation programs across the state in schools and colleges and funded seminars and conferences in creating awareness of green environment for sustainable development. Banks for sustainable renewable energy technologies in rural areas need to create income generating activities for the rural people and solve environmental problems of deforestation, soil erosion, and fuels from cooking pollution (Biswas et al., 2001).
- **Eco-friendly Products (such as Green Accounts, Green Loan, and Green Credit Cards):** For sustainable development banks across the country focused on eco-friendly products like green accounts, green loan, and green credit cards but Gramin Bank hardly provided these services to the rural customers. The challenges for the banking sector ahead is of strengthening social innovation for ecological balance for the benefit of sustainable growth of the economy (Lorek & Spangenberg, 2014). Green credit policy of China reveals that green innovators obtain more corporate loan as compared to firms having high environmental issues (Xing et al., 2021).

6.3 Literature Review

The author investigated the impact of financial development on renewable energy (Wu & Broadstock, 2015). The researcher has emphasized on the role of bank in financing renewable energy (Anto & Afloarei Nucu, 2015). Natural disasters are due to ecolephasizeddnce and rapid industrialization, and hence renewable energy is an effective way for sustainable development by using natural resources in meeting energy future demands (Rao, 2015). The researcher has assessed the role of Indian banking in developing strategies for adopting green banking across the country (Kapoor et al., 2016). Globalization has largely enhanced carbon emission in the atmosphere and it's time for ecological balance for the existence of mankind on the planet earth. The banking sector initiatives for green banking will play a very remarkable role in the adoption of green banking for the economic development. The researcher has examined the sustainability disclosure of Asia-Pacific banks such as (Australia, Japan, China, and India). Global reporting initiatives by Asia-Pacific bank in sustainability disclosure is more significant

than banks not participating in it (Islam et al., 2016). The author has found that the sustainability index in banking sector performance is adopted by banks and bank stakeholders also account for it (Rebai et al., 2016).

The researcher has focused on the practices of Bangladeshi commercial bank regulatory guidelines and green banking practices adopted from 2007 to 2014 by the banks (Bose et al., 2017). The study reveals that there is a significant impact of green banking disclosure and corporate governance mechanisms, whereas there is no relationship between green banking disclosure and independent directors. The author has examined the green banking products introduced by SBI for its corporate clients (Raj et al., 2017). The environmental degradation has adversely affected not only the economy but also society at large. The awareness and effectiveness of green banking have to be advertised extensively by banks for the customers to make it user-friendly whether it is for the use of online banking or mobile banking. The bank has to create awareness among its clients about environmental protection and encourage them to adopt its green banking products and services in Mauritius (Pariag-Maraye et al., 2017). The paper has focused on the barriers in adopting green banking technologies using factor analysis (Chan et al., 2017). The result identifies that policymakers need to provide specific solutions to problems affecting different industries. The investigator has analyzed the relationship between green product quality and loyalty of its customers (Tarabieh, 2018).

The researcher has studied the impact of green banking initiatives on the bank's customers' (Herath et al., 2019). The study concluded that there are four features that are significant in customer's satisfaction such as concern for security and trust, value creation, environmental friendly use, and social concerns. These features have enormously influenced the customers of banks. The renewable energy has been effectively backed by banks especially in EU, India, and China (Raj et al., 2017). The author has analyzed the strength, weakness, opportunities, and threats of green banking (Gopalkrishnan and Priya, 2020). The study reveals that banks for its sustainability need to formulate strategies for green products and services so as to make its operational and financing activities efficient and effective for its clients. The researcher has attempted to examine and identify the steps taken by Oman banks to reduce carbon footprints (Miah et al., 2020). The study has revealed that the banks' initiatives for environmental protection are only confined to recycling and reduction of paper consumption and energy. The author reveals that Pakistan banks are in the initial stages of implementing green banking to avoid natural resources depletion and

environmental degradation (Bukhari et al., 2020). The hurdles faced by the banks in creating awareness and the role of regulators must be considered in light of stakeholders' concern for developing economies in green banking. The researcher has examined the customer's satisfaction level and the adoption of green technology products offered by the bank in enhancing its image and its loyalty (Santikary, 2020). European banks have played a vital role in attaining sustainable development goals through its legal system and integrated report adoption (Cosma et al., 2020). Banks engaged in sustainable strategies have to develop sustainable products and be ethical in environmental protection (Aracil et al., 2021).

The investigator has examined sustainable dimensions of EU and U.S. banks and concluded that internal social dimensions of sustainability have a positive relationship with bank performance (Moufty et al., 2021). The unexploited green potential has to be recognized for saving the environment for the harmful effects of carbon emission in the air and easy green conservation is lacking by industries for financial gains (Licastro & Sergi, 2021). The study reveals that green banking has evolved in the development of renewable energy. Corporate social responsibility of both private and public sector banks has focused on enhancing its green bonds, green infrastructure, and green loans for sustainable energy growth by funding industries aiming at environmental protection (Prabhu & Aithal, 2021b). HDFC green practices have been able to save customers' energy, fuel, power, time, and money as it has been effective in creating awareness for environmental protection (Kaur & Bansal, 2020). The paper reveals that there is a significant relationship between institutional factors and green banking technology adoption. Thus, regulatory authorities and individual banks need to facilitate the adoption of green technology. Asian economy is affected by the lack of funds towards the promotion of green energy for sustainable development (Yoshino & Taghizadeh-Hesary, 2017). The Japanese financial sector is focusing on zero carbon emission due to growing climate risk by creating sustainable finance and investment for industries as per the Paris Agreement Capital Transition Assessment (Schumacher Kim et al., 2020).

The Latin American emphasis on sustainable banking contributes to the prosperity of EU countries through mutual efforts towards financial inclusion and education (Forcadell & Aracil, 2017). The banking business model is evaluated on the basis of sustainability, and the study identifies that the Germany and Norwegian bank business model is higher as compared to Spain, Hungary, Poland, UK, and Italy, with Italy ranking last (Nosratabadi et al., 2020). The researcher reveals that selected banks have effectively

implemented sustainable banking practices, and there is a huge potential for Indian banks to frame policies for the active implementation of green, sustainable banking services (Saxena et al., 2021). European banks have miserably failed in the sustainable development goal; thus, banking through green technology protects the environment for sustainable growth of the economy (Avrampou et al., 2019). The sustainable banking is largely dependent on the customer's attitude towards the services provided by bank and environmental consciousness (Taneja & Ali, 2021). The world is facing an energy crisis because of unsustainable development by industries in the various areas such as production, process, operations, functions, and huge consumption (Biswas & Roy, 2015).

6.4 Research Methodology

In the present study, the information regarding the Uttarakhand Gramin Bank and its performance has been collected from secondary data. The Uttarakhand Gramin Bank's annual reports from 2012–13 to 2020–21 has been studied by the researcher. The researcher has used primary data to collect information from the respondents across the state of Uttarakhand to know about the green banking initiatives of Uttarakhand Gramin Bank and the effectiveness of its IT-enabled banking services from its customers. Sample of 100 respondents has been randomly collected from the people of Uttarakhand. In this paper, the empirical study has been gathered through survey and random sampling method. A hypothesis is developed by the author to know the significance of green banking in attaining sustainable development through Uttarakhand bank. Chi-square is used to know the conclusion from the survey under study.

6.4.1 Hypothesis of the Study

Several studies were conducted to know the efficiency of Uttarakhand Gramin Bank, but this study lays emphasis on the role of green banking services in attaining sustainable development. The study has focused on the challenges and the relevance of the green banking concept in the future. Most of the urban banks and private banks across the world are financially strong enough to adopt the technology but rural banks aren't economically sound in implementing green technology and further it needs govt. assistance. The awareness level of consumers and RBI regulatory framework

enforcing implementation of green banking services is vital in enhancing the performance of the bank. The present research has developed a hypothesis which includes specific variables as well as other additional variables (Yadav & Pathak, 2016).

Sustainable development of green banking depends on the intention of the consumers to adopt it, concerning environmental issues (Heo & Muralidharan, 2019).

H1: Uttarakhand Gramin Bank has made significant contribution in attaining sustainable development through green banking.

H0: Uttarakhand Gramin Bank has not made significant contribution in attaining sustainable development through green banking.

6.5 Data Analysis and Interpretation

Uttarakhand Gramin Bank's development of innovative green products and services is effective. The UGB banking business in the state of Uttarakhand has increased since the last ten years (from 2012–13 to 2020–21) after it adopted technology in its operational activities and emphasized on e-banking and m-mobile services for its customers. In Indonesia, the regulatory authority examined the performance of the bank and reveals that sustainable bank disclosure had a positive impact on the efficiency of the bank (Kosasih et al., 2021).

Table 6.1 represents the respondent's demographic structure in Uttarakhand for the study. The survey participants are classified according to age, gender, marital status, qualification, occupation, and income level. The majority of the responses were gathered through face-to-face meetings and interviews with the participants in the state. The sample survey reveals that majority of the respondents consist of young and educated participants having concern for environmental protection as well as knowledge of green products (Jaiswal & Kant, 2018). The maximum age group of the respondents in the table is 25–35 years of age, followed by 35–45 years of age. The male and female respondent is about 76% and 24%, respectively. Apart from it, 78% of them are married and 22% are unmarried. According to the data above, 36% of the population under study is intermediate, followed by 28% matriculation, 25% graduates, and 11% postgraduates. Out of the total 100 respondents, 39% of them are in private jobs, followed by 26% farmers engaged in farming, 21% of them have govt. jobs, and 14% have their own business. The Table 6.1 shows that the maximum income level of 41% of

Table 6.1 Demographic Profile of the Representatives of the Study

<i>Sl. No.</i>	<i>Particulars</i>		<i>Frequency</i>	<i>Percentage (%)</i>
1	Age (years)	Up to 25	10	10
		25 to 35	38	38
		35 to 45	24	24
		45 to 55	18	18
		55 and above	10	10
		Total	100	100
2	Gender	Men	76	76
		Women	24	24
		Total	100	100
3	Qualification	Matric	28	28
		Intermediate	25	25
		Graduate	36	36
		Postgraduate	11	11
		Total	100	100
4	Occupation	Farmers	11	11
		Govt. service	36	36
		Private service	30	30
		Business	23	23
		Total	100	100
5	Marital status	Married	78	78
		Unmarried	22	22
		Total	100	100
6	Income level	Below 1,00,000	32	32
		1,00,000–3,00,000	41	41
		3,00,000–5,00,000	20	20
		Above 5,00,000	7	7
		Total	100	100

Source: Field survey.

Table 6.2 Findings

<i>Sl. No.</i>	<i>Statement</i>	<i>S.D. 1</i>	<i>D 2</i>	<i>N 3</i>	<i>A 4</i>	<i>S.A. 5</i>
1.	Do you think that Uttarakhand Gramin Bank has effectively created awareness about the green banking services to rural customers?	38	12	5	25	20
2	Is the IT-enabled banking services environmental friendly in use for the customers?	7	18	16	18	41
3	Do you feel that green products and services offered by UGB are instrumental in reducing carbon emission for sustainable banking services?	9	12	25	28	26
4.	Is the UGB's green banking policy not secured and effective as compared to other banks?	15	16	21	28	20
5	Is the bank's customer at ease with paperless work and e-banking services?	26	32	18	8	16

S.A: strongly agree, A: agree, N: neutral, D: disagree, S.D.: strongly disagree.

respondents is between Rs 1,00,000 and Rs 3,00,000, with 32% of respondents earning less than Rs 1,00,000.

6.5.1 Findings of the Survey

The role of Uttarakhand Gramin Bank in green banking and sustainable development in the state.

Table 6.2 presents statements to know about the green banking policy effectiveness in Uttarakhand.

6.5.1.1 Interpretation

Figure 6.1 shows that 38% of respondents strongly disagree and 12% disagree, while 25% of respondents agree and 20% strongly agree that Uttarakhand Gramin Bank needs to create awareness about the green banking services in the market more effectively through digital platforms and advertisements in rural areas.

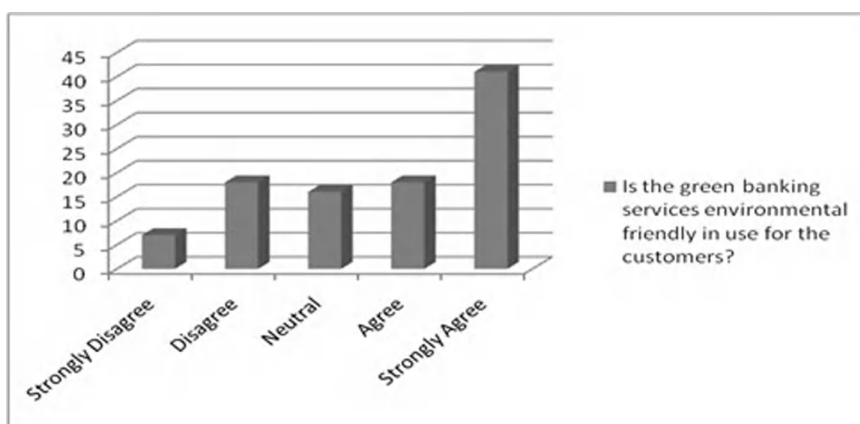


Figure 6.1 Level of awareness about Uttarakhand Gramin Bank green banking services

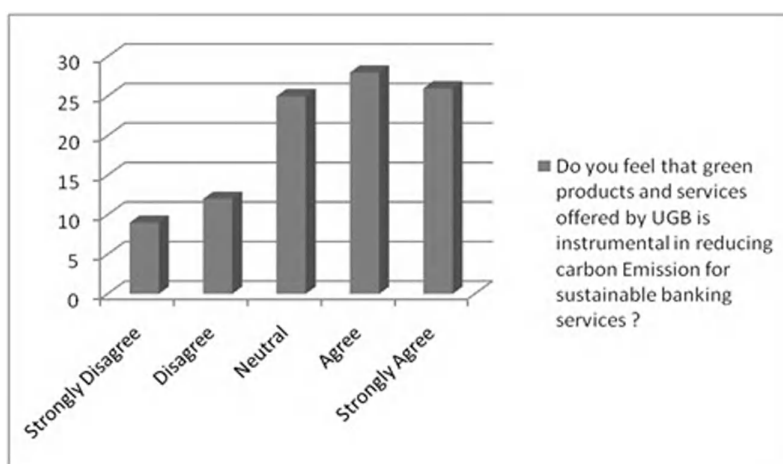


Figure 6.2 IT-enabled banking services are environmentally friendly in use for the customers

6.5.1.2 Interpretation

Figure 6.2 depicts that 41% of respondents strongly agree that IT-enabled banking is environmentally friendly in use for the customers of the Uttarakhand Gramin Bank, while 7% strongly disagree.

6.5.1.3 Interpretation

Figure 6.3 depicts that 28% of respondents strongly agree that Uttarakhand Gramin Bank is instrumental in reducing carbon emission for sustainable

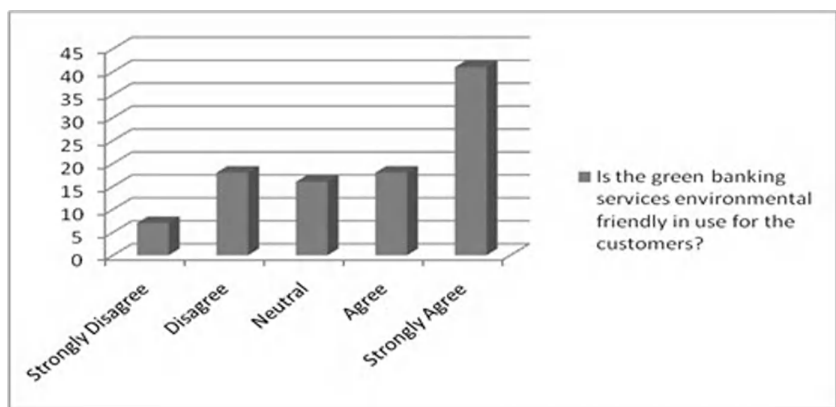


Figure 6.3 Uttarakhand Gramin Bank is instrumental in reducing carbon emission for sustainable banking services

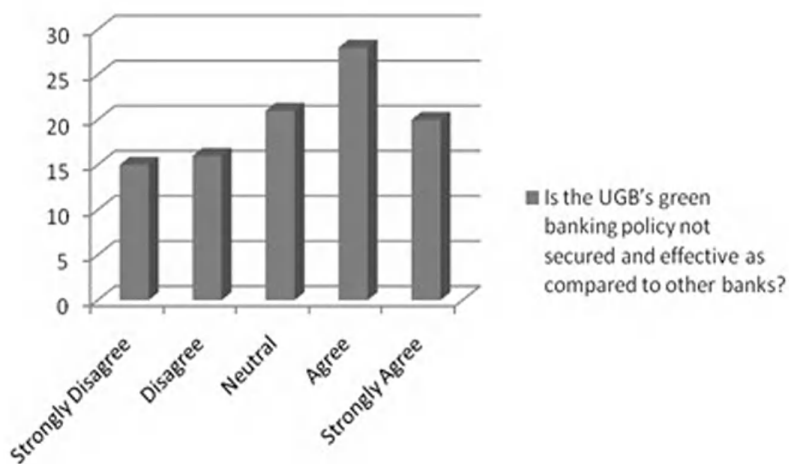


Figure 6.4 UGB's green banking policy not secured and effective as compared to other banks

banking services, while 25% are neutral and 9% strongly disagree. Hence, digital banking and mobile banking services need to be increased as they are economical not only for banks but also for their customers.

6.5.1.4 Interpretation

Figure 6.4 depicts that 28% of respondents agree that UGB's green banking policy is not secure and effective as compared to other banks, while 15% of respondents strongly disagree. Thus, the digital platforms of the Uttarakhand

Gramin Bank need to be secure, speedy, and effective to retain and increase the customer base.

6.5.1.5 Interpretation

Figure 6.5 depicts that 32% of respondents disagree that credit disbursed has been effective in the rural development of the state, whereas 16% of respondents strongly agree, and 18% are neutral regarding the effectiveness of credit in rural growth. The effectiveness of credit disbursed needs to be closely monitored for the growth of banks. Creditworthiness has a significant impact on the entire recovery of loans from borrowers; therefore, digitization is more effective in determining a borrower's creditworthiness.

6.5.2 Chi-square Test

The chi-square test was adopted by the investigator to know the impact of green banking technology in Uttarakhand Gramin Bank. The author emphasizes the need to increase the use of renewable energy to enhance green banking services not only for the operations of banking services but also for the use of its consumers. To test the significance of variables, the chi-square test was applied, and without this test, the significance of the variables under study would not be possible (Ali & Bhaskar, 2016).

H1: Uttarakhand Gramin Bank has made significant contribution in attaining sustainable development through green banking.

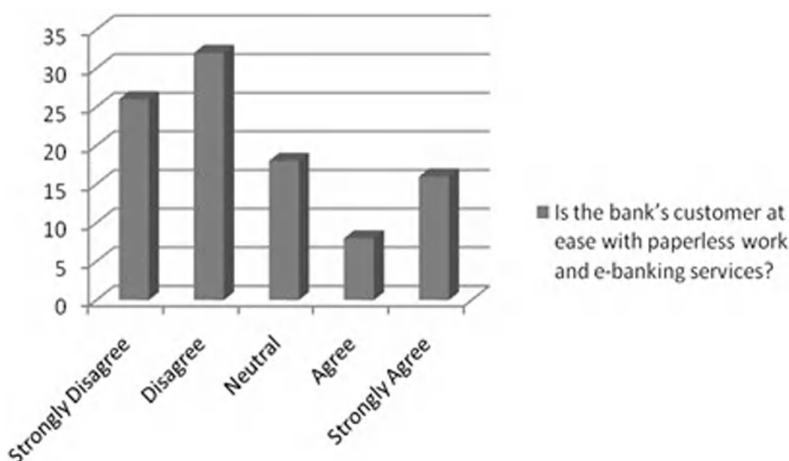


Figure 6.5 Uttarakhand Gramin Bank customer at ease with paperless work and e-banking services

Table 6.3 Chi-square Test

<i>Representatives</i>	<i>(O)</i>	<i>(E)</i>	<i>(O – E)</i>	<i>(O – E)²</i>	<i>(O – E)²/E</i>	<i>Total Values</i>
Agree	70	50	20	400	400/50	8.00
Disagree	20	30	–10	100	100/30	3.33
Neutral	10	20	–10	100	100/20	5.00

The calculated value is 16.33 and degree of freedom ($n - 1$), i.e. $3-1 = 2$

Note: O = observed ;value E = expected value.

H0: Uttarakhand Gramin Bank has not made significant contribution in attaining sustainable development through green banking (Table 6.3).

In this case, the tabulated value of the chi-square test for two degrees of freedom at a 5% level of significance is 10.26. So the null hypothesis is rejected as the calculated value is more than the tabulated value. Thus, the alternative hypothesis is accepted. Hence, the test concludes that the Uttarakhand Gramin Bank has made significant contribution in attaining sustainable development through green banking.

6.6 Application of the Study

The study will not only guide policymakers in the advancement of operational activities through green banking technology but also reduce costs and enhance sustainable development in the banking sector. The global banking sector should step forward towards the extensive use of green banking applications and create awareness about it among banking customers to ease banking facilities. The study leads to understand that the banking sector should be innovative in creating IT-enabled banking services environmental friendly in use for the customers across the globe. Customer perception reveals the inclination of bankers as well as its customers towards green banking technology to conserve energy for the future. The global summits, which usually talk of protecting the environment from pollutants, can be resolved to some extent through the adoption of innovative green banking services. After COVID-19, the global banking sector has observed that digital banking services have also been adopted by rural customers, not only in India but also across the globe. Therefore, to make it more effective, banking instruments have to be environmentally friendly, which will further help in achieving sustainable development in the banking Industry.

6.7 Conclusion

The chapter provides insight into the increased usage of IT-enabled services by Gramin banks for their customers and their impact on the profitability of banks. The findings provide an understanding that could develop the bank's business opportunities and enhance accessibility, along with fast and secure banking services in the rural areas of the state. A bank's physical existence is being rapidly substituted by the digitalization of all banking operations with everlasting online banking transactions for their customers. Thus, accuracy, transparency, and secure and fast banking services are the need of the hour for Gramin banks to retain and enhance their customer base. Environmental risk associated with the financial sector can be minimized through effective green practices by the banking sector. Thus, rural banks' traditional banking services need to be replaced by fast, secure, and effective digital banking services. Banks are expected to play a very significant role in rural development. Information technology has made the banking industry more efficient, and RRBs must adhere to financial innovative products to survive in the market. The researcher views that for sustainable development, banks should aim at designing their product services with environmental protection and user-friendliness for customers. Uttarakhand Gramin Bank has made a great effort in providing banking services at the fingertips of its customers through various digital banking services such as online banking, m-banking, UPI apps, etc., to rural customers in the state of Uttarakhand. Renewable energy sources such as solar energy and wind energy and biometric services, etc., need to be used extensively for sustainable banking services. The focus of the banks should be on solar ATM services, paperless work, green buildings, investing in green projects, and rewarding green initiatives from different sectors such as automobiles, horticulture, etc. Green banking practices of Dutch Bangla Bank Limited focus on huge investments in green buildings. The bank needs to formulate an Active Green Banking Cell to promote green banking across the country in India. The banks have to emphasize more on the automation of e-banking services, encourage green investments, and promote the digitalization of all the operational activities.

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Chapter 7

Driving Circular Economy Success: The Power of Collaborative Platforms

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Deepa Bisht, and Mohammed Ismail Iqbal

7.1 Introduction

Given the challenges of modern times, it's clear that our traditional ways of consuming and producing resources are no longer sustainable. The average American generates about 4.5 pounds of waste per day, and the global waste management market is expected to reach \$1.5 trillion by 2025 [1]. But there's a better solution: one that reduces waste while promoting economic growth, social equity, and environmental sustainability. Collaborative platforms play a key role in the circular economy by helping people efficiently share, reuse, and recycle resources. These platforms include peer-to-peer sharing services like Uber and Airbnb as well as subscription services like Netflix and Spotify. They also include material exchanges, repair centers, and waste exchanges, which promote sustainability while reducing waste. In addition to reducing waste, collaborative platforms help build stronger communities by connecting businesses and individuals who support the circular economy. They create spaces for knowledge sharing, skill development, and collective action. This chapter explores different collaborative platforms that promote the circular economy, discussing their benefits, challenges, and specific examples. It also highlights the role of technology, data privacy, and

regulation. This is a call for business leaders, policymakers, and individuals to work together to build a sustainable and regenerative economy.

7.2 The Power of Resource Sharing

Imagine a society where assets are collectively utilized instead of independently claimed. In this society, vehicles are shared among neighbors, instruments are loaned by companions, and clothing is traded with colleagues. This concept encapsulates asset sharing, a vital component for the success of collaborative stages within a circular economy. Consider neighborhood car-sharing administrations such as Zipcar. These activities ease activity blockage, reduce the need for unused vehicles, and cultivate a sense of community among users. Additionally, a tool-sharing service like Tool Bank offers enthusiasts the chance to borrow devices from one another, subsequently decreasing the need for modern acquisitions and promoting sustainable consumption practices. Asset sharing extends beyond vehicles and tools; it moreover includes the exchange of aptitudes, skill, and knowledge. For occasion, stages like Skillshare facilitate the sharing of skills and information among individuals, enhancing collaboration and mutual support in different endeavors [2].

By embracing asset sharing, we are ready to minimize waste, lower the demand for unused materials, and empower economical utilization. Besides, we can develop more grounded, more versatile communities where people join together to share and help one another. Hence, consider investigating the conceivable outcomes of asset sharing; it may very well be the pathway to a more economical, interconnected, and fulfilling existence [3].

7.3 Designing for Sustainability: The Patagonia Way

Imagine a world where products are made to last, not to be thrown away. In today's world, businesses are focusing on sustainability and circularity rather than just profits. This idea is called product lifecycle management, and it is an important element for collaborative platforms to operate in a circular economy. A great example is Patagonia, a company that has been at the forefront of sustainable design for many years. Its Worn Wear program encourages customers to repair and reuse clothing instead of buying new. By extending the life of its products, Patagonia reduces waste, the need for

new materials, and promotes sustainable practices. Patagonia also designs its products to be recycled, reused, or repaired, using environmentally friendly materials and methods. For example, their popular fleece jackets are made from recycled plastic bottles, reducing waste and supporting a circular economy. Through sustainable design, Patagonia creates new revenue streams, builds customer loyalty, and promotes a culture of sustainability. The Worn Wear program not only reduces waste but also contributes to the company's bottom line. Many participants become repeat customers, forming a loyal community that shares the company's values. Effective product lifecycle management also helps companies reduce their environmental impact. By designing products that can be recycled and reused, companies can reduce waste and rely less on new raw materials. This approach reduces greenhouse gas emissions, conserves natural resources, and promotes a more sustainable future. Product lifecycle management is an essential element of a collaborative circular economy platform. By creating products that can be reused, recycled, or repaired, companies can reduce waste, reduce the need for new resources, and encourage sustainable consumption. As consumers, we can support companies like Patagonia that prioritize sustainability and make informed choices by purchasing products that last [4].

7.4 The Power of Material Exchange Marketplaces

Imagine a world without waste, where businesses share and reuse materials instead of relying on new resources. This approach promotes sustainable production and is essential to the success of materials markets in a circular economy. Take, for illustration, the Material Exchange Platforms (MEP), an organization that is changing how businesses view waste and resources. MEP connects companies with surplus materials to others that can reuse them. This helps eliminate waste and promote sustainable manufacturing. By trading materials, the demand for unused assets is lessened, waste generation is diminished, and feasible utilization is encouraged. In addition, the impact of MEP expands beyond mere waste reduction. It builds up a system for businesses to share and repurpose materials, subsequently reinforcing sustainable production and reducing the natural impact of different businesses. For occasion, a material fabricating company can use MEP to discover a partner that will utilize its surplus materials, substantially reducing the volume of that would otherwise contribute to landfills and protecting common assets. Also, fabric trade marketplaces like MEP offer significant

advantages to businesses by lowering costs and enhancing operational efficiency. The repurposing of materials leads to diminished raw material costs and lower waste disposal costs. This not only positions businesses favorably in a dynamic market but moreover advances maintainable financial improvement.

What's in it for buyers? The MEP and similar materials trading markets help reduce the environmental impact of consumer products by promoting sustainable production and minimizing waste. For example, a clothing producer might utilize MEP to discover a company capable of repurposing their surplus materials, which would diminish the volume of waste directed to landfills and help protect natural resources. Thus, this may foster sustainable consumption and reduce the environmental impact associated with shopper merchandise.

Additionally, MEP marketplaces are likely to impact development and enterprise emphatically. In the way that MEP allows for the sharing and reuse of materials by businesses, it can help encourage the advancement of new products and administrations that are more sustainable and naturally inviting. This will lead to economic growth as well as sustainable development.

MEP marketplaces play a principal part in accomplishing victory for the collaborative stages. Such marketplaces connect the firms having excess materials to those which can reuse it, subsequently minimizing waste, upgrading sustainable production, and utilization. Customers, for their part, can advance the businesses that guarantee sustainability and circularity, as MEP, for example, does. Cognizant utilization would mean making cognizant choices within the products being acquired with reuse and recycled content. By working together, we can create a more maintainable future and reduce the natural effect of our utilization propensities [5].

7.5 Community Building: The Heart of Collaborative Platforms

Envision a world in which individuals get together to share information, abilities, and assets with each other for the creation of a more sustainable future. Typically, the world of community building—the heart of collaborative stages for the success of a circular economy. It is attainable to develop an organized network of people who engage in repair activities, share information, and take collective action towards maintainability. This approach

would empower sustainable consumption, minimize waste, and generate new business prospects. Consider the case of community repair cafes, which serve as settings for individuals to gather and repair their belongings rather than disposing of them in favor of new purchases. These cafes not only advocate for sustainable consumption but to cultivate a sense of community and belonging among members. The Repair Cafe in Amsterdam, for instance, has advanced into a dynamic center for community engagement, boasting over 1000 volunteers and offering a diverse range of repair services, extending from bikes to electronics. However, community building extends beyond the realm of repair cafes. It also includes online platforms that interface people and organizations with a shared commitment to sustainability. For instance, Shareable is a platform that encourages the sharing and borrowing of products, aiming to reduce waste and promote sustainable consumption. Similarly, Freecycle provides a space for individuals to give things they no longer need, thus preventing waste. Furthermore, community building plays a significant role in the creation of modern trade openings and the progression of maintainable financial advancement [6].

For example, the cooperativa platform helps individuals create and manage their own cooperative businesses, thereby encouraging sustainable production and consumption. Similarly, the B Corps platform enables companies to achieve social and environmental responsibility certification, thereby promoting sustainable business practices.

More to this, community building includes individuals, but it moreover concerns organizations and governments. For instance, Copenhagen as a city started numerous community building ventures. They set up a bike-sharing framework for utilization with less waste yields as well as creating a community garden to be portion of sustainable consumption and less output waste. This organization WWF propelled different initiatives such as having a platform through which they shared information and resources towards promoting conservation and consumption.

Community building is without a doubt the heart of collaborative platforms, and their victory within the circular economy depends specifically on it. It'll support a community of clients who are able to cooperate on repair activities, information sharing, and joint activity toward sustainability. It's going to contribute to feasible consumption, reduce waste, and help create new trade openings. Moving forward, there's no doubt that these sorts of platforms are aiming to reshape the way we consume and create.

Within the interest of a sustainable future, the circular economy has arisen as a progressive system, challenging the customary straight model

of “take-make-dispose.” Central to this change is the concept of collaboration, encouraged by innovative stages that unite businesses, customers, and communities to improve asset efficiency, minimize waste, and produce value. These stages transcend mere technological solutions; they speak to environments that promote shared responsibility and collective efforts. This chapter will explore how sharing stages, including collaborative initiatives, the “sharing economy,” and “item as a benefit” models, are driving the success of circular economies through viable examples of accomplishment [7].

7.6 Sharing Economy Platforms: Unlocking Idle Resources

The sharing economy speaks to the most recognizable type of collaborative platforms, fundamentally changing how people access and utilize resources. These stages decrease the need for new production by empowering people and businesses to share resources that are not fully utilized, thus promoting resource conservation and reducing waste. Consider Fat Llama, for instance. Fat Llama is a UK-based platform where one can rent their unused hardware from cameras and drones to musical instruments and control apparatuses. Individuals can borrow them from others rather than buying items that will only be utilized some of the time. It means they are extending the life of the product while reducing the demand for modern fabricating. The model also saves money for the client whereas advancing community and trust among the members.

Within the mechanical division, Floow2 has created a commercial center for businesses to share heavy machinery, vehicles, and even workforce capacity. For instance, a development company with idle excavators can rent them to another firm during downtime, ensuring that costly gear is utilized efficiently. This approach not only reduces capital consumption for businesses but also lowers the natural impression related to manufacturing and keeping up such apparatus [8].

7.7 Product-as-a-Service Platforms: Redefining Ownership

Another column of the circular economy is the product-as-a-service (PaaS) model, which centers on access instead of ownership. Rather than selling items, companies rent or lease them, maintaining control over maintenance,

repair, and end-of-life recycling. Producers are motivated to plan solid, repairable, and recyclable items because their benefit is linked to the longevity of the item. For illustration, Philips offers “Light as a Benefit” to companies:

Rather than offering light bulbs, Philips provides the lighting arrangements for businesses, with the charge based on actual utilization. At the end of their life cycle, the company retains possession and guarantees the proper recycling of these installations while remaining energy-efficient. This model has been adopted by major enterprises, such as Schiphol Airport in Amsterdam, where Philips manages the lighting foundation, reducing energy consumption by up to 50% and significantly cutting waste altogether.

The same holds true for Mud Pants, embracing a PaaS model within the design industry. Clients pay a monthly rental charge for pants and wear them as long as they wish before returning them to be reused into new denim products. This approach not only minimizes waste but also prompts buyers to reevaluate their clothing choices, fostering a culture of maintainability [9].

7.8 Repair Platforms: Extending Product Lifespans

Repair stages are fundamental in combating the predominant disposable culture that has affected customer propensities for numerous years. By giving available and cost-effective repair services, these stages contribute to extending the life of products, thereby reducing the request for new manufacturing and reducing squander. A striking example is iFixit, a global online community. The site provides complimentary repair guides and offers toolkits, enabling people to fix a wide range of items, from smartphones to household machines [10].

By demystifying the repair process, iFixit challenges the idea that items are expendable and empowers a DIY (Do It Yourself) repair culture. Their endeavors have picked up traction within the tech industry, where planned obsolescence has been a significant issue.

Repair Café activities have spread quickly around the globe. Community-run repair cafés bring volunteers and individuals together to assist in repairing everything from bikes to hardware. For example, a Repair Café in Amsterdam has saved thousands of items from landfills, fostered a community, and promoted sustainable utilization.

7.9 Waste Exchange Platforms: Turning Waste into Wealth

Businesses can now change the way they manage their waste and by-products through waste exchange platforms. These platforms create marketplaces for industrial collaboration, allowing companies to sell waste that can be reused as raw materials by other companies.

Circle Economy plays a key role in this area, converting plastic waste into high-quality PET plastic for packaging. With major brands such as PepsiCo and L'Oréal as customers, Circle has created a closed-loop system where plastic waste is reused over and over again. This reduces the need for new materials and keeps waste out of landfills [11].

Another case is Rubicon, a computerized stage that interfaces businesses with waste administration solutions. Its commercial center permits companies to discover low-cost and feasible ways to dispose of or repurpose their waste. For occurrence, a restaurant chain can utilize the platform to find a composting facility for its nourishment squander, turning what would have been waste into valuable compost for farming [12].

7.10 The Role of Technology in Enabling Collaboration

Smart technology is at the core of every successful collaborative platform, providing the foundation for collaboration, transparency, and efficiency. While the applications may vary, they all have one thing in common: the use of advanced tools such as data analytics, IoT sensors, and blockchain technology. They make processes smoother and build up trust among members, which is exceptionally important for circular economy activities to be successful. For example, when you place small computer sensors, called IoT sensors, on shared devices, like machines or tools, they send back real-time information. This information tells you how the equipment is being used, how well it is working, and when it needs to be repaired. This helps ensure that equipment is used in the best possible way, breaks down less, and lasts longer. For example, imagine a construction company that allows multiple crews to use the same piece of heavy machinery. Using these sensors, they can know when the machinery needs maintenance before it breaks down, saving money and ensuring the machinery is always ready for use.

Blockchain innovation, on the other hand, gives unparalleled straightforwardness and traceability. Blockchain creates an immutable record that shows everything that happens to a product from its beginning

(raw materials) to its manufacturing, use, and even recycling. This helps everyone involved trust each other more. In businesses such as design or gadgets, shoppers and businesses progressively request confirmation of sustainable practices. For case, a brand utilizing blockchain can demonstrate that its items are made from recycled materials, improving its validity and offer.

Information analytics makes these platforms further capable by revealing wasteful aspects and opportunities for progress. In the case of a waste exchange platform, analyzing designs in industrial by-products matches waste generators with businesses that can repurpose that material, effectively turning waste into profitable assets.

In substance, innovation is an enabler that changes over the thoughts of collaborative stages into an effective apparatus to encourage the circular economy. With such developments, businesses and communities will collaborate in a better way better toward a feasible future that's built on shared duty and believe [13].

7.10.1 Challenges and Opportunities in Scaling Collaborative Platforms

While sharing platforms promise to drive the circular economy, there are still many hurdles to overcome before everyone adopts them. Government regulations often cause problems because existing laws are not designed for these innovative new platforms. For example, local zoning or licensing requirements can make it difficult for peer-to-peer rental services to operate. Additionally, outdated waste management regulations can prevent companies from reusing byproducts. To address these issues, lawmakers need to update their rules because the circular economy requires new approaches [14].

The main problem is that many individuals and businesses are not aware of the benefits of sharing platforms. They still tend to buy directly and create waste in the usual way. In addition, resistance to change, caused by comfort or skepticism, adds to the challenge of changing the mindset. For illustration, renting items rather than owning them—a central concept within the product-as-a-service model—is new and awkward for most people. But at the same time, the difficulties give space for development and participation. Motivations through tax breaks, endowments, or gifts from governments may energize companies to adopt the circular approach. Public awareness and campaigns may increase consumers' recognition of the ecological and financial values that these sorts of platforms create and advance

supportability culture. Business leaders can demonstrate the value of circular models, such as repair shops or take-back programs, by investing in them and implementing their own initiatives.

Within the conclusion, this can be a challenge that will be overcome collectively. Working together, governments, businesses, and communities can create an empowering environment in which collaborative stages flourish, quicken the move to a circular economy, and open a more sustainable future for all [15].

7.10.2 The Benefits of Collaborative Platforms for a Circular Economy

Circular economy has developed as a transformative model for a maintainable future, changing the traditional linear “take-make-dispose” approach. These collaborative platforms refer to advanced ecosystems that bring individuals, businesses, and communities together to optimize resource use, waste diminishment, and shared value. These platforms are not just new ways of doing things; they also change the way we think, encouraging us to focus on sustainability, efficiency, and individual contribution. In this chapter, we will explore the key benefits of using these sharing platforms to promote a circular economy, showing how they help reduce resource use, create less waste, open up new economic opportunities, and reduce our impact on the environment [16].

7.10.2.1 Reduced Resource Consumption: Doing More with Less

One of the foremost critical benefits of collaborative platforms is their capacity to minimize asset utilization. In an environment where common resources are restricted and frequently overutilized, these platforms encourage the repurposing and sharing of existing resources, thus significantly reducing the need for new materials and products. This move is essential for decoupling economic development from resource extraction, which is a key principle of the circular economy. For instance, platforms within the sharing economy, such as Fat Llama and Floow2, embody this approach. They enable individuals and companies to share underutilized equipment, be it cameras, drones, or any other heavy machinery. Rather than buying something and storing it some place and having it lie there idle, one gets anything they need on demand, saving them cash and the resources needed to create, prepare, and deliver the item. For example, instead of purchasing an

expensive camera gadget, a little trade will let it lease that camera for a one-time use project, thus reducing the request for the raw materials—metals and plastics—in the long term.

Similarly, when we can access products without owning them, as with Philips' "Light as a Service" [17]. The focus is not on ownership but on the simple use of the product. People can now use lighting systems or office furniture by renting them, without having to constantly manufacture new products. This encourages companies to design sustainable and long-lasting products, which reduces the pressure on our resources. In short, sharing platforms allow us to achieve more with less, while ensuring that the resources we use are managed responsibly and equitably.

7.10.2.2 Waste Minimization: Turning Trash into Treasure

A noteworthy advantage of collaborative stages is their capacity to minimize waste generation. The straight economy model promotes the use of products only once before disposal, resulting in significant waste accumulation that ultimately contributes to landfills and environmental pollution. In contrast, collaborative systems foster mechanisms focused on recycling, repair, and reuse [18].

Repair stages, such as iFixit, empower people to patch harmed items, extending from smartphones to household appliances, rather than disposing of them. By offering repair information and essential tools, these stages extend the life of products and anticipate them from entering landfills. For example, a person who chooses to repair their tablet instead of buying a modern one not only saves money but moreover mitigates electronic waste, which is quickly becoming one of the largest waste categories worldwide.

Waste trade stages, like Rubicon, advance this concept by interfacing businesses with reusing and repurposing choices. For example, a fabricating firm can use such a stage to find a buyer for its scrap metal, which can then be liquefied and repurposed into new products. Moreover, food processing companies can offer organic waste to composting facilities, transforming what would otherwise be disposed of into valuable agricultural resources. These activities not only reduce waste but also cultivate a culture of responsibility and awareness, prompting both people and businesses to rethink their transfer hones [19].

7.10.2.3 Economic Benefits: Creating Value from Waste

Sharing platforms are not only good for the environment but also bring significant financial benefits. They create a more resilient and inclusive economy by creating new business opportunities and generating revenue

from materials that were previously considered waste. A prime case is the sharing economy, which has given rise to completely modern businesses, such as peer-to-peer rental administrations, empowering people to monetize resources that are not completely utilized. This approach not only helps generate income for some people but also makes goods and services more accessible to everyone.

Within the mechanical segment, waste trade stages afford companies the opportunity to create cash out of squander. For instance, a development company utilizing this kind of stage to turn concrete waste into riches saves on fetched since it no longer incurs disposal expenses; at the same time, it is able to make money from its products for its items from other businesses. Moreover, repair stages create work for skilled professionals and entrepreneurs in nearby financial systems while supporting small businesses.

In expansion, the demonstration empowers development and competitiveness. Companies that adopt circular hones regularly discover better approaches to include value to items and administrations, setting them apart from others within the marketplace. For case, a clothing rental benefit or a take-back program that a mold brand offers can attract environmentally conscious customers, enhancing its brand reputation and client devotion [20].

7.10.2.4 Environmental Impact: Building a Greener Future

Likely, the most influential advantage of collaborative stages is that they help improve the environment. This can be ascribed to their asset reduction and waste minimization efforts towards the use of feasible hones, consequently lowering carbon emissions and reducing footprints within the environment. For instance, a sharing economy decreases the production that must be done and subsequently reduces greenhouse gases emitted from the manufacturing process and transportation forms.

Product-as-a-service models moreover play a significant part in decreasing natural impact. By planning items for longevity and recyclability, companies can minimize the energy and assets required for production. For instance, Mud Pants leases denim items to customers and reuses them at the end of their life, diminishing the natural effect of material production.

Waste trade stages help redirect materials from landfills, which otherwise would contribute to methane emissions and other pollutants. For occasion, a company utilizing a platform for repurposing plastic waste saves money, but moreover spares the environment the harm that will be associated with creating new plastic.

7.11 A Holistic Approach to Sustainability

The genuine control of collaborative stages lies in tending to maintainability not as an arrangement of disconnected endeavors, but as an interconnected framework. Such stages outperform person benefits and combine asset efficiency, waste reduction, financial growth, and natural conservation into one coherent system. This creates a high-minded cycle that elevates society as a whole, fostering a culture of shared responsibility and collective action.

At their center, collaborative stages incite us to reconsider the way we devour, create, and arrange assets, which challenges the classic linearity of the “take, make, squander” model and empowers more noteworthy reuse, repair, and recycling, so that materials and items remain in circulation for as long as possible. This both diminishes the depletion of characteristic assets by extracting and fabricating and mitigates the related environmental degradation. A sharing economy platform that empowers the rental of tools or vehicles reduces unnecessary production and thus cuts carbon emissions as well as resource consumption.

Besides, these stages cultivate financial versatility by creating modern opportunities for businesses and people. Waste trade stages, for example, turn mechanical by-products into valuable raw materials, generating income while reducing disposal costs. Additionally, repair stages create jobs and bolster neighborhood economies, empowering communities to thrive in a maintainable way.

However, the travel towards a circular economy isn't a straightforward one. The total misuse of collaborative stages will depend on the joint exertion of all the partners included. Governments ought to be prepared to order steady arrangements that incorporate motivating forces for circular hones and controls pointed at reducing squander. It is fundamental for businesses to contribute in development and instruction to clearly communicate the esteem of maintainability to shoppers. Furthermore, people have a critical part in receiving unused behaviors and cultivating alter [21].

Eventually, collaborative stages serve as more than insignificant instruments; they act as catalysts for significant change in our interactions with the world. Through collaboration, we will harness the transformative capabilities of innovative technology, paving the way for a sustainable, impartial, and prosperous future for upcoming generations. The subsequent chapter will investigate how innovative technology is impelling this change, enabling these stages to achieve unprecedented levels of effectiveness and affect.

7.11.1 Challenges to Consider in Collaborative Platforms for the Circular Economy

In spite of the fact that collaborative stages offer noteworthy potential for progressing the circular economy, their usage faces a few challenges. On the off chance that these issues are not satisfactorily tended to, they may ruin the versatility and adequacy of these stages, subsequently obstructing the move towards a more sustainable financial system. This chapter investigates a few of the most critical challenges, such as coordination and transportation, information security and protection, and control and standardization. By comprehensively understanding and tackling these deterrents, we will enable collaborative stages to realize their full potential and drive meaningful change [22].

7.11.1.1 Logistics and Transportation: The Backbone of Circular Systems

One of the most noteworthy challenges confronted on collaborative stages is the successful administration of coordination and transportation. In a circular economy, materials and items are in a continuous cycle of use, sharing, reuse, repair, or recycling. This creates a complex network of exchanges that require consistent coordination to ensure operational efficiency and environmental sustainability. For example, on a sharing economy platform such as Fat Llama, where people rent personal items like cameras or drones, the forms of pickup, delivery, and return often occur over impressive separations. Moreover, in a product-as-a-service model like Mud Jeans, where clients rent clothing and subsequently return it for recycling, the coordination involved in collecting and redistributing these items can be very challenging. Each stage of this operation—scheduling, packaging, transportation, and tracking—demands meticulous attention to detail to prevent delays, harm, or excessive costs. Transportation itself presents another challenge, acting as a double-edged sword:

Whereas it encourages the development of merchandise, it also creates carbon emissions that can reduce some of the natural preferences related to circular economy practices. Moreover, inefficient coordination will only increase costs, making circular solutions less appealing to consumers and businesses. If the cost of transporting shared products exceeds that of purchasing a new one, customers may secure a new product, thus defeating the entire purpose of the initiative.

This would require a venture in keen coordination arrangements in collaborative stages. It would join savvy course optimization calculations, IoT-enabled tracking frameworks, and electric or low-emission vehicles for consistent operations that deliver less harm to the environment. Decentralized systems through partnerships with nearby businesses or community centers can create networks of drop-off and pickup points, which essentially decreases the length of transport included [23].

7.11.1.2 Data Security and Privacy: Building Trust in Digital Ecosystems

With sharing platforms relying heavily on digital technology, data security and privacy are major concerns. These platforms collect and process a lot of information about users, including personal data, payment information, how they use the platform, and their location history. Defending this data is pivotal not only for complying with administrative requirements but also for fostering trust among clients. Consider sharing economy stages such as Airbnb or Turo, which enable people to rent out their homes or vehicles to new clients. In these scenarios, sensitive information, including addresses and identification documents, must be securely stored and accessible only to authorized individuals. A data breach might lead to severe consequences, undermining client trust and harming the platform's reputation. Similarly, stages centered on waste trade depend on proprietary information shared between businesses concerning waste management and manufacturing processes. Unauthorized access or misuse of this information might result in unfair competitive advantages or industrial espionage. Companies using these platforms may falter to share their data, fearing that such disclosures may lead to improper handling of sensitive information. To mitigate these dangers, collaborative platforms should prioritize robust cybersecurity protocols. Implementing encryption, multi-factor authentication, and conducting regular security audits can altogether improve the protection of client information. Moreover, transparent security policies and clear communication regarding data usage can help build trust and encourage client engagement. Additionally, blockchain technology presents a promising solution for moving forward information security and straightforwardness in circular economies, as its decentralized and immutable characteristics offer noteworthy benefits [24].

7.11.1.3 Regulation and Standardization: Navigating a Complex Landscape

The circular economy speaks to a crucial change in our approaches to the generation, utilization, and transfer of items. Be that as it may, the existing directions and measures were to a great extent planned for a linear economy, which can create a bungle that can prevent the development of collaborative platforms. Clear rules for item quality, security, and responsibility in a circular economy are fundamental to ensuring consistency and reliability [33].

For example, in a “product as a service” model, who is responsible for the safety of the rented items? If the rented machine breaks down and causes an accident, will the manufacturer, the exchange, or the renter be held responsible? Without clear regulations like these, many people will hesitate to participate [31].

Essentially, during repair stages, the need of standard rules for restored items tends to be hazy. A smartphone repaired by a platform like iFixit isn’t guaranteed to be at the same level as a new gadget in terms of performance and solidness. Standardization can alleviate such issues by setting measures for repaired or reused items, thereby making them secure and reliable for shoppers [32].

Governments and industry both have a role to play in making these decisions. The development of rules for the circular economy must be a joint effort between businesses, consumers, and all other stakeholders to ensure that the public interest is protected. For example, the European Union’s Circular Economy Action Plan sets out a roadmap for regulatory change through initiatives such as extended producer responsibility (EPR) and eco-design requirements. Such activities can serve as models for other districts engaged in endeavors for circular advancement [25].

7.12 Overcoming Challenges: A Collaborative Effort

Tending to this challenge calls for engagement from all partners. This, of course, may be a collaboration between the government, businesses, and the individual—the triple-bottom-line approach to address the challenges of creating an empowering environment for circular stages. Motivating forces can be set through tax breaks and subsidies and even grants, but it’ll have an improved chance with investments from commerce to enhance coordination, information security, and assembly measures laid down within

the controls. Customers must adapt to circular solutions and advocate for change. Innovation will certainly play a significant part in addressing these challenges. Advanced data analytics can streamline coordination and lower transportation costs, while blockchain innovation can improve transparency and cultivate believe inside circular systems. Internet of Things (IoT) sensors can provide real-time monitoring of item conditions, ensuring quality and safety throughout their whole lifecycle. By leveraging these advancements, collaborative platforms can viably oversee the complexities of the circular economy and fulfill their commitment to sustainability.

Whereas the road to a circular economy is full of challenges, each obstacle presents an opportunity for advancement and development. Addressing coordination and transportation, information security and safety, and control and standardization will unlock the total potential of collaborative stages and drive the move to a more sustainable future. The journey will not be simple, but the rewards—for businesses, communities, and the planet—are well worth the effort. In the next chapter, we will see within another chapter how smart innovation is revolutionizing stock optimization, subsequently enabling collaborative stages to overcome the challenges of a circular economy [26].

7.12.1 Real-Life Cases of Collaborative Platforms Driving the Circular Economy

The circular economy is no longer just an idea; it is a reality, and many forward-thinking companies and organizations around the world are embracing it. Using shared platforms and smart technology, these groups are finding new ways to manage, use, and reuse resources. This chapter looks at four concrete examples of innovative projects that are driving the circular economy, demonstrating how technology and collaboration can create sustainable solutions for a better future.

7.12.1.1 Patagonia's Worn Wear Program: Repairing the World, One Garment at a Time

Patagonia, an open-air attire company that has, for decades, pledged to demonstrate its commitment to sustainability within the environment, has recently made history in decreasing material waste through its Worn Wear program. This site serves as a compelling example of how collaborative stages can advance the adoption of feasible hones among consumers,

consequently enhancing community engagement. The Worn Wear initiative is established on a clear yet impactful principle.

Repairing and reusing clothing is essentially more sustainable than disposing of it. Patagonia effectively empowers its clients to bring in their worn articles of clothing for repair, offering both in-store services and DIY (Do It Yourself) repair packs. Furthermore, the company organizes repair workshops to teach clients how to repair their clothing and extend its life expectancy. What distinguishes this program as innovative is its integration of technology. Clients can conveniently schedule repair orders, track the status of their items, and indeed trade utilized clothing for store credit through Patagonia's website. This approach effectively combines physical services with advanced components, upgrading comfort for clients while fostering a culture of sustainability. The impact of Worn Wear is significant. By promoting the repair and reuse of clothing, Patagonia has markedly reduced the request for new materials, thereby minimizing its environmental impact. Moreover, the program has developed customer loyalty, as people value the company's commitment to ethical practices. Beyond being a mere business strategy, Patagonia's Worn Wear initiative represents a challenge to the fast fashion industry's culture of disposability. It empowers consumers to ended up specialists of change in maintainability, illustrating how small actions can lead to critical changes [27].

7.12.1.2 H&M's Garment Collection Program: Transforming Used Apparel into New Possibilities

H&M stands as one of the biggest mold retailers universally and has made striking advances in progressing the circular economy through its Article of Clothing Collecting Activity. This activity embodies how major organizations can use their measure and impact to cultivate maintainable hones.

The program welcomes clients to return utilized clothing, regardless of brand or condition, to any H&M location. The collected items are sorted for recycling into modern materials or repurposed for alternative applications, such as insulation or cleaning materials. Furthermore, some wearable garments are exchanged as second-hand items, thereby extending their lifecycle.

H&M's methodology is supported by cutting-edge innovation. The company utilizes information analytics to upgrade the proficiency and maintainability of its collection and reusing operations. Moreover, H&M's online platform serves to inform clients around the importance of reusing and provides transparency regarding the destiny of their donated clothing.

The Article of Clothing Collecting Activity has evidently contributed to the diminishment of material waste. Since its inception, H&M has accumulated thousands of tons of clothing, effectively redirecting it from landfills and diminishing the dependence on virgin materials. This program is additionally in line with H&M's overarching sustainability objectives, which incorporate accomplishing 100% recycled or economically sourced materials by 2030.

In any case, the activity faces feedback. Spoilers argue that H&M's fast-fashion model fundamentally negates the principles of sustainability. In spite of these challenges, the Article of Clothing Collecting Activity represents a noteworthy progression. Through the integration of innovation and collaborative efforts, the activity suggests pathways to reduce the environmental footprint of the mold industry [28].

7.12.1.3 The Repair Café Movement: Building a Culture of Sustainability

The Repair Café development speaks to a grassroots activity that has accomplished noteworthy worldwide recognition, enabling communities to join together in the effort to repair damaged items rather than disposing of them. This movement exemplifies how collaborative stages can develop a culture of sustainability within local communities. Repair Cafés serve as community gatherings where talented volunteers, proficient in various areas from sewing to electronics, help inhabitants in patching their broken belongings. These occasions are frequently organized through online platforms that encourage associations among volunteers, participants, and event coordinators. The Repair Café Foundation, which underpins these activities on a global scale, offers assets and instruments to help communities in setting up their own events. The charm of the Repair Café movement lies in its simplicity and inclusivity, as individuals come together to exchange skills and knowledge, thus not as it were minimizing waste but also strengthening community ties. Participants leave with repaired items and a renewed understanding of the importance of repair and reuse. Technology is poised to play a crucial role in the success of this development. Organizers can efficiently coordinate events and manage registrations through online platforms. Additionally, social media enables the movement to reach a broader audience, inspiring more communities to engage in this activity. The strength of the Repair Café movement lies in collective action, countering a prevailing culture of disposability. Sustainability, therefore, isn't solely the responsibility of corporations but moreover includes the activities of people and communities [29].

7.12.1.4 The Material Exchange Platform (MEP): Redefining Resource Management

The Fabric Trade Stage (MEP) stands as a spearheading activity that joins people with excess materials to endeavors capable of utilizing them. MEP embodies the successful application of innovation in upgrading asset productivity and advancing a circular economy within the mechanical sector.

Working as an advanced commercial center, MEP permits businesses to list their abundant materials—be it textile, metal, or plastic—for purchase and repurposing by other companies. This approach not only mitigates waste but also provides businesses with an additional income stream. Modern algorithms facilitate the association between suppliers and buyers, fostering sustainable material utilization.

A key advantage of MEP is its adaptability. The stage cultivates associations among companies over different businesses and geographical areas, subsequently maximizing opportunities for fabric reuse. For example, texture remnants from a material maker can be utilized by a furniture producer, while excess steel from a development firm may find new life within the car sector.

The natural and financial points of interest of MEP are considerable. By redirecting materials from landfills and lessening the dependence on virgin assets, the stage plays an imperative part in fostering a more sustainable generation cycle. It not only brings down costs but also improves the sustainability profiles of participating businesses.

MEP is a great example of how technology can completely transform a traditional supply chain into a circular one. It shows that sustainability and efficiency can go hand in hand and that we can achieve this through innovation and teamwork [30].

These four examples demonstrate the power of sharing platforms to drive a circular economy. They cover a range of initiatives, from incentivizing customers to repair clothes to facilitating the exchange of surplus materials between companies. They show how technology and innovation can create sustainable solutions for a better future. As we explore the connection between smart technology and better inventory management, these real-world examples provide valuable insights.

7.13 Concluding Remarks

The move from a direct economy to a circular economy isn't just a unique concept; it speaks to an imperative and attainable alteration that's as of

now developing through innovative collaborative initiatives. These initiatives, which may concentrate on asset sharing, extending product lifespans, or repurposing waste, are illustrating that sustainability can coexist with economic progress. Examples such as Patagonia's Worn Wear, which advances article of clothing repairs, and H&M's Article of Clothing Collecting Activity, which changes ancient clothing into new possibilities, illustrate how businesses, communities, and individuals can collaborate with each other and with the environment to foster a future that's less wasteful and more resource-efficient. The Repair Café movement highlights that significant change often starts at the community level, where people join together to repair and reuse items, thereby nurturing a culture of sustainability. Moreover, initiatives like the Material Exchange Platform (MEP) exhibit how technological advances can change businesses by converting waste into valuable resources, generating economic opportunities while reducing environmental harm. These stories extend beyond simple waste reduction; they emphasize the need to reconsider our consumption, production, and interpersonal associations.

Of course, there are still challenges ahead. We need to address issues around coordination, data protection, and compliance before these solutions can be widely adopted. However, by combining innovation, collaboration, and working together, we can overcome these challenges. The concept of a circular economy is not solely the commitment of businesses or governments; it is a collective vision that requires cooperation from all segments of society. By embracing collaborative stages and making mindful choices in our everyday lives, ready to cultivate a regenerative and equitable economy that serves both humanity and the environment. This chapter serves as a call to action—a reminder that the path to supportability could be a shared journey. It may be a collective endeavor that thrives through creativity, partnership, and a dedication to change. Together, we can transform our understanding of how to live, work, and consume in a way that is in agreement with our environment. Long-term is circular, and it is our duty to bring it to fulfillment.

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Chapter 8

Harnessing Artificial Intelligence in Business Intelligence Systems: Advancing Smart Sustainability in Management

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8.1 Introduction

Sustainability has become a higher priority in the current scenario of business climate anticipated to increase in weight for social behavior and moral behavior. Artificial intelligence (AI) integration offers a rebellion towards effectuating sustainability objectives, building persistence, and guaranteeing long-term viability. The chapter clearly explains the improvement and regeneration of business. The old format of business models and various strategies will not be supportive to improve the regeneration of business. The serious discussions over sustainability in the business would speak on the stumbling block; the perfect possibility must be thought that improves the standard of living in sustainable development. Ameliorating the regeneration of business can guide us to think on what basis inventive compounds will reduce waste minimization, resource management, and moral supply chain procedures are needed. Adapting the new generation of business will have to give throughout possible feedback in the case of returns, where the stakeholders

will demand responsible corporate circumstances and other liability. In this sense, the situation here shows itself to be an effective instrument that may potentially improve policymaking, optimize the operation, and promote an eco-friendly environment. The proper intelligent tools achieve institutional efficiency gains, which will help improve operational efficiency and customer satisfaction to supplement their potential growth.

This chapter clearly delves into various AI applications that clearly support long-term business sustainability. It highlights that AI-driven insights will enhance logistics, machine learning aids in waste minimization and increased recycling, and predictive analytics will optimize resource utilization. By leveraging big data and advanced analytics, AI optimizes resources efficiently by reducing the environmental footprint. In addition, the chapter explores AI's impact on battling climate change through smart grid technology and real-time energy management systems that enhance energy efficiency. Through real-time case studies, it denotes how AI powered innovations have been helping the business navigate consumer expectations, environmental shifts, and economic uncertainties. The process by which AI is integrated for sustainability will present challenges and ethical concerns such as machine learning bias, data theft, and social impacts. It also has a balanced approach to ensure AI's benefits are equally distributed while aligning with social values. The actual need for strong governance and transparency frameworks to declare the ethics, accountability, and inclusivity in AI-driven sustainability initiatives is emphasized. AI has an immense strategy to regenerate corporate sustainability by fostering adaptability and resilience. The change-over is of exceptional importance for overall economic development because it focuses primarily on waste minimization within sustainable managing systems.

Integration of artificial and business intelligence systems provides an effective approach that perhaps enhances the progress towards achieving sustainability in management. It also makes a prototype shift in predictive analytics, enabling the transfer of raw data into actionable insights. The chapter further examines transformative impacts on business management, and its convergence of intelligence offers different organizations a unique opportunity to predict market changes, optimize operations, and improve customer experiences with precision. It makes both technologies adequately strong and visualizes data on AI's capacity by analyzing and predicting trends related to market. On the basis of innovation, it will likely make predictive analytics more accessible and scalable, fostering widespread adoption across industries. Enterprises that invest in integrating the latest technologies will likely remain the fastest-growing, competing with other industries in the

field. By engaging with these kinds of technologies, they will make better profits and understand or predict market trends according to the navigation of the business scale.

8.2 Literature Review

Ramirez and Clark (2024): Moral value of AI on sustainable development goals is that the study examines honest elements that occur while implementing AI system for SDG desired results. The transparency will exist only when establishing the fairness in sustainability programs which will remove the usual systematic bias. Ethical implementation should be responsible to sustain social justice alongside equal delivery and prejudice changes.

Kim and Lewis (2024). “Predictive Analytics for Environmental Sustainability.” *Sustainability Analytics Review*: The investigators analyze how AI-based predictive analytics helps environmental monitoring and risk evaluation tasks. Through specific case examples from energy and water resource management the authors demonstrate how AI systems detect patterns and anticipate environmental risks while maximizing resource distribution. The chapter demonstrates how AI facilitates early prevention strategies to decrease environmental harm while enhancing decisions supporting sustainability goals.

Singh and Nguyen (2024). “AI in Renewable Energy: Integration and Optimization”: The investigation looks at AI techniques which improve renewable energy operations starting with forecasting production rates and grid-level integration of renewable power sources. Study examples from solar and wind power energy projects demonstrate how AI technology makes operations more efficient and helps reduce system downtime while managing supply versus demand of electrical energy. The research investigates both battery storage optimization using AI algorithms and AI advancements in smart grid technologies.

O'Connor and Wang (2023). “Machine Learning in Carbon Footprint Reduction”: This research investigates industrial machine learning algorithms that trace and interpret and forecast carbon emission data within industrial environments. Researchers provides guidelines for natural gas through the implementation of three basic artificial intelligence suspension which includes digital energy monitoring systems together with AI of carbon trapping mechanism and automated emission recorders. Established reduction goals of enterprise have become achievable through the implementation of entire process.

Ahmed and Thompson (2023): Research evaluates how AI formulates with intelligence of business by proving its ability to generate automated sustainability reports, highlighting the importance of business analytics. Research shows that artificial intelligence enables enterprises to leverage data for sustainability compliance, aligned with international standards.

Rivera and Jones (2024): Main constitute of this research which consist of intelligence application dedicated to product life cycle management and recycling systems. This paper clearly examines how AI technology bring about waste minimization and material optimization and also sustainable product development.

Chen and Morales (2024). “AI in Sustainable Urban Planning”: The article interprets that how artificial intelligence supports urban development through its arrangement of optimal transport management systems and advanced energy systems and waste recycling programs. The article investigates on how smart city solutions enabled by AI technology enhance operational effectiveness of cities through congestion reduction and emission decrease while providing better sustainability results. Predictive traffic control operations combined with artificial intelligence resource management receive support from relevant case studies. The content studies the data protection challenges for AI-based urban planning systems and presents guidelines to establish these systems.

Kumar and Lopez (2023). “AI and Sustainable Consumer Behaviour”: This piece of research studies how customers react to sustainable buying decisions under recommendation frameworks combined with sentiment analytics tools which measure cognitive evaluation processes. Researchers have learned through AI-powered personalization methods that sustainable ethical products obtain better consumer acceptance because they become better visible in recommendation systems. This study evaluates privacy-linked ethical matters while scrutinizing the modifications that occur during data gathering following marketing system AI integration.

Martin and Zhao (2024): Intelligent technology sensors enable continuous environmental monitoring in real time. *Sensor Technology Journal*. The article evaluates how wearable AI technology systems help enable continuous environmental surveillance. AI-enabled sensor networks deliver immediate accurate measurements of environmental conditions that include air pollution levels and water contamination along with the analysis of ecosystem state. The research identifies AI systems that discover irregularities and forecast environmental hazards before serious manifestations occur. The practical applications demonstrated by case studies demonstrate how AI

systems help stop disasters and fulfill regulatory requirements. The authors explore sensor deployment difficulties which encompass both expense considerations and protection of data security.

Taylor and Singh (2024): This study explains how an enterprise had sustainability metrics become instantly accessible through AI technology thus improving their response capabilities to environmental changes. Data analytics plays an essential role in the research to support ESG reporting and supply chain management and corporate sustainability assessment tasks. Organizations can use AI analytics to achieve transparency and sustainable goal accountability through their systems. Businesses embrace AI technologies because they need to consolidate their operations while getting rid of algorithmic prejudices.

Lin and Parker (2024): The authors assess AI technology in their review of resource management techniques that conserve energy and water at optimal levels. AI solutions by this technology lead operations to decrease waste production and achieve better predictive maintenance and operation efficiency. This paper strictly analyzes AI technology implementation through case studies that demonstrate its effect on agricultural sustainability progress through industrial operational effectiveness improvements. Research evaluates the role of artificial intelligence in aiding economic sustainability and environmental performance maintenance for economies.

Patel and Green (2024): The *Water Sustainability Journal* discusses about drought modeling along with advanced irrigation systems and predictive analytics to explore AI packaging developments for water conservation within its pages. Artificial intelligence systems prove their effectiveness for water preservation by improving irrigation patterns and automatic leak detection and optimizing automated irrigation systems based on environmental factors according to the written research. The newly developed applications serve as dual sustainability boosters because they protect water resources while making operational resources more efficient.

Walker and Ahmed (2024). "Digital Transformation for Sustainable Business Practices." *Journal of Business Innovation* examines the business transformation for sustainability with AI-powered BI systems as digital tools in detail. Digital transformation assists organizations to select better decisions that enable more operational efficiency for the development of sustainable business models. The evaluation presents the method through which artificial intelligence technology enables automated sustainability assessment reporting along with regulatory compliance management.

Zhang and Patel (2023). “Framework for Optimization”: AI-powered systems used at the *International Journal of Logistics and Sustainability* help manage supply chain productivity by cutting down waste while tracking products better as an operational enhancement for logistics. Through concrete data the research study investigates firms which use AI to boost sustainability performance with related cost reductions. The research presents specific implementations of AI technology in forecasting demand and route optimization as well as supplier sustainability evaluation methods.

Gupta and Chen (2023). “AI-Driven Risk Assessment in Sustainability”: *Risk Management Journal* examines the manner in which AI systems detect sustainability risks particularly among establishments that operate under climate change threats. The research base leverages AI models to anticipate operational and financial risks which stem from environmental concerns. This article demonstrates how AI systems improve operational resilience and risk management while securing sustainable business operations over the long term.

Silva and Moreno (2023). “AI and Energy Demand Forecasting.” *Energy Analytics Journal*: This study assesses artificial intelligence forecasting systems which help lessen dependence on fossil fuels and enable renewable energy grids while forecasting future demand quantities. Through machine learning algorithms the study shows how forecasted energy consumption patterns aid utilities in achieving optimal operation of energy generation and delivery systems. AI-powered accuracy improvements enable the smooth integration of intermitting renewable systems wind and solar into the power grid which leads to more sustainable electricity networks.

Olsen and Wang (2023). “AI in Environmental Impact Assessments.” *Environmental Studies Review*: The research paper explores how AI eliminates environmental impact assessment delays by using scenario analysis models as well as automatic regulatory control systems. The combination of AI technology and automated assessment processes allows researchers to assess environmental risks quickly thus enabling faster project approvals that fulfill both environmental rules and speed up evaluation times. AI enables accurate future environmental predictions according to the research which allows public officials to make decisions with better information.

Choi and Evans (2023). “AI-Powered Decision-Making in Circular Supply Chains.” *Circular Economy and Innovation Journal*: A team of authors researched how circular supply chain decision-making receives support from AI technology to provide financial advantages to organizations and environmental benefits. The predictive capabilities of AI tools minimize supply

chain expenses through two related strategies: optimized logistics and minimized waste to augment product service duration along the entire lifecycle. AI platforms operate as tracking solutions to monitor materials during their complete lifecycle for operations such as reusing materials and recycling them and remanufacturing them. Artificial intelligence in the analytical system builds circular supply chain operations that simultaneously remove waste and decrease carbon impact for enhanced business sustainability levels.

Harris and Kumar (2023). “AI in Sustainable Retail Management.” *Retail Technology Insights*: The examination in this study focuses on AI technology expertise for inventory management improvements and waste reduction objectives in retail operation sustainability outcomes. AI-based demand forecasting enables businesses to align their inventory more effectively by hearing customer needs while lowering production amounts and creating important waste reductions. Supply chains enable better logistical operation through AI technology thus corporations reduce transportation expenses alongside emissions of greenhouse gases. AI technology allows retailers to achieve sustainability goals by improving store operational efficiency and decreasing waste production and obtaining sustainable products according to the research report.

Yang and Smith (2023). “Future Trends in AI for Sustainable Manufacturing.” *Industrial Technology Review*. This research project uses prediction analysis to foresee upcoming improvements in AI technologies which prioritize sustainable production operations across robotics and energy-efficient and waste-reducing solutions. The article explains how robots powered by AI together with automation systems lead to improved manufacturing efficiency along with diminished energy usage while lowering production expenditures. The research evaluates how AI monitors manufacturing operations in real time to identify operational inefficiencies and generate appropriate enhancement suggestions. The research shows how AI enables manufacturing plants to use renewable energy while supporting industry transition toward sustainable operations.

8.3 Objectives of the Study

- To analyze AI Integration and validate the role of AI in BI systems and its significant impact on sustainable management and decision-making.
- To assess how AI-powered BI tools optimize resource utilization, leading to a better efficiency along with a reduction in fraudulent consumption.

- To examine the contribution of artificial intelligence in lowering carbon emissions along with enhancing energy-related efficiency.
- To investigate AI technological solutions for building predictive analytics that aid sustainability planning as well as risk evaluation processes.
- To explore how the deployment of AI allows organizations to build greater transparency through supply chain monitoring and ethical framework support.
- To propose new sustainable frameworks that merge artificial intelligence technology with business strategic planning based on defined sustainability objectives.
- To identify the challenges and opportunities and also analyze the technological, ethical, and operational challenges and opportunities in AI adoption for BI systems.

8.3.1 Aim

1. This chapter aims at exploring on ways in which artificial intelligence (AI) improves business intelligence (BI) systems in promoting sustainable business and minimizing on the effects on the environment.
2. In the present study, the researcher seeks to understand how AI enabled BI tools can be used in advancing resource management and promote ethic supply chain and corporate sustainability.
3. Thus, the focus is on examining opportunities and risks and defining the concepts underlying the use of AI in sustainable management that respect both business and environmental goals.

8.3.2 Research Methodology

The survey has targeted among 243 business professionals who aimed to understand artificial intelligence's influence on sustainability best practice improvement. The objective of this research examined the environmental and social value alongside economic contributions of AI technology by maximizing resource use and decision quality and corporate efficiency. All data were obtained through a robust random sampling process that focused on data fairness. By using this selection method, the research achieved higher reliability while decreasing systematic errors because it provided participants with equal opportunities to participate in research. Set survey questions aimed to embed structured and semi-structured elements for assessing the AI implementation levels and both advantages and difficulties of AI usage in sustainability practices within organizations. A research combining

exploratory factor analysis and multiple regression analysis tested hypotheses regarding the relationships between AI technology integration levels and business sustainability performance. The analytical approach defined core elements about AI adoption criteria together with performance levels needed to achieve sustainable business targets while presenting exemplary implementations and assessment benchmarks. Research findings provide executives along with policymakers with important data about how AI serves as a strategic foundation for implementing sustainable business operations in today's economic environment.

8.4 Findings

1. AI Adoption and Sustainability:

The results further reveal that AI education and training have a positive influence on the sustainable use of resources; this correlation was complemented by observations that noted a high significance and positive link between AI and improvements in sustainable practices since the ($r = 0.7642$, $p < 0.01^{**}$).

2. Impact on Decision-Making:

The data revealed that AI-driven BI tools explained 42% of the variations in enhanced decision-making regarding the consumption of energy and utilization of waste.

3. Challenges:

The results for this test were that the cost of implementation of AI is negatively related to the use of AI with a correlation of -0.58 , which is significant at 0.05 .

4. Sector-Specific Insights:

The industries using AI for sustainability more frequently were manufacturing (65%) and renewable energy, while the least frequent were the retail industry (30%).

5. Proposed Framework:

The analysis identified three key factors influencing successful AI integration in sustainability: The six factors include technological readiness, organizational commitment, and stakeholders’ participation (Tables 8.1 and 8.2).

8.4.1 EFA

Interpretation:

- The KMO value (0.863) indicates that the data is fit for factor analysis, since the values exceeds 0.60 and is considered adequate.
- Bartlett’s Test shows a significant *p* value (<0.001**), confirming that the correlations between variables are highly significant for factor analysis.

Table 8.1 General Details

<i>Variable</i>	<i>Respondents</i>	<i>Total Percentage (%)</i>
Gender		
Males	147	60.50
Females	96	39.50
Total	243	100
Age		
Below 40 years	79	32.50
40–45 years	92	37.90
Above 45 years	72	29.60
Total	243	100
Media platforms		
Social network	85	35.00
Media sharing network	71	29.20
Discussion forums	64	26.30
Others	23	9.50
Total	243	100

Table 8.2 KMO and Bartlett’s Test

Test	Value
Kaiser-Meyer-Olkin (KMO) measure	0.863
Bartlett’s test of sphericity	$\chi^2 = 1235.78$, $df = 45$, $p < 0.001$

The four factors taken together account for a total of 77.83 percent of the variations. The study depicts that the first factor accounts for 25.97% variance, followed by the second factor with 20.31%, the third factor with 17.09%, and the fourth with 14.46%. Collectively, they explain the majority of variance in the observed data as it revealed areas that are most influential to the total amount of variation. Table 8.3 shows factor distribution.

The plot illustrates eigenvalues against component numbers, as shown in Figure 8.1. The plot shows that the first component has the highest total trace value and that the second component declines sharply thereafter. Subsequent elements make a lesser proportional input towards the total variation. This type of plot is useful in defining how many factors should be retained depending on the “elbow” or breakpoint after the first few components (Table 8.4).

Development of the Factors:

Factor Number	Factor Name	Statements
1	AI and sustainability reporting	Automated sustainability reporting, transparency in sustainability reporting, AI-driven risk management for sustainability, AI-enhanced corporate social responsibility
2	AI-driven optimization of resources	Predictive analytics in resource management, machine learning for waste reduction, AI for optimizing energy consumption, real-time monitoring of sustainability metrics
3	Supply chain sustainability and efficiency	Enhanced supply chain efficiency through AI, Integration of AI with circular economy, AI-powered environmental impact forecasting
4	AI for strategic decision-making and predictive analysis	Data-driven decision-making for sustainability, AI-powered environmental impact forecasting, predictive analytics in resource management
5	Ethical and responsible AI	Ethical AI for sustainable business practices, automation in sustainability compliance

Table 8.3 Total Variance Explained

Component	Initial Eigenvalues	% of Variance	Cumulative %	Rotation Sums of Squared Loadings	Total	% of Variance	Cumulative %
1	7.314	42.84	42.84	4.672	25.97	25.97	25.97
2	2.286	13.68	56.52	3.505	20.31	46.28	46.28
3	2.101	12.38	68.9	2.937	17.09	63.37	63.37
4	1.585	9.33	78.23	2.468	14.46	77.83	77.83
5	0.719	4.23	82.46				
6	0.648	3.82	86.28				
7	0.53	3.12	89.41				
8	0.462	2.72	92.13				
9	0.365	2.14	94.27				
10	0.278	1.64	95.91				
11	0.231	1.36	97.27				
12	0.214	1.26	98.53				
13	0.189	1.11	99.64				
14	0.162	0.95	100				

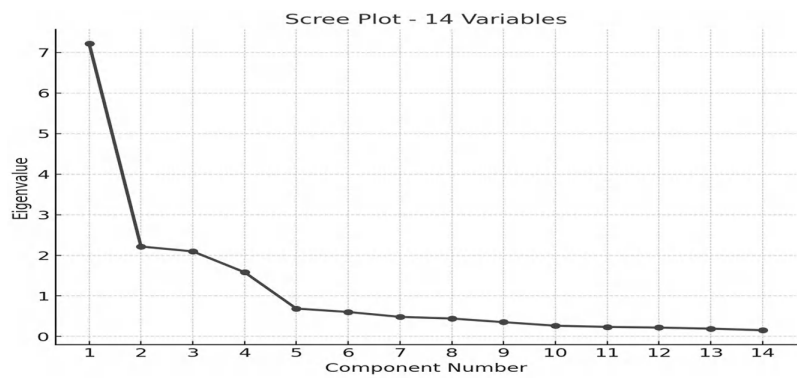


Figure 8.1 Factor Development

Table 8.4 Factors and Variables

S. No.	Statements	Factor Loading	Factor Reliability
1	Automated sustainability reporting	0.77	0.84
2	Data-driven decision-making for sustainability	0.72	0.79
3	Predictive analytics in resource management	0.69	0.82
4	Machine learning for waste reduction	0.74	0.81
5	AI for optimizing energy consumption	0.76	0.83
6	AI-powered environmental impact forecasting	0.7	0.8
7	Real-time monitoring of sustainability metrics	0.75	0.85
8	Enhanced supply chain efficiency through AI	0.78	0.79
9	Integration of AI with circular economy	0.73	0.77
10	Transparency in sustainability reporting	0.79	0.86
11	AI-driven risk management for sustainability	0.71	0.78
12	Automation in sustainability compliance	0.68	0.76
13	Ethical AI for sustainable business practices	0.77	0.84
14	AI-enhanced corporate social responsibility	0.72	0.8

8.4.1.1 Interpretation of Cronbach's Alpha

Table 8.5 shows the reliability of each factor, and all factors have acceptable to excellent reliability (Cronbach's alpha values above 0.7). Cronbach's alpha values for the factors—AI and sustainability reporting, AI-driven optimization of resources, supply chain sustainability and efficiency, AI for strategic decision-making and predictive analysis—are 0.85, 0.83, 0.80, and 0.82, respectively, showing good internal consistency with the reference value. Cronbach's alpha value for the factor ethical and responsible AI is 0.78, showing acceptable internal consistency. This suggests that the items within each factor measure the same underlying construct and are internally consistent (Table 8.6).

8.4.2 MRA

Explanation of the Columns:

1. The *R value* shows the strength of the relationship between the variables. Here, the *R Value* is 0.89, and it depicts a strong and positive correlation between the predicted and actual values.

Table 8.5 Reliability Statistics

<i>Factor Name</i>	<i>Number of Items</i>	<i>Cronbach's α</i>	<i>Interpretation</i>
AI and sustainability reporting	4	0.85	Good
AI-driven optimization of resources	4	0.83	Good
Supply chain sustainability and efficiency	3	0.8	Good
AI for strategic decision-making and predictive analysis	3	0.82	Good
Ethical and responsible AI	2	0.78	Acceptable

Table 8.6 Model Summary

<i>Model</i>	<i>R</i>	<i>R²</i>	<i>Adjusted R²</i>	<i>Std. Error of the Estimate</i>
1	0.89	0.79	0.78	1.28

2. *R square* (R^2) denotes the sharing of variance in the dependent variable described by the independent variables in the model. Here, the R^2 value is 0.79, which shows that 79% of the variability in the dependent variable is described by the model.
3. Adjusted R^2 value in this study is 0.78, providing more accuracy in comparing models with different numbers of predictors. The adjusted R^2 accounts for overfitting. If the value is lower than R^2 , the model may not be fitting the data well.
4. A lower value of *Std. Error of the Estimate* depicts the fitness of the model. In this model, Std. Error of the Estimate is 1.28. It gives a measure of how well the model is predicting the dependent variable.

The ANOVA explains the differences between the dependent and independent variables both within and among groups (Table 8.7).

Interpretation:

- Since the p Value is less than 0.01, this indicates that the regression model is significant. The F -statistic (32.52) is large, implying that the independent variables do a good job of explaining the variation in the dependent variable.

Multiple Regression Analysis of Business Intelligence on Factors of Smart Sustainability in Management

<i>Dependent Variable</i>	:	<i>Business Intelligence</i>
Independent variable	:	AI in sustainability
		AI-driven optimization
		Resource allocation
		Supply chain efficiency
Multiple R value	:	0.89
R^2 value	:	0.79
F value	:	32.52
P value	:	<0.001**

** is less than .005

The multiple correlation coefficient of 0.89 reflects the strength of the relationship between the actual and predicted values of business intelligence. Since the predicted values are derived from a linear combination of AI in

Table 8.7 ANOVA^a

<i>Source of Variation</i>	<i>Sum of Squares</i>	<i>df</i>	<i>Mean Square</i>	<i>F</i>	<i>Sig.</i>
Regression	189.72	4	47.43	32.52	<0.001**
Residual (Error)	124.11	238	0.52		
Total	313.83	242			

** is less than .005

Table 8.8 Coefficients

<i>Variable</i>	<i>Unstandardized Coefficients (B)</i>	<i>Standardized Coefficients (β)</i>	<i>Standard Error</i>	<i>t-Statistic</i>	<i>Sig. (p value)</i>
Constant	0.759		0.219	3.464	<0.001**
AI in sustainability	0.412	0.247	0.107	3.848	<0.001**
AI-driven optimization	0.311	0.215	0.108	2.889	<0.001**
Resource allocation	0.267	0.185	0.1	2.67	<0.001**
Supply chain efficiency	0.195	0.136	0.09	2.167	0.031*

Note: ** Denotes significant at the 1% level and * denotes significant level at the 5% level.

sustainability (X1), AI-driven optimization (X2), resource allocation (X3), and supply chain efficiency (X4), the coefficient suggests a strong and positive association between these variables.

The coefficient of determination (R^2) measures how well the estimated sample regression plane (SRP) explains variations in the dependent variable. With an R^2 value of 0.79, this indicates that 79% of the variation in adjustment is accounted for by the model, which includes depression and anxiety as independent variables. The R^2 value is statistically significant at the 1% level.

The regression equation is as follows:

$$Y = 0.759 + 0.412X1 + 0.311X2 + 0.267X3 + 0.195X4$$

Each coefficient represents the partial effect of an independent variable on business intelligence while keeping other variables constant:

- $X1$ (AI in sustainability) = 0.412: A one-unit increase in AI in sustainability is associated with a 0.412 increase in business intelligence. This effect is positive and significant at the 1% level.
- $X2$ (AI-driven optimization) = 0.311: A one-unit increase in AI-driven optimization leads to a 0.311 rise in business intelligence. This coefficient is also significant at the 1% level.
- $X3$ (resource allocation) = 0.267: A one-unit increase in resource allocation results in a 0.267 increase in business intelligence, with significance at the 1% level.
- $X4$ (supply chain efficiency) = 0.195: A one-unit increase in supply chain efficiency leads to a 0.195 increase in business intelligence. This coefficient is statistically significant at the 5% level.

Based on the standardized coefficients, AI in sustainability (0.412), AI-driven optimization (0.311), and resource allocation (0.267) are the key factors influencing business intelligence. Supply chain efficiency (0.195) plays a moderate role in comparison.

8.5 Conclusion

The use of AI in BI systems has recently been revealed as a key revolutionizer in the corporate environment and is changing the management of sustainability in companies. Given the emerging global issues of the environment and social challenges, companies aim at looking for ways in which they can measure up to the sustainability challenges without compromising on their grip on the market. Due to its function as a data-driven field that involves schedule, program, and process predicting, analysis, and improvement, AI appears as a promising tool for incorporating sustainability into business models. This article aims to offer a detailed evaluation of various attributes of BI systems, focusing on AI potential to promote smart sustainability within BI systems by increasing resource productivity, environmental responsibility, efficiency, and circular economy.

Therefore, the aim of this study was to ascertain how AI can contribute to sustainable development from business intelligence systems, specifically in areas such as resource management and allocation, energy efficiency, waste minimization, and supply chain management. The evidence supports the hypothesis that AI holds arguably the greatest potential for promoting sustainable business practices since they foster more informed organizational

choices. With the help of larger sets of various and intricate data inputs, AI-driven BI systems can reveal trends, make accurate forecasts, and deliver recommendations that will enable businesses to improve effectiveness and minimize negative effects on the environment.

Perhaps one of the most important advances of this research is to bring light into AI's contribution in BI for better resource management. Today organizations are under pressure to deliver more with less, and AI is an answer for it as they help present predictive insights that can help organizations anticipate demand, manage supply chains, and therefore resource allocation. Using data from previous interactions with buyers, AI can make accurate forecasts of demand and make suggestions as to where resources should be invested to avoid waste and to achieve optimum benefits. This can lead to great cost savings as well as add to environmental initiatives through elimination of overstocking and subsequent waste.

Further, energy efficiency and reduction in carbon emissions are other major areas where AI has an active contribution. By incorporation of big data and use of intelligent systems the business is able to track and manage the energy use in real time. AI can quantify areas of wastage of energy, be it in production, in transportation or in offices, and provide strategies on improving on the same. This directly corresponds to global sustainability goals, as companies attempt to achieve emission goals and decrease environmental impacts. Making it possible to vary the energy consumption in real time, artificial intelligence guarantees that companies and organizations are not just environmental friendly but also profitable in their activities.

Another factor is the capacity of AI to improve sustainability in the area of the supply chain. The study shows that AI has the potential to advance supply chain processes of inventory, demand, and logistics. Business intelligence systems incorporating artificial intelligence can enhance visualizations of the supply chain, making it easier to monitor the movement of inventories within a firm or across the value chain, leading to better cost optimization in distribution logistics and reduction of carbon footprint for organizations. Also, AI can assist the company in making better usage of sustainable materials by analyzing environment and social effects of various suppliers and then comparing the result with the best option. This feature of AI ensures sustainable business practices and fosters the development of responsible supply chain networks to advance long term goals of sustainability.

The second noteworthy revelation of this research is the central role of AI in sustainability and the circular economy. In the circular economy context, businesses are encouraged to abandon the conventional linear economy

generation model and embrace approaches that support the recycling and regeneration angles. AI helps organizations understand where potential exists for streamlining the product life cycle management activity relating to the flow of materials and products across the life cycle. Using AI, companies can predict when a product or its component will become physiologically obsolete and identify how to renovate, remanufacture, or recycle it. This is important in managing several resources with an aim of avoiding wastage as embraced in the circular economy system.

Besides such operational advantages, AI integrated BI systems can also support overall CSR initiatives of organizations. A major issue that arises in the process of CSR is the necessity of reporting sustainability activities and the degree of achievement of sustainability results per specific reporting period and to various stakeholders. AI technology can help with reporting since it can collect, conduct, and present analytical data which leads to ease reporting on compliance to sustainability regulations. AI can also be useful for reporting different types of sustainability, for example, carbon footprint, energy usage, or recycling statistics needed by the organization to meet legally mandated benchmarks and to ensure openness to the market, consumers, investors, and other interested parties. This increases the credibility of the organization and its sustainability issues hence matching the organization's image of its market standing.

The research also reveals the potential of the AI to enhance decision-making in the framework of sustainable development. This is due to the large volumes of data that is produced within different realms of operation in a business environment, which can easily overwhelm decision-makers when they are seeking to establish issues that they can work on. Machine learning and advanced analysis help businesses to make the right decision, to find out unknown correlations and trends, which will happen in the future. It can also be useful when applied to risks pertinent to sustainability, for instance, fluctuations in energy prices, unreliable supply chain, or unanticipated changes in the laws and regulations. Through AI, such risks can be evaluated before they occur hence business being able to incorporate sustainability in every decision that is made.

However, it should also be stated that this study that also highlights several challenges associated with the integration of AI into BI systems. Its major limitation is that timely, accurate, and credible statistics are particularly difficult to obtain. Machine learning models base their results on big data that are clean and contain accurate information. Data is mostly fragmented in many organizations by departments where its use is intended and hence

does not coordinate well. Moreover, organizations require the optimized techniques and capabilities required to implement AI applications, which can be expensive as well as time-consuming. However, there are many advantages of applying AI in the process of making an organization more sustainable, and the longer-term benefits will accrue to those organizations that start investing in such technologies.

This chapter concludes that artificial intelligence has an important part to fulfill in the progress of sustainability by utilizing business intelligence systems. Through analytical tools, forecasting, and optimization, AI offers organizations opportunities to make sustainable solutions in various business processes. Through the means of increasing resource utilization, cutting down on wastage and energy consumption, optimizing supply chain, or advocating for appropriate sourcing, use of AI in BI systems gives business organizations for the client control they require to operate sustainably. Especially as more and more companies experience a push from investors to address their ESG performance, AI offers a chance to develop better and more efficient business models. But ultimately, if AI is to reach its greatest potential of improving sustainability, technology, data, and talent assets will need further investment. As for the further studies, the authors should pay attention to the expanded AI practices in the field of sustainability in relationship to new sectors and existing and new trends in legislation. In conclusion, AI can be seen as a factor critical to the ongoing sustainable business evolution and a tool that ensures that companies are able to respond to sustainability challenges while maintaining competitiveness at the global level in the conditions of a steadily growing number of regulations.

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Chapter 9

AI and Sustainability Corporate Governance Reporting

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9.1 Introduction

In the modern world, with fast changing in the corporate environment, AI has transformed the way businessmen conduct their work, e.g., in product development, customer service, supply chain management, and risk assessment. It is altering every business activity in a company by increasing productivity, effectiveness, and the ability to expand. At the same time, our planet is facing more and more environmental and social realms. Therefore, AI is seen as a key instrument to implement sustainability solutions. Therefore, the growth of AI in the corporate setting offers tremendous opportunities to improve sustainability initiatives. However, it raises complex governance issues that need to be addressed to avoid the harm and/or misuse of these technologies and to ensure their responsible, ethical, and sustainable use.

I've always loved movie robots, even the bad ones. But as the machines around us become unnervingly smarter, it's hard not to worry that artificial intelligence with malign intent—some version

of the Terminator or HAL—will eventually be unleashed on the real world.

Gardiner Morse (HBR Magazine/May-June 2020).

I'm not alone in this bleak thought, of course. Stephen Hawking warned that “the development of full artificial intelligence could spell the end of the human race.” And when the Oxford philosopher Toby Ord examined a host of existential threats—asteroids, nuclear war, climate change—for his bracing book *The Precipice*, he ranked “unaligned artificial intelligence” the most probable of all.

Gardiner Morse (HBR Magazine/May-June 2020)

This chapter analyzes the relationship between artificial intelligence, sustainability, and corporate governance reporting. It demonstrates the role of artificial intelligence technologies in improving the processes of sustainability reporting, increasing the accuracy, efficiency, and transparency of environmental, social, and governance (ESG) disclosures. Historically, the burden of sustainability reports has fallen on companies' owners as a tedious approach dependent on manual work for the collection of data for subsequent analysis. AI algorithms have the ability to fetch and compose large amounts of data in a relatively shorter time and in a more accurate way. Such possibilities allow companies to optimize many of these procedures, ensuring reduction of errors and greater reliability of sustainability reports. AI can also facilitate the collection of relevant ESG information from third-party sources and databases, enabling timely reports on their sustainability orientation to stakeholders. This makes it easier to achieve efficiency and consistency of information over time while enhancing the level of accountability and reporting.

However, its ability to be applied alongside significant data volumes opens up new directions for environmental and social impact on business. For instance, AI can be used to monitor trends in resource/waste/energy consumption and generation, allowing entities to implement more efficient and environmentally friendly methods. Fortunately, companies are no longer bound by the reactive approach to the proactive approach. In other words, companies are not only ready for the challenges of AI but also serves as a tool for proactive early detection of possible environmental or social problems, risks, and troubles, thereby preventing further degenerate in the future. Machine learning, predictive analytics, and natural language processing

(NLP) tools can help companies forecast future sustainability issues and manage risk in near real time. This capability not only helps increase the operational efficiency of an enterprise but also turns it into an environmentally and socially responsible corporate citizen, able to contribute to global sustainability problems.

However, it is not just about information gathering and dissemination, but AI is at the center of company improvement in more than one way and in all areas of sustainability performance. Companies, through the application of AI technology, can gain a more complete picture of the environmental and social impacts of their activities. For example, AI analytics could be applied to monitoring and evaluating the effectiveness of green initiatives, producing evidence that leads to further enhancement. The use of AI for following supply chain compliance on environmental and social standards might be extended to cover such compliance issues, making compliance with environmental and social standards a reality for the entire value chain of corporations. In addition, due to the lending power of AI, companies are in a position to view it as a metric for resource use, waste reduction, and carbon reduction, thereby delivering short-term efficiency, long-term sustainability, and long-term survival.

As AI technology becomes more important to the overall concept of sustainable development, it is critical to understand the governance concerns regarding AI's application. This encourages collaboration between sustainable development and AI through the corporate governance arrangements which, to a certain degree, provide the strings to the proper development and utilization of AI technology with respect to corporate goals. Proper governance ensures that the set systems are aimed at the reduction of risks, injustice, and bias, while enhancing the fairness and transparency of the decision-making processes. AI systems can reinforce discrimination when accessed without a clear strategy for guidance, enabling unethical decisions made on biased algorithms and predictions. For example, AI prediction models which rely on racially biased data sets will predict perpetuation of discrimination within its American geographical scope. This will be prevalent in recruitment, credit, and customer profiling. Indeed, what is necessary is for AI systems to be implemented within a strict governance framework that guarantees fairness, transparency, and accountability of the AI decision systems.

In addition, governance frameworks assist businesses in dealing with the regulatory environment related to AI and sustainability. With AI emerging, it evolves simultaneously with the regulations concerning its application.

Each market has its regulatory framework; hence, all businesses are required to comply with both local laws and international regulations concerning the use of AI technologies. For example, the EU has taken a more active approach to the regulation of AI technologies and data rights in the implementation of any of its GDPR constituent principles. Likewise, certification details on whether or not the entity responsible has complied with GRI and SASB standards are becoming stricter as institutions are required to report on ESG metrics more transparently. Strong governance ensures that AI technologies work within the law, allowing the companies to operate in a legally compliant environment without the risk of legal exposure.

Corporate governance during the interlude is a structure through which the goals of the stakeholders are to be defined or settled. An ethical issue that requires further consideration is the research and the development and implications of AI for sustainability in a broad range of stakeholders, such as investors, customers, employees, and regulators. However, in the professional investor environment, it is clear that recently there has been increasing attention paid to firm-level ESG challenges related to investment decision-making, motivated by the shared experience of having the need to produce a [kind of] evidence of what the firm is doing in terms of AI and SDG. Not only does the introduction of sustainability and ethics into AI technologies build confidence, credibility, and a positive image for the companies developing them, but it also it build them, as a competitive edge in the marketplace.

This is the chapter where the issue of alignment between AI technologies and sustainability objectives is best emphasized. It is true that AI offers many opportunities to improve sustainability, but it must also be embedded into corporate practices carefully and strategically. The use of AI technology solutions requires attention not only to the technological aspects but also to other ethical, social, and ecological dimensions. This includes the requirements that AI should be employed in such a way that it does not damage economically disadvantaged groups, deepen existing inequalities, or degrade social and environmental conditions. In order to realize the full potential of AI in the long run, ethical concerns, which should ideally accompany AI systems, and sustainability goals, which should guide the adoption of AI systems in organizations, need to be integrated into the strategy for AI systems in organizations.

Hence, AI has the potential to drastically change ESG reporting practices in a company's approach by offering the means to improve data quality, which in turn will result in higher levels of transparency and a higher

degree of accountability in ESG disclosure. However, it is the combination of which governance concerns have to be taken into account. Corporate governance is a key mechanism to ensure the sustainable development and deployment of artificial intelligence technology in the sense of sustainability targets and moral values. The success of governance structures enables organizations to mitigate risk, show compliance with regulatory factors, and build stakeholder trust. As AI development progresses, companies sufficiently committed to exploiting the potential of this technology together with an ethical governance structure will be best positioned to create sustainable value, contribute to global sustainability initiatives, and thus facilitate ubiquitous beneficial change within business.

9.1.1 The Role of AI in Enhancing Sustainability Reporting

The unison of artificial intelligence with a focus on sustainability is changing the entire approach of organizations regarding the management, analysis, and dissemination of their environmental, social, and governance (ESG) data. The prominent problems that existed during reporting are being addressed by AI, providing solutions that lead towards real change in sustainability reporting practices. This is followed by a comprehensive assessment of the ways in which AI supports the evolution of sustainability reporting in the performance of a number of key functions.

The compilation of sustainability reports involves sourcing information from multiple internal and external databases, including operational, supply chain, and other stakeholders. As a result, AI completes this task efficiently using its automation capabilities to reduce the time required for data accumulation while guaranteeing adequate coverage.

Real-Time Monitoring: Due to the incorporation of AI, AI-powered Internet of Things (IOT) devices and sensors can autonomously perform the fast calculation of environmental measurements (e.g., energy usage and carbon footprint as well as water usage). This is the payoff of data rekeying being reduced, and it has resulted in the elimination of errors and delays.

Example: AI systems can monitor greenhouse gas emissions across a global supply chain, pinpointing areas where inefficiencies or non-compliance occur automatically.

Data Integration: AI platforms can integrate data from multiple sources, such as enterprise resource planning (ERP) system data, pre-fit databases, and satellite images, and create a combined dataset on which to conduct a deep analysis.

Advanced Analytics: AI algorithms create an entire space of pharmacopeias by processing relevant data in the pursuit of patterns and trends that allow companies to translate into operationalizing, discovering, and predicting possible emerging sustainability results.

Improving Data Accuracy and Transparency: Accurate and trustworthy data are key in securing the trust of stakeholders and in meeting the requirements of regulatory regimes. AI facilitates the verification of the accuracy of ESG reporting.

Error Reduction: AI tools assist in the reduction of manual involvement in data entry, data calculation, and reporting, which in turn enhances the credibility of sustainability reports.

Compliance with Standards: AI solutions are designed to be compliant with the largest-scale sustainability frameworks like the Global Reporting Initiative (GRI), Sustainability Accounting Standards Board (SASB) requirements, and the Task Force on Climate-related Financial Disclosures (TCFD), fostering uniformity and comparability of disclosures across entities.

Audit Trails: AI systems automatically maintain a large number of logs of data sources utilized and processes performed, providing traceability and the ability for external agency audits to be conducted.

Example: An AI system could cross-check energy usage data with utility records, flagging discrepancies before the data is published.

9.1.1.1 Identifying New Sustainability Metrics and Indicators

AI might be beneficial not only in determining areas of concern or areas of innovation but also in identifying metrics which did not form part of the conventional view of a sustainability report.

Custom Metrics: AI algorithms are capable of processing a large number of data sets and making recommendations on indicators that are suitable for the particular industry and its functions. For instance, an AI could determine that business entities in areas of water shortage should monitor water stress as a major dimension.

Dynamic Benchmarking: AI tools position the achievements of an organization within the context of the industry in which its operations are centered, enabling its clients to use relevant emerging metrics and drop those which are becoming irrelevant.

Scenario Analysis: Predictive analytics models the organization's operations in different sustainability environments and assesses the risks, such as climate change, that affect them.

Example: AI could propose new metrics like biodiversity impact or social equity contributions based on an organization's geographical and operational footprint.

9.1.1.2 *Enhancing Stakeholder Engagement and Communication*

Sustainability reporting is no longer a purely compliance process but also a major driver for stakeholders, including investors, regulators, employees, and customers. This engagement is enhanced by AI as the ESG data is more available, tailored, and actionable.

Interactive Dashboards: AI-enabled platforms offer interactive dashboards with real-time interactive visualization (e.g., charts, heatmaps, and trend lines) through which all parties can interrogate ESG information in real time.

Personalized Reporting: Natural language processing (NLP) can automatically create audience-specific ESG reports. For example, investors might be given an overview of the assessment (or even consumers might hear (sic) of what the responsible designed products of the corporation are).

Sentiment Analysis: Thanks to the chance to implement the power of AI technologies, it has become feasible to quantify social media and civil opinion to measure stakeholder sentiment around sustainability initiatives, thereby modifying organizational communication activities.

Two-Way Communication: Real-time communications could be made available through artificial intelligence (AI) chatbots/assistants to give feedback on sustainability and to receive feedback.

Example: A company could use an AI-driven platform to offer investors an interactive breakdown of its carbon reduction strategies while simultaneously providing customers with compelling narratives about community-focused initiatives.

9.1.2 *Governance Challenges and Best Practices for AI in Sustainability*

Artificial Intelligence (AI) technologies in sustainability reports, as well as in practice, are quite ushering in governance challenges and transformative opportunities. In order to fully harness the capabilities of AI while seeking to cognize ethical considerations and operational risks, robust governance structures must be put in place. Thus, a detailed communication is being made here below on the optimal practices and challenges in relation to AI and sustainability management.

9.1.2.1 Ensuring Ethical and Responsible AI Development and Deployment

Challenges:

- **Bias in Algorithms:** AI systems can operate with specific biases if the data they infuse is non-representative or erroneous in nature, thus creating disequilibrium in the sustainability targets.
- **Ethical Dilemmas:** Using AI-based technologies to observe and control ESG factors like employee benefits or community issues can be associated with respect and self-determination related concerns.
- **Unintended Consequences:** Models driven by AI could stress smoothing operations rather than sticking to ethical practices, for instance, excessive cost reduction measures that run counter to sustainability.

Best Practices:

- **Adopt Ethical AI Frameworks:** Implement AI ethics guidelines that prioritize fairness, accountability, and inclusivity in model development and deployment.
- **Diverse Data and Teams:** Apply heterogeneous, representative data sets and incorporate multidisciplinary teams in the design of AI to prevent biased models.
- **Ethics Committees:** Organize projects and maintain adherence to the organization's sustainability principles by establishing AI ethics councils.

Example: A company using AI for supply chain monitoring could include external stakeholders in its ethics committee to ensure fair treatment of suppliers in developing regions.

9.1.2.2 Mitigating Potential Risks and Biases

Challenges:

- **Data Vulnerabilities:** AI systems need a lot of data, which makes them vulnerable to errors, lack of data, and data tampering.
- **Bias Amplification:** Sustainability measurements or reports may be biased, and, on the other hand, be distorted if AI models are not kept in check.

- **Over-reliance on AI:** Making decisions depending on AI without human supervision may be risky as and lead to wrong assumptions, especially for multi-dimensional and delicate sustainability situations.

Best Practices:

- **Regular Audits:** It is also imperative to perform routine audits of AI models and their outputs to identify and correct biases and/or error.
- **Bias Detection Tools:** The use of the latest tools and methods for BIAS detection and mitigation during the training and operation of AI models.
- **Human-in-the-Loop:** AI output must be checked with human oversight and supervision at key decision points in order to ensure that the output is contextually lawful as well as to meet sustainability goals.

Example: AI-generated ESG reports should be reviewed by sustainability experts to ensure alignment with organizational goals and stakeholder expectations.

9.1.2.3 *Establishing Clear Accountability and Oversight Mechanisms*

Challenges:

- **Lack of Ownership:** The failure of accountability when bad things happen is due to a lack of coherence between ownership of responsibility and to whom the task of making an AI decision lies.
- **Regulatory Gaps:** Technologies aimed at artificial intelligence (AI) are designed and implemented at unprecedented tempos in social and workspace design before corresponding regulatory regimes appear, resulting in companies being left to deal with regulatory sandboxes.
- **Cross-Functional Complexity:** Multidisciplinary regulation of AI is not only desirable but also potential conflicts may arise between different disciplines (e.g., information technology (IT), environment, and law).

Best Practices:

- **Accountability Frameworks:** In order to accurately delineate the responsibility of each party in relation to AI decision-making (e.g., model design, model deployment, and consequent output), it is first required to determine the responsibility of each party.

- **Board Oversight:** In addition, the Board of Directors oversees AI projects in order to ensure they remain in keeping with corporate governance and sustainability strategy.
- **Collaboration with Regulators:** Proactively participate in the establishment of area-specific regulations in the area of sustainability and use of AI.

Example: A company deploying AI for climate risk analysis could assign accountability to a cross-functional team, ensuring alignment between technical capabilities and governance standards.

9.1.2.4 Promoting Transparency and Disclosure of AI-Related Information

Challenges:

- **Opaque Algorithms:** The internal workings or features of numerous AI systems are inaccessible or hidden, which cumulatively leads to a situation where many users do not know how the AI was tuned to make such decisions.
- **Stakeholder Distrust:** The inadequacy or absence of transparency in AI's operations tends to create mistrust among investors, clients, and even those who regulate the companies.
- **Insufficient Disclosure Standards:** Most of the organizations have no clearly set rules for making the AI information known, thus resulting in a diversity of practices.

Best Practices:

- **Explainable AI (XAI):** Develop explainable AI models, i.e., models that are intrinsically explainable so that stakeholders can interpret the reasoning of an artificial intelligence system within the context of its actions.
- **Transparent Reporting:** Detailing which elements of AI methodology, data, and decision-making process are as open as possible in sustainability reporting.
- **Stakeholder Engagement:** Effectively involve stakeholders and explain why artificial intelligence (AI) is used in sustainability projects and how it is being applied.

Example: A company using AI for ESG scoring could publish a transparency report outlining the data sources, algorithms, and criteria used to calculate scores.

9.1.3 The Future of AI and Sustainability Corporate Governance Reporting

The incorporation of artificial intelligence (AI) enhanced innovation within the sphere of sustainability as well as the area of corporate governance reporting. In this regard, the world has observed the trend that advances in technology, new regulation, or new engagement by super stakeholders shortly alter the landscape within which organizations have to operate. In relation to the future of AI within this space of intervention, a number of critical factors shaping it have been elaborated below.

Emerging Trends and Technologies: AI is evolving and so its application in the field of sustainability reporting will grow further in accordance with advances in technologies and approaches.

Advanced Predictive Analytics: An AI and blockchain hybrid strategy will enhance the provenance and verifiability of ESG data by providing irrefutable evidence of sustainability activities and establishing trust among stakeholders.

- **AI-Blockchain Integration:** The two technologies, AI and blockchain, will increase the precision of verification of ESG data. They should also create an everlasting record of dedication to being sustainable and bring confidence to the stakeholders.
- **IoT and Edge Computing:** When combined with edge computing, IoT devices will enable organizations to gather real-time variance data on critical parameters such as emissions levels, energy consumption, and waste management, hence lowering latency while increasing accuracy.
- **Generative AI for Reporting:** New developments, e.g., the adoption of applications such as ChatGPT (and associated technology), will allow scaling of personalized ESG reporting to be timely and responsive enough to address the needs of a dispersed community of stakeholders as well as comply with regulatory requirements.
- **Digital Twins:** Using artificial intelligence-driven digital twins, these organizations will not only be able to simulate sustainability scenarios, but also to challenge the consequences of a proposed project and to optimize use of resources prior to its application.

Example: A manufacturing company could use AI and blockchain to verify the carbon footprint of its supply chain and communicate this transparently to consumers and regulators.

9.1.3.1 *The Evolving Regulatory Landscape*

The regulation of artificial intelligence (AI) and sustainability disclosures continues to be one of the most challenging and complex challenges to confront directly for companies that aim for ESG and AI responsible applications.

- **Global ESG Reporting Standards:** There are also cases, e.g., the International Sustainability Standards Board (ISSB), that are promoting the harmonization of ESG reporting standards; thus, standardization of metrics and methodologies by stakeholders will be required.
- **AI-Specific Regulations:** Legislators, governments, and international organizations are scrambling to legislate the ethical application of AI, e.g., The AI Act of the European Union, which attempts to bring transparency, evaluate risk, and liability of such AI systems.
- **Mandatory Climate Disclosures:** In multiple jurisdictions, climate-related financial disclosures will be made mandatory, and in doing so, companies will be expected to use AI solutions in order to gather, analyze, and reveal the required information.
- **Auditing and Verification Requirements:** There is a burgeoning interest in third-party verification of ESG reporting, at which point third-party verification may be going further into AI-powered audit tools with a view to improving both compliance and accuracy.

Example: The SEC's proposed rules on climate-related disclosures in the U.S. could drive the adoption of AI to meet the requirements for detailed and verifiable sustainability data.

9.1.3.2 *The Role of Stakeholders in Shaping the Future of AI and Sustainability*

Institutional investors have been increasingly assertive on the issue of better fidelity, open, and robust ESG disclosure. They are, in fact, also promoting the ubiquitous industry-standard adoption of AI-based tools in order to enhance reporting quality and to enable evidence-based decision-making.

- **Investor Expectations:** Institutional investors are demanding more detailed, transparent, and reliable ESG disclosures. They are also pressuring organizations to adopt AI-driven tools that enhance reporting quality and facilitate informed decision-making.
- **Consumer Advocacy:** In addition to demanding sustainability and best practices, consumers are also calling on companies to use AI to better ensure the transparency of the source of products (e.g., origin/sourcing of the product), environmental and occupational states, etc.
- **Employee Participation:** Staff actively participates in responsible development of AI and creates organizational expertise on sustainability, which in turn results in improved internal governance and policy within the organization.
- **Collaborative Efforts:** Partners have collaborated to break down silos between industry, government, and academia to the point that best practices have been developed and standards have been established for the implementation of AI and sustainability reporting.
- **Regulatory and Policy Influence:** Stakeholders, for example, NGOs and advocacy organizations, therefore influence regulations and policies on ethics, and the regulation of sustainable development of such ethics regulations for AI.

Example: Shareholder resolutions filed by large institutional investors often call for greater use of AI to improve the transparency and accuracy of climate-related disclosures.

9.2 Literature Review

The merger of artificial intelligence (AI) within the area of sustainability and corporate governance reporting is changing the process of gathering, analyzing, and disclosing information on environmental, social, and governance (ESG) issues. On the other hand, installing a wide range of AI systems at such enterprises solves a number of operational problems. These systems allow the company to simplify the compilation of integrated data significantly, ensure better and clearer reporting about the sustainability agenda, and make wiser decisions. At the same time, however, the implementation of AI systems creates new problems that need to be addressed.

An interesting aspect of AI in ESG reporting is its automatic solving of the collection and analysis of a huge AI volume of data. Most of the time,

information related to ESG is provided through long and tedious manual processes, which are liable to human error. Zhang and Li (2023) show how the incorporation of AI can fully transform these processes by automating the collection of data and making it possible to track data in real time. With AI on their desks, board members and sustainability managers are able to have dashboards indicating the performance on sustainability parameters updated on a daily basis. This technology has made it easy to gather data, which reduced the time and other resources needed to do so, making the reports on sustainability pure and devoid of material waiting periods. However, the use of AI techniques involves high costs and privacy issues, which make their widespread use difficult. Another important aspect of the literature is AI's potential to improve the overall quality and credibility of ESG reports. Johnson and Kumar (2024) point out to the use of AI algorithms to identify discrepancies in the sustainability narrative in a bid to help curb the likelihood of greenwashing practices. Greenwashing occurs when companies make misleading or false environmental claims to improve their public image without implementing meaningful sustainability practices.

AI can assist in cross-checking the dissonance that exists between a company's professed environmental and social goals and its actual performance, ensuring that its claims regarding ESG have a basis and conform to what the company is doing. Natural language processing (NLP) tools can even add to accountability by enabling corporate documents to meet the requirements of international sustainability standards for reporting, such as GRI, SASB, TCFD, and others. These tools can scrutinize textual materials in corporate reports to ascertain adherence to reporting frameworks and indicate areas where companies might be in violation of certain requirements.

Moreover, AI helps to foster transparency while enhancing the efficiency of governance mechanisms, and decision-making. Anderson and Lee (2024) recount how AI may be deployed for risk management and risk scenario analysis for the evaluation of sustainability risks by corporate boards, which may be long term in nature such as climate and social justice risks. With the aid of AI, different scenarios are recreated, and the impacts of multiple sustainability policies are evaluated. This sort of risk evaluation fosters the ability to identify threats and opportunities in a way that allows businesses to implement more strategic sustainability measures, positioning them better for future difficulties. Furthermore, the application of AI within governance systems makes the decision-making process more precise and less subjective, enhancing accountability. Gupta and Fernandez (2023), for instance, examine the role of AI in the advancement of the quality of ESG reassurance services.

AI is able to increase the correctness of ESG reporting by decreasing human error in the course of automating auditing practices. Automation in auditing tasks using these tools will allow ESG information to be scanned for correctness and substantiated with the documentation. This also lessens the amount of time and resources needed to review the account books, hence making the process more efficient. In addition, Gupta and Fernandez investigate the scope of AI opportunities in merging with blockchain technology, which improves the traceability of data and its integrity. The blockchain presents a reliable and accurate record of transactions that can help eliminate misinformation and lack of accountability for ESG data. This means that the reports produced by the companies would not only be accurate but, with the help of traceable evidence, authentic in nature.

Although those benefits are reported elsewhere in the literature, the following limitations are reported in the application of AI to sustainability reporting. One of the most significant challenges is algorithmic bias. AI yields no better than the data used to train it, and if the data used to train AI models is heterogeneous and too small to extract meaningful information, the AI model will yield a similar result as that of a small dataset. Chatterjee and Smith (2024) being asked about potential algorithmic bias in AI, particularly in the creation of sustainability stories. For instance, when an AI learns from data that poorly represents a wide range of environmental and social problems, it will not be able to detect most of the most urgent risks and opportunities for improvement. In the risk mitigation plan, a particular issue for organizations is how best to show that their AI systems are trained to be diverse and representative and can be continually audited to ensure that the models are unbiased. Another challenge is data privacy. Information related to the management of company employees, the supply chain, financial information, etc. may be hidden in the ESG data extraction and processing. Decisions of artificial intelligence systems (AI) around Europe, which are covered by data protection legislation, must be aligned such as to respect individual data privacy and foster trust among stakeholders. AI systems are to be designed in a way that personally identifiable data management is protected and that the system processes information in a safe, demonstrably responsible and explainable manner.

Furthermore, for AI to be effectively transferred to the sustainability reporting space and practically applied to sustainable reporting, cooperation between AI and sustainability experts is required. O'Neill and Wu (2024) consider how to leverage AI to enhance the quality of climate risk disclosures using TCFD principles. In fact, it is argued that "AI technologies

embedded in corporate governance structures hold the potential to deliver more accurate-and-useful information on the risk of climate change and thus allows them to embed sustainability considerations in the making of top-tier international standards.” Nonetheless, representing AI as part of ESG reporting task demands a real “multidisciplinary enterprise” that can allow AI professionals to take an active role in the sustainability team to ensure that the AI employed for ESG reporting is in line with the company’s sustainable vision. As noted by Deloitte (2024) and McKinsey Company (2023), the transformative potential of artificial intelligence for ESG reporting, among other aspects, is at the center of the discussion. These communications demonstrate the possibilities offered by AI for the standardization of data capture, the augmentation of the quality of written reports, and the easing of operating costs, especially in companies that aim to create a framework of compliance with reporting on ESG issues. Reports, however, also identify the barriers to AI adoption, including the need for large financial investments in AI infrastructure and the continuous need for ethical regulation.

In conclusion, AI can be used more effectively for enhancing data quality, transparency, and decision processes in sustainability and corporate governance reporting. AI is also able to drive automated data capture, anomaly detection, and real-time intelligence capability and is a useful tool for the development of ESG reporting. Nevertheless, the implementation of such AI comes with some consequential issues, e.g., bias of an algorithm, privacy threats related to data, or the development of effective regulatory schemes. By working together with AI researchers, sustainability professionals, and policy officers, the ethical and practical application of AI technologies can be confirmed to result in a trustworthy relationship between all actors regarding their sustainability goals and a shared commitment to achieving their shared vision for the future. Nonetheless, the ongoing development of AI technologies will continue to play a fundamental role in reshaping the landscape of corporate governance and sustainability reporting.

9.3 Methodology

This chapter pursues a wide range of strategies in order to understand how technology such as artificial intelligence (AI) interacts with the concepts of sustainability and the governance of firms’ reporting. The methodology starts with a broad literature review that includes academic documents, reports, and documents of related regulations. There is a need to examine

academic literature such as peer-reviewed articles, books, and conference papers, in order to set the context on the issues revolving around AI, sustainability, and corporate governance. Moreover, reports from organizations such as the World Economic Forum, the United Nations, and top consulting companies have been used to address the application of AI in sustainability reporting and the challenges it faces. Other regulations relating to this study, such as those on sustainability reporting, data protection, and AI regulations, among others, have been examined in order to evaluate the socio-legal issues applicable to the use of artificial intelligence. Furthermore, the methodology involves the detailed study of a selected group of companies that are characterized by active use and integration of AI technologies into their sustainability management and reporting. The case studies will provide examples of AI application in practice with regard to enhancing the position of sustainability and developing planning, evaluation, and reporting practices.

By comparing these case studies, it is possible to determine the most relevant success factors, constraints, and best practices. The multi-faceted approach will allow for a comprehensive and in-depth analysis of the key aspects related to AI, sustainability, and corporate governance reporting.

9.4 Analysis

This study, following discussions on the hosting of the first meeting on artificial intelligence (AI) for sustainability and corporate governance reporting and the synergies between AI technologies, environmental, social, and governance (ESG) metrics, and the evolving regulatory landscape, also raises the question of the sustainability dimensions of corporate reporting in relation to AI technologies. However, the AI tool can also generate ethical, regulatory, and operational concerns that must be resolved prior to responsible adoption and sustainable operation.

9.4.1 AI's Role in Enhancing ESG Reporting

AI, especially machine learning, natural language processing (NLP), and prediction analytics, is increasingly used on a large scale to collect, process, and report ESG data. The ability of AI to analyze vast amounts of data from anywhere, anytime, and from almost any description will enable companies to introduce data-driven, real-time sustainability performance views — this will

of course be fundamental to the decision-making process for environmental, social, and governance (ESG) risk management. These technologies can automatically generate patterns from large datasets, detect anomalies, and forecast future ESG performance, all leads to a better quality and reliability of ESG reports. For example, natural language processing can leverage textual information from sustainability reports produced by companies to help confirm their adherence to the global principles regarding sustainability reporting (e.g., Global Reporting Initiative (GRI), Sustainability Accounting Standards Board (SASB), and Task Force on Climate-related Financial Disclosures (TCFD)). This allows the company to better reflect globally recognized instruments in the subject area for the purpose of increasing the validity of their reports as well as the confidence of stakeholders (e.g., investors, regulators, and customers) in the information being reported.

9.4.2 Ethical and Regulatory Challenges

Although there is an undeniable advantage of artificial intelligence (AI) for ESG reporting, the introduction of AI into corporate governance and sustainable operations already triggers an incredibly large question from the ethical and regulatory perspectives. Privacy issues, addressed by laws such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA), are relevant. As more companies bring AI to scale to analyze large amounts of ESG data, a huge question about how these privacy regulations can be complied with. Furthermore, AI systems should be engineered to respect both ethical limitations—such as transparency, fairness, and accountability—concerning the lack of and reporting on the existence of algorithm bias and fabrication of data. With the introduction of AI in sustainability reports, research attention has been paid to the open AI governance field. However, AI systems may sometimes provide advice or decisions that are problematic for stakeholders, raising the issue of responsibility, especially with AI assistance of AI for ESG disclosure material. Organizations must identify governance environments that not only ensure the veracity of AI applications but also uphold ethics and accountability. This encompasses the development of definable rules and principles for the use of AI, the interpreter in decision-making, and the design of procedures to audit and correct errors in AI models.

The study examines certain best practices and problems that AI systems have faced in working alongside sustainability reports via the case study method. AI has been effectively used by leading companies for near

real-time forecasting and reporting. For example, the convergence of IoT and AI platforms enables businesses to monitor their environmental performance in energy use, water consumption, and carbon emissions. These technologies support the management of sustainability strategies by providing regular updates on the performance of operations. However, the case studies also show several difficulties, including the technological barriers of combining AI with diverse datasets. AI systems complete tasks better when a human supervises them. AI systems can achieve only as much as the data they receive during the training stage, unbalanced or incorrectly labeled datasets can distort outcomes. Additionally, there is a gap between the AI outputs and the decision-making framework in the organization. The case study on Microsoft Corporation offers a good illustration of how AI systems are changing the practice of reporting on ESG matters. Companies such as Microsoft use AI-enabled carbon accounting, collection, and use of real-time data and reporting.

A combination of these factors has contributed to Microsoft's ability to improve the accuracy of its sustainability reports, enhance compliance with requirements, and achieve higher stakeholder engagement. However, Microsoft also mitigated challenges related to integrating models, AI model bias, and resource-intensive AI deployment. The experience of the company supports the need for collaboration across functions, including sustainability, governance, IT, and data science stakeholders, to embed AI effectively into corporate governance and corporate sustainability.

The earlier research has established that AI companies show a 20–30% rise in data accuracy and effectiveness of reporting. This is an illustration of the potential impact of AI on how ESG reporting costs can be reduced and what information or data is needed for effective ESG reporting. Qualitative themes emerging from the discussion on the ethical use of artificial intelligence, the scale at which data governance frameworks are to be applied, and the degree of participation among stakeholders are captured. These folds reflect a heightened sense of the need to deliver AI to the doorstep in a responsible manner, along with a threat to the user and the system, with considerable emergent concerns.

9.4.3 Emerging Trends and Future Outlook

The future is marked by some changes in sustainability reporting. Digital twin, blockchain embedding, and predictive analysis technologies will be required to play a valuable role in making a significant contribution to

achieving higher levels of accuracy, openness, and accountability in the dissemination of ESG disclosures. For example, digital twins are virtual representations of physical objects/processes, enabling organizations to model and offer real-time optimization of sustainability performance. When combined with the power of AI, blockchain has the potential to provide an absolute and auditable record of ESG data, which, in turn, can lead to the creation of trust and reduce the chances of data falsification. Evidence also suggests that organizations with a proactive AI governance agenda are better equipped to respond to changes in regulatory patterns, seize technological opportunities, and manage stakeholder interests. As a consequence of adopting an integrative approach to AI management, corporations can ensure that the company meets AI-related as well as national and international regulations that are likely to appear in the near future concerning AI, sustainability, and corporate governance.

9.5 Discussion

The adoption of artificial intelligence (AI) within the realms of sustainability and corporate governance reporting is certainly a game-changing phenomenon that is overhauling the ways businesses interact with their various stakeholders and report on their environmental, social, and governance (ESG) activities. This study has investigated such dynamic crossroads, accentuating the major benefits AI brings, the challenges that accompany its use, and the strategies that institutions should pursue to harness AI in this area.

9.5.1 AI's Impact on ESG Reporting: Enhancing Accuracy, Efficiency, and Transparency

Integrating AI into ESG reporting for corporations striving to fulfill stakeholders, regulatory requirements, and sustainability goals has proven to be a breakthrough. AI tools, such as natural language processing (NLP) and machine learning, enable the collection, analysis, and reporting of ESG data more efficiently and accurately. AI has the potential to streamline exhausting data entry procedures, spot trends and outliers within extensive data, and even assist with real-time insights that could be valuable to a business in terms of risk and opportunity assessment. With this combination of reduced risk exposure and forecast improvement, improved data quality and more dependable ESG disclosures result in greater clarity regarding corporate

sustainability efforts. For example, Microsoft Corporation's incorporation of AI technologies that enable the automatic collection of data and viewing of dashboards at any time improved the firm's interaction with its stakeholders. It is possible to sustainably track sustainability parameters in these networks and offer stakeholders, both private and external, timely and useful information. As a result, AI enhances trust and interaction—helping stakeholders be better positioned to assess companies against their sustainability targets and understand much more complex data.

The application of NLP and other AI technologies to a large volume of unstructured data has also enabled companies such as Microsoft to identify ESG risks off the balance sheet and deal with them in a manner compliant with their policies of more transparency and accountability in the business world.

9.5.2 Ethical and Regulatory Considerations

Unsurprisingly, at the heart of sustainability reporting of the future lies the ethical and regulatory issue that is on today's agenda much more powerfully. However, these issues also provide significant liabilities in the absence of control. Ethical challenges, which are most salient, include data privacy, algorithmic bias, and the erosion of human control over decision-making processes. Regulatory frameworks, including the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA), are in order to safeguard individuals' privacy from being infringed upon by institutions by appropriately safeguarding personal information. In order to comply with such legislation, companies have to establish effective data protection mechanisms such as data anonymization, encryption, and the protection of data being stored/maintained. Furthermore, algorithmic bias should also be adequately addressed when using AI to report on ESG. In practice, AI systems can have a tendency to unintentionally produce biased ESG reports or to misvalue risks due, for example, to biased data on which they are trained. It is a special issue, as its areas of application include environmental impact, social justice, and even policy writing. Although companies will still need to give their utmost attention to fairness, transparency and accountability regarding how AI systems are designed so that systems are continuously checked for bias and the decision process of such systems can be examined and defended. The precautionary attitude towards this issue is also a case study of what constitutes good practice in which Microsoft being a positive role model. AI governance frameworks have been established by a

team whose agenda consists of the integration of innovative and accountable approaches. These paradigms are pertinent for the ethical use of AI to prevent privacy/bias risks and enhance the utility of AI-based sustainability reporting. With the application of this balanced leadership model, Microsoft illustrates how innovation at the company can be both scalable and revolutionary, delivering trust to all relevant stakeholders and translating into real, quantifiable sustainability targets.

9.5.3 Technical and Operational Challenges in AI Integration

AI certainly has a lot of promise when it comes to enhancing ESG reporting practices. However, its application within the realm of corporate governance and sustainability is not without impediments. For its economic impact to be realized, AI needs access to technology, data infrastructure, and knowledge such as natural language processing and computer vision. AI is effective for understanding data, but adequate AI capabilities must be built. Also, even though the incorporation of AI into existing models of sustainability reports may be desirable, it is often difficult due to the factor of data merging. ESG performance is assessed through numerous systems over many departments, for instance, finance, operations, and environmental management systems. Managing the integration of these rather unrelated departments, such as operation, marketing, and finance, is also a daunting task because it requires consideration of other complex factors in the company as well. On the other side of the coin, organizations also need to keep in mind that AI systems will need consistent fine-tuning. This is important especially with regard to sustainability because new regulations arise frequently and economic and environmental issues change.

This reaffirms the need for rolling out AI in a stepped and well-thought-out manner so that organizations are able to develop their AI capabilities gradually rather than implementing such drastic changes all at once and taking on the associated risks.

9.5.4 Key Success Factors for AI Adoption in ESG Reporting

Several key success factors emerge for the effective adoption of AI in ESG reporting. These factors include the following:

Cross-functional Collaboration: Integration of AI into sustainability reporting units (e.g., IT, data science, sustainability governance) is a priority as well. Cross-functional teams are capable of ensuring that AI systems are

consistent with business and, just as importantly, legal/compliance needs as well as complete data purchase and processing of necessary data.

Stakeholder Involvement: In practice, the participation of the stakeholders, ideally from the very beginning of the process, cannot be under-rated to address whether AI projects meet their expectations and progress according to the needs of the stakeholders. When considering stakeholders such as investors, customers, and regulators, businesses may be prepared to provide the data around which the AI-driven sustainability reports will ultimately deliver and ensure that the AI system offers sufficient evidence of transparency and accountability.

Continuous Improvement: AI systems must be considered living systems that require a continual and adaptive process of attention and tuning. As a consequence of technological advances and growing regulatory needs, organizations also need to consider refreshing or adapting their AI models to remain current with the advances currently taking place. This demands continuous financing for AI competence and regulation.

9.5.5 Emerging Technologies and Future Outlook

Concurrent with these novel technologies, certain advancements are then expected to further advance AI in sustainability reporting, etc. Aggregative representations that generate digital twins of the built environment or processes (i.e., online models of sustainability performance) can be used. Integration of artificial intelligence and digital twins enables objects to predict the extrinsic effects of their own motion, to explore other environmentally sustainable alternatives, and to operate in a data-driven manner to reduce carbon footprint.

Blockchain and AI together can offer an open and immutable audit trail to ESG, such that it might help achieve authenticity of the sustainability report. By no means is this true in the case of the ethics disclosures performed, as the purportedly no falsified and therefore ratified route to building stakeholder trust.

Then, in part due to the power of advanced predictive analytics, companies will be able to analyze not just past ESG performance, but ESG-accompanied future outcomes. By pattern recognition, AI can be applied to assist companies in predicting the risk of the impact of climate change, social crises, and governance issues so that companies will be able not to react after the plan is built, but to prepare how to prevent these risks.

In conclusion, AI has the potential to be disruptive in the areas of sustainability and corporate governance reporting. To take advantage of this ability, however, a range of ethical, technical, and governance issues have to be addressed. Companies will be required to commit resources to AI education, establish proper AI governance processes, and improve communication between units within a company. Policymakers will also have to develop regulations that are stringent enough to safeguard but not too restrictive to stifle AI innovation, while investors should support companies that are willing to use AI to enhance their ESG performance. The case of Microsoft turned out to be a good lesson on the fact that AI, when properly directed, tends to efficiently improve ESG reporting mechanisms, expand transparency, and highlight other risks that would have otherwise gone unnoticed. Using appropriate AI solutions and governance systems, corporations will increase their credibility to stakeholders and simultaneously improve their sustainability standing, thereby contributing to the global sustainability agenda. Without a doubt, AI will change the face of corporate governance and sustainability reporting, and organizations that embrace such technology will not only succeed but also be ready to deal with current transformational shifts in transparency, accountability, and sustainability paradigms.

9.6 Conclusions and Recommendations

The final thoughts of the research give several practical solutions for organizations, investors, and policymakers. Companies need to incorporate AI literacy, develop ethical AI governance structures, and encourage appropriate practices regarding their sustainability reporting. This will help firms improve their ESG performance, enhance the confidence of their stakeholders, and improve compliance with the law as it continues to evolve. Investors must advocate the use of AI for ESG reporting and demand relevant reports that are coherent and essential. The authorities should be formulating laws that allow creativity and new inventions without overregulation, so that AI does not bring additional risks. All in all, this study emphasizes the impact AI has on enhancing sustainability and restructuring corporate governance reporting. For reporting organizations' characteristics and ESG performance improvement, the approach to AI technologies should be responsible and properly strategized. This is the course of future direction of AI in global sustainability reporting. Organizations that prioritize ethics, governance, and innovation will survive the difficulties that the more complex and controlled world market has to offer.

9.7 Limitations

This part of the work is also included with a reduced number of variables to predict the situation, with the aim of supporting further research. Although it is the target literature of this work that already describes the embeddings of AI and sustainability or corporate governance disclosure reporting, readers should note the potential limitations (the concern of generalizability and long-term validity reported) that may continue to grow.

9.7.1 *Data Availability and Accessibility*

One drawback in this study is the use of data that is already in the public domain. This is a common challenge for studies on the application of AI in corporate governance as a lot of companies may have their AI systems or sustainability systems but do not let the public know of their existence. Such tools or strategies in most cases are simply defended for reasons of competition and as such never make it into the study. So, it means that the study may only reflect a fraction of the number of times AI has been used in corporates' sustainability reports, which in turn could limit the breadth of the conclusions reached. This limitation is especially critical as some of the most advanced AI techniques within the sustainability domain are still under wraps, which is often the case in new offerings of these technologies or when the main reason for using them is to gain competitive edge in the market. One consequence of this is that the AI tools employed may not be exhaustively highlighted, especially those pertaining to specialty markets or that are not frequently disclosed owing to business confidentiality. Subsequent investigations may try to overcome this limitation by collaborating with companies or conducting an AI survey to encourage companies to expose their internal AI usage.

Moving away from a more singular approach, one might utilize industry reports and case studies to amplify their understanding of AI as technology across sectors.

9.7.2 *Generalizability*

The applicability of findings from this study also forms another notable concern. The case studies and expert interviews conducted in the research are centered on a few organizations, which may not capture the variability of industries, organizational sizes, or geographical regions. Different sectors have different levels of technology sophistication, regulation, and

sustainability issues that will determine the manner in which AI is utilized and integrated into the process of sustainable reporting. For instance, technologies and resources found in finance or technology sectors may better help integrate AI systems into their sustainability reporting compared to the agriculture and manufacturing sectors that face different operational conditions and regulatory requirements. In addition, the regulation of AI and sustainable reporting varies across regions. While the European Union has strict regulations such as GDPR and sustainability frameworks like the European Taxonomy for Sustainable Activities, other regions may not have similarly comprehensive regulations, which could affect the way AI is adopted and the kind of data that can be used for reporting.

9.7.3 Rapid Evolution of AI Technology

The landscape of AI is changing rapidly. Because of the exponential increase in novel technology, algorithms, and tools, the literature results are extremely hard to review. Since in that paper it discusses a few of the AI technologies which may be out of date very soon or even be replaced by much more powerful technology, the conclusion may turn out to be a waste of time. Accordingly, the technical development of the last few years is also challenged by this current work with the issue of long-term validity. Specifically, the AI-based methods and instruments (e.g., natural language processing (NLP) or machine learning (ML) algorithms aimed at ESG data analysis) will probably be superseded by even more sophisticated systems (e.g., generative AI, deep learning models, or AI-powered digital twins) not too long in the future. Hence, companies must keep up to date with such developments and be prepared to continuously adjust their practices in terms of artificial intelligence so as to remain competitive and productive in sustainability reporting. Future research must address the dynamic, changing nature of AI and implement a longitudinal study design in which AI adoption and its accompanying consequences are observed and debated, where the most recent developments in AI technology are taken into account. In so doing, the work can continue to be topical and provide evidence of the main trends in AI and sustainability reporting.

9.7.4 Ethical and Governance Challenges

While the study postulates some of the ethical and governance challenges posed by AI, it does not delve into specifying some of the more critical issues that AI introduces to sustainability reporting. Issues such as

algorithmic bias, privacy restrictions arising from the implementation of AI, and the undesirable side effects of AI “in use” remain an urgent and increasingly poorly understood concerns. In particular, algorithmic bias in artificial intelligence (AI) algorithms can lead to discriminatory outcomes, especially for enterprise governance and social responsibility (ESG) data, due to the fundamental subjectivity of social and environmental problems. AI models trained on biased data could promote historical unfairness or misrepresent some subgroups, thereby, regrettably, slowing progress towards equitable sustainability reporting. Furthermore, data privacy issues, particularly with respect to the disclosure of personal data in ESG reports, could lead to breaches of applicable legislation or stakeholder trust if improperly addressed. Although highlighting the actual stakes of robust governance and responsible AI in practice, the study does not present the steps and workflow procedures available to companies to address these risks. It would be valuable perspective to state a set of brief guidelines on how to utilize AI appropriately (e.g., by developing fairness-aware algorithms or audit logs for AI reasoning power) as an area of future research. Furthermore, emerging as a result of the advent of AI systems in corporate governance sustainability, companies will need to articulate integrated AI governance principles such as data governance, ethical issues, and legal compliance. Research should progress to the point where the next steps in research in terms of “what if” should occur in order to address these questions, for example, how do companies have the prospect of designing more robust “smart” AI governance arrangements and ethics to make these aspirations a reality that AI can be an asset to humankind, rather than an additional source of risk.

9.7.5 Limited Stakeholder Perspectives

Experience in the past and “thinking out loud” have reminded the research community, a dynamic community of stakeholders such as the chief executives of companies, ecologists, and computer experts, what to do. Although all are insightful, they fail to encompass the rich range of stakeholders potentially affected by or interested in AI-enhanced sustainability reporting. For the purpose of bringing together a wider group of stakeholders, i.e., members of the community, NGOs and NGO’s, customers, and investors, investigation into public perceptions of AI and its impact on these various stakeholders may yield an even more inclusive appreciation of how the public views AI. For example, NGOs and community organizations may have disagreements about the level of openness/transparency and fairness

of artificial intelligence models used to address sustainability reporting in light of the social and environmental justice challenge. Also, there has been an indication that investors might raise concerns about how much the impact of AI has been sustained, and about the likelihood that the shortcomings in liability or the source of reports about output from an AI will remain unknown. More perspectives of stakeholders can ultimately lead to better study outcomes and, ultimately, contribute to the understanding of the impact of AI on sustainability and corporate governance per se. Further research is presented as a suggestion for further inclusiveness of a more representative panel of stakeholder participants, and therefore, studies of AI modalities and the emotions and wishes of all constituencies affected by AI in such a way.

9.8 Implications for Future Research

To conclude, though this study contributes to the understanding of how AI might be integrated into the reporting of sustainability and the governance of corporate affairs, its scope should remain confined due to the goal of this study, which is to explain the state of affairs as far as the application of AI in ESG reporting is concerned. This work is a case study and should therefore be substantiated by the evaluation of a broad cross-section of case studies as well as the scope and pace of the evolution of AI technology. Future studies should also seek to overcome the said limitations by broadening the range of sources of data as well as the types of stakeholders or respondents considered, and the changing nature of AI solutions targeting sustainability reporting. Additionally, the creation of adequate ethical and governance mechanisms to minimize the risks associated with AI should be given much more emphasis. By addressing these limitations, further research can build on this study and contribute to both development of corporate governance and sustainable practices of international organizations.

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Chapter 10

Carbon Taxation and Sustainable Business Practices: A Blueprint for India's Green Economy

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10.1 Introduction

10.1.1 Climate Change and the Need for Carbon Taxation

Our current era faces climate change as a top challenge that produces serious threats which impact ecosystems together with economies and societies across the globe. Greenhouse gas (GHG) emissions derived mainly from fossil fuel consumption lead to global warming, so governments need to establish policies that reduce these dangerous effects. Carbon taxation has risen as a fundamental emission control instrument because it adds monetary expenses to carbon usage. Since polluting activities become unprofitable (Stern & Coria, 2012) through this strategy, businesses along with individuals opt for cleaner energy sources and sustainable practices. Various countries worldwide have put carbon taxes into practice, which proves their capability both in lowering emissions and enhancing economic strength. Swedish officials implemented a high carbon tax back in 1991 that cut emissions by 27% by 2018, yet their economy showed no negative impact (Carl

& Fedor, 2016). Through its federal carbon pricing system, Canada connects incentives for sustainability to the equal distribution of revenue by sending funds to low-income households (Government of Canada, 2023).

10.1.2 India's 1.2 Perspective: Challenges and Opportunities

India stands as the third-largest carbon dioxide emitter while dealing with special hurdles to implement carbon taxation because its economy heavily depends on coal as well as other fossil fuels for energy generation and development (Banerjee, 2019). The nation's multiple developmental aims, which contain poverty reduction and industrial development, make it difficult to establish strong carbon pricing systems (MoEFCC, 2022; Bureau of Energy Efficiency, 2021). Following an environmental mandate, India launched its carbon pricing effort by implementing the coal cess system in 2010. The initial ₹50 levy on each ton of coal has grown over time, while its associated revenue was directed specifically toward renewable energy development projects. The potential of the coal cess diminished when the Indian government combined it with the Goods and Services Tax (GST) compensation fund in 2017 (Ministry of Finance, Government of India, 2020). This made the coal cess to lose its role as a specific carbon pricing tool. Despite this, India stands to benefit from incorporating a carbon tax implementation as part of its wider policies for environmental and financial targets. Increasing carbon tax implementation through National Action Plan on Climate Change initiatives, combined with targeted revenue investments in renewable projects and energy efficiency, brings India closer to developing its low-carbon economic model (Dasgupta & Bhattacharya, 2021).

10.1.3 Sustainable Business Practices: Global and Indian Context

The business world has turned toward sustainability measures because of both carbon pricing regulations and growing demand from clients for environment-friendly business products. Unilever and Microsoft among others dedicate their efforts to carbon neutrality by implementing renewable energy systems and investing in energy-efficient technologies (Unilever, 2022; Devis & Kilian, 2015). The Indian companies Tata Group and Infosys serve as national leaders because they advance sustainable operations through renewable energy utilization alongside waste reduction and supply chain sustainability. Indian organizations will gain market competitiveness through carbon taxation by promoting mass implementation of sustainable practices (Kumar

et al., 2019). The inclusion of sustainability elements into business core strategies lowers environmental risks and builds better reputations and operational performance (Tata Group, 2022; Gupta & Verma, 2019). The implementation of these practices makes Indian businesses both environmental contributors to the country's green economy and global sustainability leaders. Today, sustainable business practices are gaining extensive global popularity since businesses identify both their roles to protect the environment and build economic durability (Mahindra & Mahindra, 2020). The practices use strategies that focus on resource reduction, carbon emission minimization, and social responsibility advancement. Major multinational companies worldwide have established sustainable practices as their new performance standards. Unilever maintains a complete sustainability framework with objectives to become net-zero by 2039 and, at the same time, integrate renewable energy sources and develop eco-friendly products (Unilever, 2022). The Microsoft Company aims to achieve carbon negativity status by 2030 through renewable energy investments, carbon capture technology development, and system-wide change initiatives through strategic partnerships and advocacy (Microsoft, 2022; Sen & Das, 2020). Sustainability has transformed into a strategic core value that brings lasting value while moving past its previous status as a strict compliance requirement. Sustainable business practices continue to grow in popularity because of policy requirements together with stakeholder demands and competitive market needs. The Tata Group, together with Mahindra & Mahindra, serves as inspiration for sustainable corporate management within India. Sustainability plays a central role in Tata Group strategy through its programs on renewable energy usage combined with sustainable supply chain management and widespread community development initiatives (Tata Group, 2022). The solution to these problems necessitates partnerships between authorities and business organizations along with financial establishments to establish access to technological equipment combined with fiscal resources and institutional training initiatives. A properly designed carbon tax system will drive business transition toward sustainable approaches because it makes damaging practices unsustainable, yet provides financial benefits for green innovation (Ghosh, 2021).

10.1.3.1 National Mission for Enhanced Energy Efficiency (NMEEE)

NMEEE began its operations under India's National Action Plan on Climate Change (NAPCC) in 2008 to develop energy efficiency initiatives within industries and specific sectors. Through market-based tools, NMEEE works

to decrease energy usage and boost performance as well as decrease carbon dioxide emissions while protecting economic development (Mani & Ramesh, 2021). The banner initiative under NMEEE consists of the Perform Achieve and Trade (PAT) scheme because it designs energy reduction goals for industries operating in the steel, cement, and textile sectors. Commercial entities that surpass their energy reduction targets can sell remaining Energy Saving Certificates to enterprises that did not fulfill their energy use reduction targets, thus providing a financial advantage for implementing energy-efficient technology. Other significant programs under NMEEE include the Market Transformation for Energy Efficiency (MTEE), which promotes energy-efficient products through demand-side initiatives like the UJALA scheme for LED bulbs; the Energy Efficiency Financing Platform (EEFP), designed to connect financial institutions with energy efficiency projects; and the Framework for Energy Efficient Economic Development (FEEED), which supports policies encouraging investment in energy efficiency through risk-sharing models. The various agreements reinforce NMEEE as India's vital component for its energy transformation approach.

10.1.3.2 Renewable Energy Certificate (REC) Mechanism

The REC system represents a market structure which supports renewable power production among renewable energy generators who need to meet their Renewable Purchase Obligation requirements. The RPO system forces distribution companies, open access consumers, and captive power producers to acquire a particular level of their energy from renewable resources. The REC mechanism enables renewable energy generators to distribute electricity to power grids by allowing the sale of their renewable attributes as separately traded certificates (Mehta et al., 2019). REC trading provides renewable investors with supplemental revenue as well as motivation to establish new renewable projects. There exist two REC types: Solar RECs, which deliver power from solar generation, and non-Solar RECs, which achieve power from wind and biomass sources. Obligated entities use trading platforms IEX and PXIL to obtain RECs that enable them to fulfill their RPO requirements through alternative means to renewable project investments. Challenges related to volatile REC market prices together with market overproduction and inadequate understanding among smaller companies have restricted the effectiveness of these assets. REC and NMEEE work together as major pathways to build a sustainable energy system, allowing India to excel economically through its low-carbon economic transition.

10.2 Review of Literature

Understanding this subject involves the evaluation of various research studies examining the relationships between regulatory guidelines and corporate approaches to achieving environmental success. Academic scholars, together with practitioners, have made major contributions that supply important knowledge for both theoretical work and real-world implementation. Theoretical research has been the primary focus of studies where Smith and Wheeler (2000) examined environmental externalities internalization through carbon taxes designed to resolve greenhouse gas emission-based market problems. Through his work, Johnson produced an evaluation model that demonstrates how carbon taxes fulfill the dual purpose of economic performance and environmental protection (Johnson, 2005). These vital research studies enabled subsequent exploration of methods that use carbon pricing to motivate more sustainable carbon transition activities. Research by Anderson et al. demonstrated how the 1991 carbon tax in Sweden succeeded in lowering emissions while preserving economic expansion (Anderson et al., 2010). Morris and Taylor evaluated federal Canadian carbon pricing mechanisms to highlight their ability for balancing different regions alongside revenue neutrality (Morris & Taylor, 2012). Scientific investigations served to inspire governments around the world that carbon taxation presents a suitable solution for climate policy implementation. Facing implementation obstacles remains a major challenge for developing countries when they attempt to adopt carbon tax systems. Ghosh investigated India's coal cess system, showing its restricted capability since authorization shifted into the Goods and Services Tax system (Ghosh, 2015). Zhang and Wei researched China's pilot carbon markets to deliver important knowledge regarding carbon tax implementation within comprehensive environmental policy structures (Zhang & Wei, 2016). A well-structured carbon tax designed according to Porter and van der Linde (1995) stimulates innovation since it creates financial advantages for environmental enhancements. Studies conducted by Renwick et al. (2018) proved the validity of the "Porter Hypothesis" by demonstrating that European industries use higher carbon prices to adopt energy-efficient technologies.

Revenue recycling as a policy uses carbon tax revenue to decrease other tax types like the income tax while generating dual economic and environmental advantages. Ohlendorf et al. (2020) studied worldwide case examples to establish that giving carbon tax revenue to vulnerable groups helps prevent social injustice while making carbon tax measures more popular with

the public. Success rates in carbon taxation largely depend on the utilization of transparent approaches for distributing tax revenues in equitable ways (Morris & Pickering, 2012; Mukherjee et al., 2022).

The strategies employed by companies toward carbon taxation have become a notable research area. The research performed by Mishra et al. (2020) showed that Reliance alongside ITC, as Indian conglomerates, follow carbon-neutral targets through carbon pricing system implementation for their risk reduction programs. Bose and Chakraborty (2021) observed that sustainability reporting together with voluntary carbon disclosure serve as vital business tools that help companies present accountability while establishing trust with stakeholders. Carbon taxes have become a main topic in research about their ability to enhance innovation while creating sustainable funding structures. Costs induced by elevated carbon prices lead to investments in both renewable projects and energy-saving infrastructure, according to Ramakrishnan et al. (2019). Chakravarti and Patel (2022) demonstrated the potential of green bonds along with sustainability-linked loans to work with carbon pricing standards for securing substantial funding for climate mitigation activities. Arab Nation organizations extensively scrutinize how people perceive and react to carbon tax programs. According to Singh and Deshmukh (2020), European countries proved that strategic public communication helps public acceptance of carbon taxes by demonstrating positive impacts through awareness campaigns. Research conducted by Rao et al. (2018) revealed that giving public rebates alongside improvements such as cleaner air positively affects community opinions regarding carbon taxes. The implementation of carbon taxes receives support through developments in digital technology systems. The article by Sharma and Kapoor (2021b) presented blockchain technology integration in carbon credit markets to achieve transparency while fighting market fraud and improving traceability systems. The work of Malik et al. (2022) delved into AI predictive analytics implementation for improving carbon emission monitoring and reporting.

Scientists have continuously examined the role of carbon taxation in global climate objectives. Krishnan (2021) recommended that India should integrate its carbon pricing framework with international standards, including the EU Carbon Border Adjustment Mechanism (CBAM), to facilitate smooth trade and global collaborations. South-South cooperation holds significant importance for efficient carbon pricing strategies according to Kumar et al. (2020). Climate decarbonization that impacts economic viability stands as a crucial issue that needs examination. The research of Prasad and Sharma (2022) demonstrated that carbon taxes offer economies two benefits:

job creation in eco-friendly sectors and clean industrial growth. The need for dealing with fossil-fuel-dependent regions during the transition process emerges similarly from findings by Das and Bhatnagar (2021). When discussing carbon taxation policies, agriculture together with land use practices tend to get disregarded.

10.2.1 Research Gap

There are a lot of studies regarding carbon taxation and sustainable business practices that have achieved extensive publication, but multiple research gaps persist, especially for emerging economic conditions such as India. The research lacks specific information about implementing carbon taxes within Indian firms, including rural sectors and small and medium enterprises (SMEs). Studies from around the world reveal how revenue recycling combined with behavioral economics improves carbon tax efficiency, but they provide insufficient attention to assessing carbon taxation's socioeconomic impact on marginalized populations throughout India for jobs and income distribution, along with social equality.

10.3 Objectives and Methodology

The investigation analyzes carbon taxation as an instrument for developing sustainable business practices across India while creating an integrated blueprint. This study applies both qualitative case studies and quantitative methods to explore Indian industrial green initiatives and carbon tax effects on emissions and economic metrics.

10.4 Carbon Taxation

The worldwide initiative against climate change relies on carbon taxes as a central mechanism that calculates the environmental costs of carbon releases. Through increased fossil fuel prices, the system stimulates organizations and citizens to embrace environmentally friendly technologies while changing their behaviors. Several nations worldwide have implemented carbon taxes with varying degrees of success, and the scholarly research on this topic now judges its impact across three key dimensions. Developed countries have already introduced carbon taxes, but India along with other

emerging economies now explores this possibility through localized adjustments of international experiences.

10.4.1 Global Trends in Carbon Taxation

International case studies prove that Sweden, along with Canada and the United Kingdom, has applied carbon taxes in diverse ways, which produced different outcomes. The Swedish carbon tax, established in 1991, stands as a frequently studied show of success because it produced major emission decreases alongside ongoing economic expansion (Fowlie et al., 2019a). According to Fowlie et al. (2018), Sweden demonstrates through its effective design that properly implemented carbon taxes can fulfill environmental sustainability targets while safeguarding industrial market position. Climate research conducted by the Canadian Climate Institute supports the national carbon pricing system instituted by the Canadian government (Canadian Climate Institute, 2020). The examples emphasize that governments should establish carbon tax rates that both encourage behavioral change and avoid unnecessary burdens on businesses and sustainable populations.

10.4.2 Carbon Taxation and Business Behavior

Academic research has deeply examined the influence of carbon taxes on business actions, especially as they affect corporate sustainability efforts. According to Porter and van der Linde (1995), “Porter Hypothesis” establishes that properly structured environmental mandates similar to carbon taxes create business opportunities through innovation and efficiency improvements. Research conducted throughout the European Union and the United States demonstrates that carbon tax incentives drive businesses to choose cleaner technologies along with energy-efficient solutions, creating competitive advantages for sustainability (Renwick et al., 2018a). Tata and Mahindra among other Indian companies have integrated sustainability into their operations because of regulatory requirements and voluntary corporate responsibility initiatives, as described by Ghosh (2017). India faces specific opportunities and challenges when it implements carbon taxation policies. Ghosh (2015) studied the coal cess tax applied to coal output production in India to support renewable energy growth. Due to its limited nature, the coal cess triggers widespread complaints regarding its insufficient capacity to minimize emission levels. The government of India is developing multiple

carbon pricing mechanisms, such as carbon taxes and cap-and-trade systems, because of its Paris Agreement climate commitment requirements.

10.4.3 Revenue Recycling and Equity Considerations

A research proves that revenue recycling distributes carbon tax advantages uniformly when funding green positions while decreasing income taxes. The Indian socioeconomic disparities require proper carbon tax revenue distribution because it will both enhance public acceptance and lower opposition to this policy. According to Sethi and Deshmukh (2020) a strategic approach is needed to use tax funding for both energy-efficient programs at renewable energy projects and social service programs for marginalized groups.

10.4.4 Role of Hybrid Approaches

Most of the current academic research focuses on studies about combining carbon tax policies with ETS and REC systems. Several experts, including Stavins (2017) and Mani and Ramesh (2021), confirm that unity between carbon taxes and cap-and-trade systems provides both adaptability and economical means of lowering emissions. Indian carbon reduction strategies benefit substantially from hybrid control systems, because the country maintains existing protocols of the National Mission for Enhanced Energy Efficiency and Renewable Energy Certificates, which line up perfectly for comprehensive carbon taxation implementations. Scientists evaluate hybrid models in different pilot tests that demonstrate the ability to unite rules with market-oriented systems (Sharma & Kapoor, 2021a). The effectiveness of climate change mitigation through carbon taxation depends on appropriate system design combined with correct implementation practices alongside particular environmental factors. World experiences offer important lessons to India, but the nation needs tailored policy modifications because of its unique social context.

10.5 Sustainable Business Practices in India

Management practices that support sustainability have become essential to the corporate strategies of Indian businesses since they recognize a mandate to meet international sustainability goals. Indian businesses prioritize sustainability because they want sustainable development that harms the

environment minimally and because clear shifts in customer choices and changing regulations are key drivers of these developments.

10.5.1 Drivers of Sustainable Business Practices in India

There are various elements that affect the decisions of businesses to implement sustainable operational methods. The government supports sustainability through new regulatory programs that offer benefits to organizations. To drive sustainable project investments through CSR expenditures, companies need to follow the requirements specified in the Companies Act of 2013. This development makes the sustainable operations approach visibility more pronounced in business practices. Sharma et al. (2021) demonstrate that Indian businesses employ sustainable practices mainly because compliance requirements guide them, and they seek enhanced reputation and stakeholder satisfaction. The supply chains operated by HUL and ITC have adopted sustainable sourcing practices for ethically sourced product manufacturing driven by market demand increases (Singh & Kapoor, 2020). The rising acceptance by modern financial markets of companies showing solid ESG performance drives all businesses to develop sustainable operational models.

10.5.2 Challenges in Implementing Sustainable Practices

The most prevalent challenge is the lack of proper infrastructure and the high upfront investment costs of green technologies. Smaller entrepreneurs are seen as unable to make the significant capital investments that are needed to move to cleaner technologies in sectors such as manufacturing and energy. According to Singh and Kapoor (2018), Reliance Industries and Tata Group are large corporations with the potential to implement sustainability practices, but SMEs in India encounter financial and technical resource constraints when adopting sustainable technologies. Furthermore, an unskilled workforce and a lack of awareness among local businesses in implementing sustainability practices pose additional challenges. However, many businesses have overlooked the advantages of adopting energy-efficient practices or renewable energy solutions, thereby delaying the adoption. In addition to this, unsystematic regulatory enforcement and vagueness in policy frameworks commonly lead to business uncertainties and a lack of clarity in planning (Gupta et al., 2020).

10.5.3 Government Initiatives and Policies

A variety of Indian government policies and programs exist to encourage companies to practice sustainable business. A detailed roadmap to reduce the carbon emissions and improve the energy efficiency in all sectors is provided in the National Action Plan on Climate Change (NAPCC). With the implementation of implementing the Perform, Achieve, and Trade (PAT) scheme and the Renewable Energy Certificates (REC) mechanism, industries are motivated to follow energy-efficient technologies. According to Gupta et al. (2021), they have advanced energy conservation efforts in energy-intensive industries such as cement and steel. In addition, the government has set demanding renewable energy goals, such as achieving 500 GW of capacity from non-fossil fuel sources by 2030. Hence, this has catalyzed a lot of renewable energy investments, and businesses are starting to consider alternative energy solutions to reduce their dependency on conventional energy sources (Mehta & Joshi, 2021).

10.5.4 Role of Technology in Sustainable Business Practices

Technology acts as an essential factor in boosting sustainable business practices throughout India. AI and IoT devices assist companies with supply chain optimization through reduced waste and decreased energy usage, and these devices provide industrial facilities with real-time water and energy monitoring capabilities, according to Sharma and Joshi (2020). The agricultural sector utilizes technology, according to Mehta and Joshi (2019), to develop precision farming systems that decrease irrigation needs while increasing yield production. The modern energy sector in India is being transformed through the adoption of clean technology systems that include solar and wind power generation. Businesses are now adopting green energy solutions for their operational power needs while also decreasing their environmental impact because renewable technologies demonstrate enhanced affordability.

10.6 Role of Carbon Taxation in Fostering Sustainable Business Practices

The economic instrument of carbon taxation functions through business taxation that reflects their carbon dioxide (CO₂) emissions quantities.

Governments worldwide implement carbon taxation as a solution to decrease greenhouse gas emissions since climate change remains a global threat. The increased cost of carbon-intensive activities through carbon taxes leads businesses to decrease their carbon output while adopting green technologies for sustainable practices. India views carbon taxation as a fundamental step to unite economic development with environmental preservation because industrial growth has generated increased emissions throughout the country.

10.6.1 Mechanism of Carbon Taxation

Businesses must pay carbon taxes based on their volume of greenhouse gas emissions because this pollution tax follows the “polluter pays” policy. Companies need to measure their CO₂ emissions through mandatory reporting processes to comply with the established tax rate, which charges based on each ton of CO₂ emissions. Companies face two options under carbon tax systems: they must decrease their emissions while also finding methods to reduce their tax expenses by adopting cleaner technologies. The market stimulus methodology encourages businesses to implement energy-efficient operations by offering financial incentives and encouraging them to substitute their energy supply with renewable sources while reorganizing supply chain operations. Carbon taxation elevates product and service prices with carbon content, which guides consumers to choose sustainable alternatives.

10.6.2 Economic Incentives and Sustainable Innovation

The implementation of carbon taxes sends businesses-specific economic messages to make them implement sustainable practices. Research by Fowlie et al. (2019b) establishes that properly set carbon taxes redirect investments from carbon-intensive businesses into sustainable clean energy options. Companies choose to spend money on technologies that improve energy efficiency and the purchase of renewable energy systems and carbon capture and storage (CCS) equipment. This enables them to decrease both carbon emissions and taxable liabilities. The transition results in double benefits because businesses decrease their environmental effects and achieve decreased operational expenses from improved energy efficiency measures.

10.6.3 Global and Indian Perspectives on Carbon Taxation

Numerous nations across the world use carbon taxes as climate change solutions for fulfilling Paris Agreement obligations. Sweden, along with Canada and the United Kingdom, established carbon tax programs and pricing systems which motivated both emission decreases and renewable energy replacements. Several indirect programs introduced by the Indian government serve equivalent purposes to carbon taxation despite the national implementation of carbon taxation not being complete. The government promotes business climate responsibility through the combination of three programs: the PAT scheme, Renewable Energy Certificates, and GST tax on fossil fuels. The application of a national carbon tax faces difficulties within India since the country heavily depends on coal and other fossil fuels to reach sustainable development goals (Canadian Climate Institute, 2020).

10.6.4 Challenges in Implementing Carbon Taxation in India

Several obstacles exist for implementing carbon taxation in India. Providing carbon taxation faces major difficulties because India maintains a heavy carbon-emitting economic foundation consisting of steel production and coal mining along with cement manufacturing. A rushed implementation of carbon tax legislation would negatively impact these heavy industries by increasing production expenses that may automatically get shifted to consumer prices. Smaller businesses, including medium- and small-sized enterprises (SMEs), could experience difficulties in bearing increased financial costs, which might result in short-term job losses and economic instability. The Indian government must carry out carbon taxation through progressive implementation while creating supportive measures that guide sectors toward sustainable practices as specified by Porter and van der Linde (1995). India can support its green transition through renewable energy project subsidies, energy technology promotion, and programs promoting green business financing access. The implementation of carbon taxation faces resistance from politicians within India because the government must balance sustainable development with economic progress in this developing nation. Stakeholders will resist policies which they believe hurt the economy, particularly those operating in energy-intensive businesses. Carbon taxation enforcement becomes difficult because India does not have a thorough emission monitoring and reporting infrastructure in place. To enforce carbon tax compliance properly and with fairness in India, the Ministry of

Environment, Forest, and Climate Change (MoEFCC) identifies the requirement for building strong emission tracing systems and data collection programs (Renwick et al., 2018b).

10.6.5 Carbon Taxation in Achieving India's Climate Goals

The implementation of carbon taxation stands crucial for India to accomplish its climate commitments despite existing difficulties. Under the Paris Agreement, India set goals to decrease its carbon intensity by 33–35% between 2030 and 2005 levels. Proper implementation of carbon taxation schedules would empower India to reach its emissions reduction targets. Carbon taxes serve as an incentive, supporting the advancement of clean technologies as well as environmentally friendly energy sources, thus helping to build a green economy through renewable energy job growth together with sustainable industrial techniques (Ghosh, 2017).

In India, the revenue would sustain green technology transitions while enhancing climate resilience and providing help to communities that experience climate change effects.

10.7 Comprehensive Blueprint for Integrating Environmental and Economic Goals

Environmental and economic objectives unite as the core matter when discussing sustainable development. Economic growth together with industrial development has led to a greater understanding that the environment should remain intact through economic expansion. The goal aims to advance sustainable green technologies, develop circular economic systems, and promote inclusive development, which reduces environmental impacts of industrial growth.

10.7.1 Establishing Clear Policy Frameworks

The key to environmental and economic integration depends on developing specific policy structures that can be both enforced and operationalized. Governments throughout the world require policies that unite environmental sustainability with economic development. Robust policy should contain carbon tax systems together with financial incentives for sustainable technology

adoption and stringent ecological governance. Carbon taxation creates two advantages for business efforts—carbon emission reduction and monetary rewards for renewable energy investments. The Indian government has established the National Action Plan on Climate Change (NAPCC) through MoEFCC (2020), which integrates both environmental protection measures with national development objectives through its focus on sustainable resource usage. The guidelines should receive regular updates to address developing environmental threats and economic conditions both domestically and worldwide.

10.7.2 Promoting Green Innovation and Technology

To integrate environmental objectives, the focus needs to revolve around innovative technologies that minimize environmental harm while simultaneously stimulating economic expansion. Investing in clean technologies, including solar power systems, electric vehicles, and energy-efficient manufacturing, allows businesses to create new commercial opportunities and promote employment creation on their journey toward sustainability. The emerging market world views green innovation as an essential factor that fuels economic development. The implementation of renewable energy systems in India's solar and wind facilities has produced employment opportunities, effectively boosting national economic development while decreasing environmental pollution, according to Gupta and Rathi (2021).

10.7.3 Sustainable Resource Management and Circular Economy

Businesses within a circular economy work on waste reduction and resource reuse while promoting product recycling functions without relying on primary natural resources. The circular economy brings profitability to sustainable markets of recycling and remanufacturing and sustainable design while simultaneously helping the environment by decreasing resource usage and waste. The Indian government has started implementing circular economy principles through optimizing agricultural waste management procedures to boost resource utilization (Gupta & Rathi, 2021). Organizations can use product life cycle management to design products for reuse, recycling, and remanufacturing purposes, which creates dual advantages of economic gains alongside ecological sustainability.

10.7.4 Green Financing and Investment

Promoting green financing stands as a necessary step for achieving integration between environmental conservation and economic development by funding sustainable development projects. Public authorities, together with financial institutions, should back green bonds along with climate-friendly funds and related funding mechanisms that drive money into sustainable initiatives such as renewable energy systems, sustainable farms, and energy-efficient structures. Green investments lead to extended financial profits because sustainable products and services experience rising market demand. The business and government understanding of environmental sustainability enhancing financial success requires financial incentives for investors to base their choices on ESG standards. Green financing strategies have become operational in India through the National Clean Energy Fund (NCEF) that enables clean energy project development throughout the nation (Gupta & Rath, 2021).

10.7.5 Collaboration between Government, Industry, and Civil Society

Successful integration of environmental and economic drives requires government agencies to join forces with industrial leadership and public institutions. The government needs to develop policies suitable for sustainability, while businesses must set sustainability as their main organizational objective. Civil organizations should function as advocacy bodies. The government serves as an enforcer of environmental regulations for business activities and as a support provider for green innovation development. Business enterprises need to prioritize emission reduction while adopting renewable energy sources to establish sustainable products and services. Nonprofits, alongside local community groups, perform vital duties by informing people about sustainability while fighting for law improvements that help marginalized groups benefit from sustainable advancement. Sweden demonstrates that by uniting forces through public-private partnerships, sectors can work together for a transition to a green economy (MoEFCC, 2020).

10.8 Findings and Suggestions

10.8.1 Findings

10.8.1.1 Policy Integration Is Crucial

Countries using public policies that merge green technology development with economic benefits generate more balanced economic development results. The National Action Plan on Climate Change (NAPCC) demonstrates excellent integration by implementing the National Mission for Enhanced Energy Efficiency (NMEEE) under its climate change goals.

10.8.1.2 Green Innovation Drives Economic Growth

In India, solar and wind power received investment which produced new job opportunities while creating economic benefits and decreasing the nation's carbon emissions. The implementation of public-private partnerships (PPPs) demonstrates efficiency in both promoting green innovation and the large-scale deployment of sustainable technologies.

10.8.1.3 Circular Economy Is the Future

The implementation of circular economy concepts shows promise toward three essential achievements, which are waste elimination, resource protection, and resource protection alongside new business growth. Circular economy advantages have grown within India because the country has started prioritizing waste management along with sustainable farming. The transitional process remains in its earliest stage because it needs expanded government policy backing alongside stronger industrial involvement.

10.8.1.4 The Role of Green Financing

Sustainable development initiatives require essential funding, which comes from green financing. Financial institutions are now placing ESG factors at the forefront, through which sustainable investment funds and green bonds have emerged as prominent financial tools. The NCEF, alongside a developing green bond market, represents two strategic vehicles through which funding reaches environmentally sustainable projects in India.

10.8.2 Suggestions

10.8.2.1 Strengthen Policy Frameworks

The new policies should provide economic advantages to businesses that embrace environmentally friendly approaches, which include carbon alignment systems, renewable power selection decisions, and waste management initiatives. Strategic guidelines and robust enforcement systems will establish an equal competitive zone for businesses that want to practice sustainability. Long-term sustainability policies must replace short-term gain objectives because they prevent environmental damage that results from accelerated industrial development.

10.8.2.2 Increase Investments in Green Innovation and Technology

Public and private entities need to enhance their funding of green technologies, which present scalable and cost-efficient systems for diminishing emissions, together with renewable energy solutions and resource management. The Indian government should maintain investments in solar energy structures alongside electric vehicle promotion to build employment while decreasing environmental emissions. Sustainable business solutions, along with technological advancements, need public and private sector collaborations to speed up their implementation on a wider scale.

10.8.2.3 Promote Circular Economy Principles

As government leaders, we need to provide incentives by putting a policy environment in place, joining industry efforts, and promoting information and education. Demand for sustainable goods will be created by its own market for recycled materials, remanufactured products, and sustainable design practices, as well as by the reduction of pressure on natural resources. So, in India, regulations could be enforced such that waste management becomes stronger and businesses can be led into making products that are recyclable or can be reused to generate a sustainable business ecosystem.

10.8.2.4 Facilitate Green Financing Mechanisms

The government needs to collaborate with financial institutions to develop existing green financing programs. The government and financial institutions should construct several synergies by implementing tax rebates for green

bonds, combined with low-interest green project loans and sustainability-based portfolio demands for institutional investors. India should develop its green finance structures by building an efficient green bond system combined with tax benefits for environmentally friendly financial commitments to attract capital for sustainability projects.

10.9 Conclusion and Direction for Future Research

Environmental sustainability, combined with economic growth, represents an essential approach for developing sustainability in the future. The research gathered from worldwide frameworks and Indian policy structures, which include NAPCC alongside renewable energy initiatives, demonstrates rotational coordination between environmental preservation and financial development goals. Environmental damage reduction depends strongly on the implementation of a carbon tax implementation and the promotion of sustainable business practices, which simultaneously generate new economic potential. These measures require improved implementation and scale-up because major obstacles continue to obstruct their successful deployment. Progress has started, but various limitations exist on the way toward achieving total sustainable economic integration. Faster implementation of circular economy principles and green financing systems remains essential since they need wide adoption, especially in developing economies like India. Some rural and underserved areas fail to leverage advanced tools such as AI and big data technology to monitor and manage their sustainability while these tools become effective means for tracking sustainability.

10.9.1 Direction for Future Research

In the future, researchers should analyze how improving policy structures of developing economies can synchronize environmental and economic initiatives. Researchers should examine carbon taxation policies along with green technology subsidies and international climate agreements that form national economic strategies (Kumar & Yadav, 2022). Additional research needs to study political and economic factors that determine the success or failure rate of environmental policies throughout emerging market nations. Research about adoption factors that support and obstruct the use of green technologies in renewable energy and transportation systems and industrial manufacturing is currently insufficient. Studying public-private partnerships for

scaling green innovation alongside technology will deliver essential knowledge about the best ways to speed up sustainable development (Sharma & Kapoor, 2021a). Evaluation of the economic advantages from clean technology adoption must explore job creation together with GDP growth along with its financial benefits in countries that are developing similarly to India.

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Chapter 11

A Study on Perception of Gen Z Customers on Artificial Intelligence in Chennai City

K. Sangitha

11.1 Introduction

Artificial intelligence has reshaped the way businesses engage with customers and has significantly transformed industries from healthcare to entertainment. Individuals born between 1997 and 2012 are the most influential consumer groups, who are known as Generation Z consumers. These individuals are grown up in a digital world where artificial intelligence and themselves are in commonplace. A unique perspective on artificial intelligence plays a crucial role in the Gen Z's routine lives. Customers specifically from Gen Z are characterized by affinity for technology, social consciousness, and diverse interests.

Understanding how Gen Z consumers perceive these artificial intelligence technologies is crucial for businesses aiming to cater to their needs. Artificial intelligence is increasingly integrated into various consumer experiences through chat bots and virtual assistants for personal recommendations (Kumar et al., 2023b). A deep immersion in the digital landscape from a young age makes Gen Z customers their experiences with technology distinct from those of previous generations. Gen Z customers are more critical and discerning when it comes to ethical implications, privacy concerns, and transparency when adopting and interacting with AI (Devi, 2024).

The respective study aims to discover the demographic profile of customers, especially from the Gen Z generation, to venture into the perceptions of customers, especially from the Gen Z generation, regarding AI and to examine their attitudes towards its utility, effectiveness, and ethical considerations (Kumar et al., 2023a). The chapter aims to seek and uncover the influence of AI on their decision-making, engagement with brands, and overall customer experience. By understanding the prerequisites and morals of Gen Z users, businesses can better tailor their AI-driven strategies to their perspectives (Fayad & Paper, 2015).

11.2 Objectives

- To understand the degree of awareness of artificial intelligence by Gen Z customers..
- To identify the association between gender and how do they feel about the increasing presence of AI in their life.
- To examine the level of trust in AI technologies by Gen Z customers.
- To explore the data privacy and security issues of AI by Gen Z customers.

11.3 Scope of the Study

Developing into the beliefs, opinions, attitudes, and expectations of Gen Z customers in various aspects of their lives towards artificial intelligence is the study's main scope. The study is geographically restricted to the Chennai region. The study aimed to include the defined age range of the generation born between 1997 and 2012. This age group is highly relevant as they have grown up in a digital nativity environment. The study will examine the far-ranging applications of AI in Gen Z customers' lives that influence their behavior, such as Chat bots, virtual assistants, personalized assistants, social media, entertainment, etc. Concentrating on Gen Z customers' awareness, interactions, and perceptions are the facets of AI's impact on this demographic. It also examines concerns such as surveillance, bias in AI algorithms, and the transparency of AI decision-making (Kumar et al., 2023a). The study period is from June to December 2024. The period of six months will be used to collect data through questionnaires to capture the most

updated views. The data is collected from Gen Z customers on AI (Kumar et al., 2023b).

11.4 Review of Literature

1. Bunea, Monica Triculescu et al. (September 2024)—the study explores the buying decisions of customers of Generation Z in online shopping. The Technology Acceptance Model (TAM) is adapted with the impact of AI to analyze the study. The study gives output to enhance customer buying activities, highlighting the capability of AI for online retailers. The study focuses on the managers' proactive approach to optimize the user experience on artificial intelligence applications that delivers benefits to the consumers which are tangible in nature.
2. Tanay Saxena (December 2024)—this article explores the history and evolution of marketing with an emphasis on Gen Z, the first digital-native generation. It focuses on the Indian market and how artificial intelligence is influencing marketing strategies.
3. Ruiz-Viñals et al. (October 2024)—this article research is on how AI influences the purchase process in the fashion industry while limiting its full exploitation. The results showed that the attitude towards AI and recognized effectiveness have a positive usefulness on buying propensity of Gen Z customers.
4. Hima Bindu (January 2024)—The research sole purpose of the article is not only to understand the lifestyle choices and frames of reference of customers from Gen Z with regard to e-shopping. The findings demonstrate that smart technologies have a considerable influence on the experiences of the customers who belong to Gen Z. The Gen Z consumers expect new devices to be used and anticipate electronic processes to be adopted on a large scale for making consumers to exercise more independence. This generation of youths primarily relies on personal experience while making purchasing decisions, focusing mainly looking at quality and prices, although they often overlook other choices based on their own understanding. Even though the internet is the primary source to seek the information for Gen Z customers, they will also seek advice from other people who have prior experience with a particular product when making the purchases of goods and services (Arora et al., 2025). For purchase-related decisions Gen Z customers will consult people who have knowledge of the product.

5. the environmentally responsible buying behaviors of Gen Z consumers from the university campus by analyzing and testing the various precedent and moderating influences of their environmentally responsible buying behaviors (Chan & Lee, 2023).

Indicators of the study show the responsibility of the Gen Z customers in society like feelings, engagement, and expectations. Incentives that are external in nature, such as social and material, have an affirmative influence over the sustainable interests of customers, specifically from Gen Z. There were no statistically significant effects from collectivist cultural values on Gen Z customers. It also shows environmentally conscious buying among the consumers of Gen Z. Further, the moderating effects of self-defeating mindsets, imposed obstacles, and understanding of the ramifications of environmentally sustainable consumption actions on the sustainable consumption behavior of Gen Z consumers were insignificant (Cota & Paiva, 2024).

6. Salam and colleagues explore how marketing has evolved due to the consumers born between the mid-1990s and early 2010s, who are called as Gen Z. These Gen Z customers, basically called “digital natives,” are tech-savvy and have distinct shopping habits. The research delves into their preferences and effective ways to build lasting relationships with them. The findings reveal that Gen Z favors product lines that give precedence to societal importance, nature-related issues, and green practices of sustainability. Gen Z customers lean towards experiences over physical goods and heavily rely on social media. Gen Z customers’ preferences and effective marketing strategies are studied for the purpose of building long-lasting relationships with them. The study attempted to collect qualitative data from 2010 to 2024 and drew insights into Gen Z customers' tastes, preferences and behaviors (Devi et al., 2024).
7. “Consumer Decision-Making Style of Gen Z,” by Packiara Thangavel and team, investigates the online shopping behaviors of Gen Z. The study identifies four types of shoppers: quality-focused bargain hunters, time-conscious shoppers, bargain hunters, and brand-loyal shoppers. For e-retailers, these insights are invaluable for understanding how Gen Z approaches online shopping their products and services (Bindu, 2024). By using generation segments on Gen Z online shoppers, a conceptual framework will provide a wide range of insights to e-retailers. Internet speed and the rapid advancements in online shopping would have stimulated online retailers to offer a large-scale variety of products with utmost streamlining, unlike the long-standing

retailers. The ramifications of the findings for professionals in marketing and online retail are highlighted at the end of the study (Bhatnagar & Rajesh, 2024).

8. Prakash Singh's study, "What Drives or Decelerates Generation Z?," examines factors influencing Gen Z's online buying intentions. The research focuses on calculated and strategic risk, benefits, user-friendliness, protection of personal information, security, and dependability. Using the Technology Acceptance Model, the investigation explains how these determinants shape Gen Z's online buying decisions. Companies can use these insights to create targeted marketing campaigns for Gen Z, though the study's findings are limited by factors like a small sample size and a focus on India.

11.5 Features of Artificial Intelligence

To transform numerous industries and aspects of daily life, a variety of powerful features are enabled by artificial intelligence. Here are some of the features of AI:

- It can analyze large datasets and learn patterns. It also improves its performance over time without being explicitly programmed.
- It can understand, interpret, and generate human language through text and speech, enabling effective communication.
- It can also analyze the text to figure out the feeling and attitude, whether optimistic, pessimistic, or unbiased.
- On images and videos, it can clearly identify and classify objects.
- In crowded environments, AI can detect and recognize human faces.
- From household chores to industrial automation, AI-powered robots can perform tasks without human intervention.
- To perform delicate tasks with precision, AI enables robots to interact with objects and people.
- For decision-making processes, AI can analyze the historical or past data to predict future events and trends.
- It can evaluate risks by analyzing patterns and anomalies in data.
- For quick and accurate decisions based on predefined rules and data analysis, AI helps more than humans.
- For products, services, and content based on user preferences, artificial intelligence will provide personalized recommendations.

- Smart speakers and virtual assistants are more user-friendly, as they can understand and respond to spoken commands.
- For note-taking and documentation, AI is used where it can convert spoken language into written text.
- To mimic the human brain's structure and function, artificial intelligence uses complex neural networks which ultimately enable advanced tasks like image and speech recognition.
- By learning from the consequences of actions, artificial intelligence improves its performance.
- According to individual user preferences and behaviors, artificial intelligence can tailor the experiences, services, and contents.
- In fraud detection, cybersecurity, and quality control, artificial intelligence can detect unusual patterns and behaviors.
- To increase efficiency and reduce human error, artificial intelligence automates repetitive tasks.
- For customer support in natural conversation with users, artificial intelligence can engage AI-powered chatbots.
- For tasks like reminders and information retrieval, artificial intelligence assists with Cortana, Siri, and Alexa

11.6 Advantages of Artificial Intelligence

To enhance the experiences of Gen Z customers across various aspects of their lives, artificial intelligence provides various advantages. Here are some of the advantages.

- Artificial intelligence will analyze the data to provide personalized recommendations and enable tailored experiences. It also makes interactions more relevant and engaging.
- It offers instant support and assistance through AI-powered chatbots and virtual assistants. It will free up time for more important activities by automating routine work.
- Customer satisfaction from human agents is quite less compared to the process and response system from artificial intelligence.
- Artificial intelligence reduces waiting time and improves service delivery by optimizing workflows.
- To enhance their overall digital experience, Gen Z customers can benefit from the latest technological advancements.

- To make everyday tasks more enjoyable and efficient, AI is coming up with new and creative ways to solve all sorts of problems we face. It's like having a super-smart helper that can think of things we might not even consider.
- To help customers make informed decisions, artificial intelligence can evaluate substantial data sets to offer key takeaways and meaningful observations.
- It enables proactive and smarter choices to predict trends and behaviors of Gen Z customers.
- To lead to a better and overall experience, Artificial Intelligence can resolve issues quickly and accurately.
- Multiple language assistance is provided by AI by breaking communication barriers.
- For disabled individuals, artificial intelligence can enhance accessibility by providing features like voice recognition and text-to-speech.
- Artificial intelligence offers personalized entertainment options such as music and movies, making accurate content based on preferences.
- According to the individual needs and learning styles, artificial intelligence can cater to personalized learning experiences.
- Educational tools of artificial intelligence can make learning more interactive and enjoyable.

11.7 Disadvantages of Artificial Intelligence

In transforming the world in remarkable ways, artificial intelligence is playing a vital role, but it does have its own set of challenges and disadvantages. Here are the disadvantages of artificial intelligence listed below.

- In sectors like manufacturing, customer service, and transportation, automation of artificial intelligence can replace human jobs. This will lead to unemployment and economic displacement.
- In areas like hiring, law enforcement, and lending, artificial intelligence can perpetuate existing biases in data, which will lead to unfair treatment and discrimination.
- In privacy and surveillance, artificial intelligence raises problems as it involves the accumulation and evaluation of vast amounts of personal information.
- It is vulnerable to hacking and manipulation, leading to misuse or malicious actions.

- The decision-making process in life-and-death situations involving artificial intelligence raises ethical questions about the potential for autonomous weapons.
- Depending more on artificial intelligence systems could cause a reduction in human skills and critical thinking abilities. It is making society more vulnerable to technological failures.
- It is costly, complex, and limits accessibility for smaller organizations and developing countries. This is caused by the development and maintenance of advanced AI systems.
- It can be challenging to determine who is responsible for the outcomes. It can lead to accountability issues.

11.8 Basic 10 Usages of AI in Daily Life

Replication, imitation, and reproduction of human intelligence techniques by computer systems is called as artificial intelligence. It involves teaching machines to learn from data and make decisions with minimal human interventions. AI's potential benefits promises continued advancements and integration into various aspects of life. Some of the usages of AI in daily life are as follows:

1. **Taxi Booking Apps:** A revolution in urban transportation has been achieved through taxi booking apps. Their features make it easier and more convenient to move from one place to another with services ranging from economical to . Examples include Uber, Ola cabs, Savaari, Goibibo, Mega cabs, Tab cabs, etc.
2. **Voice Assistants:** To perform a variety of tasks using voice commands, an AI-powered tool is called a voice assistant. It is integrated into many devices such as smartphones, smart speakers, and cars. Examples include Siri, Alexa, Google Assistant, Cortana, and Bixby.
3. **Chat-bots:** To simulate human conversation through text or voice interaction, an AI-programmed design is called a chat-bot. It can learn from interactions and responses and analyze conversations to adapt to new inputs. Examples include NLP, machine learning, context awareness, and integration.
4. **Entertainment streaming apps:** Through an offering of a vast library of content at our fingertips with AI, these are called as entertainment streaming apps. They feature user-friendly interfaces and provide personalized recommendations. Examples include Netflix, Amazon Prime, Disney+ Hotstar, Hulu, YouTube TV, etc.

5. **Personalized Marketing:** A strategy that tailors communication to individual customers based on their tastes and preference with the inference of AI is called personalized marketing. Customers feel valued and understood, resulting in high satisfaction. Example: Amazon, Netflix, Spotify, Flipkart, etc.
6. **Image Recognition through Google Lens:** An image recognition technology that provides information about whatever objects, things, or scenes captured in the lens. Example include Google Lens, etc.
7. **Smart Input Keyboards:** The keyboards with enhanced functionality and convenience compared to traditional keyboards are called smart input keyboards. Features like gesture controls, wireless connectivity, and touchpads make them easier for customers to use. Examples include the customers use with ease. Examples include OnePlus Smart Wireless Keyboard, Google input tools, and Amazon Basics Wireless Bluetooth Keyboard, etc.
8. **Fall detection and car crash detection:** A technology designed to help senior individuals by automatically detecting falls and alerting emergency services is called fall detection. To detect severe car accidents and to provide timely help, car crash detection is used. Examples include Apple devices, Google devices, Medical alert devices, etc.
9. **Email filtering:** A technique used to organize and manage incoming emails is called email filtering. It automatically sorts emails based on predefined criteria and helps in reducing spam, phishing attempts, and other unwanted emails. Examples include Gmail, Microsoft Outlook, Clean Mail, etc.
10. **Navigation and travel:** Navigation technology has significantly enhanced AI technology, making it more easier and more convenient to explore new places. Travel technologies have made easy bookings for flights, hotels, etc., easier. Self-driving cars using AI for navigation and traveling are the latest. Examples include GPS systems, augmented reality, and voice-activated assistants.

11.9 Characteristic Features of Gen Z Customers

There is a demographic generation born between the 1990s and 2010s are generally called Gen Z or Zoomers. They were raised in an era where technology was all around. They set themselves apart from previous generations with some unique characteristics. They are as follows:

- Gen Z customers are highly proficient with technology. The life of Gen Z customers is not known without the usage of the internet and smartphones. Gen Z customers spend a significant amount of time online.
- They prefer quick and engaging content. Gen Z customers are accustomed to rapid-fire content consumption.
- Gen Z customers are more interested in entrepreneurship, where they are creating their own opportunities.
- Acceptance of diverse perspectives and openness to accept are characteristics of Gen Z customers.
- They are more practical and financially cautious as they lived through economic crises and the COVID-19 pandemic.
- Gen Z customers support brands that align with their values, as they are passionate about social and environmental issues.
- In the purchasing decisions of Gen Z customers, platforms like TikTok and Instagram play a significant role.
- Compared to the previous generations, Gen Z customers are more grounded and practical.

11.10 Statistical Facts about Gen Z Customers

- In the world's population, Gen Z makes up about 32%.
- As they are more confident in their tech skills and non-tech skills, Gen Z's ownership of smartphones is about 98%.
- The maximum population accounts for about 40% in the United States.
- Gen Z prefers shopping online monthly, with 52%.
- Gen Z owns an average of three electronic devices, including smartphones, tablets, and laptops, with 52% in the United States.
- They make purchases based on social media recommendations, with 70% and 90% of Gen Z following brands on social media.
- Gen Z considers themselves loyal to a single brand, with only 29% preferring to explore new options.
- Gen Z is willing to expend more for sustainable products with 73%.
- Gen Z customers regularly create videos, blogs, or social media posts with 40%.
- Gen Z prioritizes mental health and well-being, with 65% seeking out wellness products and services.

11.11 Statement of the Problem

It runs through various sectors and is significantly influencing consumer behavior and expectations. Gen Z customers are at the forefront of AI-adopting generations as they are a digitally savvy and technology-driven generation. Gen Z customers are not only familiar with AI technologies but also engage through platforms like social media, e-commerce, and entertainment services.

A very little is known about Gen Z customers' deep-seated perceptions, concerns, and expectations related to AI technologies despite their high interaction with AI. While AI is offering various advantages in the form of personalized services, convenience, and efficiency, it also raises significant ethical issues like data privacy, transparency, and algorithmic bias. AI-powered products and services are potentially impacting the trust, adoption, and concerns of Gen Z customers. The study aims to explore the lack of comprehensive insights into how customers of Gen Z perceive and engages with AI. Valuable insights from the study will provide information to businesses, policymakers, and also to AI developers to tailor their offerings to face the unique purpose and concerns of Gen Z customers by addressing these gaps.

11.12 Need for the Study

Reshaping industries were thought of as futuristic which were made real with the rapid advancement of artificial intelligence. Businesses are increasingly relying on AI for personalized product recommendations and customer experiences. The demographic set born between 1997 and 2012 is significantly influencing the market today. Gen Z is the early adopters and critics of technological innovations like AI. There is a critical gap in understanding how Gen Z perceives these technologies. The study also aimed to understand how the adoption of these technologies may reshape the future. Businesses aiming to cater to the preferences and concerns of Gen Z have to look into the insights of AI's benefits, risks, and ethical implications.

In the global consumer market, Gen Z represents a significant portion with increasing purchase power and a strong presence on digital platforms. Businesses that wish to maintain competitiveness and relevance have to understand the relationship with AI and Gen Z customers. To improve AI-based products and services, companies can identify strategies by

exploring Gen Z's view on AI. This study also provides valuable insights for implementing AI technologies that are both effective and ethical. To anticipate the needs of tomorrow's consumers, this study will lay out a platform.

11.12.1 Limitations

- The study solely focused on the Chennai region.
- Perception regarding AI by Gen Z customers may change quickly as new developments occur.
- Only 386 customers are included in the sample.

11.13 Research Methodology

Study Area:

The assessment is implemented among the Gen Z customers in Chennai district only.

Design of Sample and Size of Sampling:

The survey method was used to collect the primary data. A well-formulated questionnaire was made to conduct and collect the data. For generating data, random sampling was applied and the samples were selected systematically. A total of 368 samples were collected and all were found suitable for the study.

Sampling Collection Range:

The primary data is collected through a random sampling technique. Justification for the sampling method is provided for collecting the samples from Gen Z customers in the Chennai district only.

Designing of the Questionnaire:

The empirical and original variables are obtained by means of a Google Forms survey only. The various contributors of the study are inquired to give their assessment relating to the perception of AI in Gen Z customers. The demographic factors were comprised in the first part of the questionnaire with choice-based questions. The second part includes general usage of AI in their daily life. The third part consists of understanding, trust, data privacy, and security issues of Gen Z customers with a 5-point Likert scale.

Data Analysis:

The empirical and original collected information is processed using the PSPPP software. The results were obtained using the statistical tools below. They are:

- Descriptive statistics using mean and standard deviation. It is shown in Table 11.1.
- Chi-square test. This is shown in Table 11.3.
- *T*-test. This is shown in Table 11.2.
- ANOVA. This is shown in Table 11.4.
- Regression analysis. This is shown in Table 11.5.

Interpretation:

The major part of the respondents is female, as indicated by a mean value of 1.59. The majority of Gen Z customers fall under the age group of 18–24, with a mean of 1.16 under this study. The educational qualification of the respondents are predominantly at the undergraduate level with a mean

Table 11.1 Descriptive Statistics

	<i>Total Number of respondents</i>	<i>Minimum</i>	<i>Maximum</i>	<i>Mean (μ)</i>	<i>Standard Deviation</i>
Gender	368	1	2	1.59	0.493
Age	368	1	2	1.16	0.370
Educational qualification	368	1	4	2.15	0.795
Marital status	368	1	2	1.84	0.370
Income	368	1	3	1.42	0.708
Valid <i>N</i>	368				

Table 11.2 *T*-Test

	<i>No. of Variables</i>	<i>M</i>	<i>Std Dev.</i>	<i>Std Err M</i>
Gender	368	1.59	0.493	0.026
Clear understanding of AI	368	4.02	0.767	0.040
Differentiate between traditional programming and AI	368	3.91	0.776	0.040
Most people understand what AI	368	3.91	0.831	0.043
Seek information regularly for advancements in AI	368	3.91	0.748	0.039
Easy to explain about AI to others	368	4.00	0.781	0.041

Table 11.3 Chi-Square Tests

<i>Gender</i>	<i>Very Positive</i>	<i>Somewhat Positive</i>	<i>Neutral</i>	<i>Total</i>
Male	88 (89.2)	27 (29.7)	37 (33.0)	152 (152.0)
Female	128 (126.8)	45 (42.3)	43 (47.0)	216 (216.0)
Total	216 (216.0)	72 (72.0)	80 (80.0)	368 (368.0)
Indication: 1. The importance within () relates to row percentage				
	Value	df	Asymptotic Significance (Two-Sided)	
Pearson chi-square	1.265	2	0.531	
Likelihood ratio	1.262	2	0.532	
Linear-by-linear association	0.448	1	0.503	
No. of valid cases	368			

value of 2.15, and most of the customers are unmarried with a mean value of 1.84. Respondents dominant share fall in the income group of below 20,000 with the mean value of 1.42.

Interpretation: From the above it is revealed that a generally a high level of understanding and engagement with AI is there by the dataset of 368 respondents. The gender variable suggests a higher representation of female with a mean value of 1.59. Based on the mean scores, it is evident that a clear understanding of AI is considered the most important factor with a mean value of 4.02. This is followed closely by the ability to explain AI to others with a mean value of 4.00, and other factors such as the ability to differentiate between traditional programming and AI, the belief that most people understand what AI is, and regularly seeking information about advancements in AI with a mean value of 3.91 for all the other factors.

Null Hypothesis: Between the gender and how do they feel about the increasing presence of AI in their life there is no association.

Table 11.3 presents the association between gender and respondents' feeling about the increasing presence of AI in their lives using the chi-square test.

Table 11.4 ANOVA

ANOVA						
		<i>S of S</i>	<i>Deg freed</i>	<i>M S</i>	<i>F Value</i>	<i>P Value</i>
Provide accurate information	Between groups	4.294	3	1.431	3.213	0.023
	Within groups	162.141	364	0.445		
	Total	166.435	367			
AI makes unbiased decisions	Between groups	7.200	3	2.400	4.149	0.007
	Within groups	210.539	364	0.578		
	Total	217.739	367			
Confidence in the security of my data	Between groups	9.106	3	3.035	5.634	<0.001
	Within groups	196.111	364			
	Total	205.217	367			
Rely upon for critical decision making	Between groups	17.595	3	5.865	12.278	<0.001
	Within groups	173.883	364	0.478		
	Total	191.478	367			
Trust recommendations provided by AI algorithms	Between groups	6.729	3	2.243	5.351	0.001
	Within groups	152.575	364	0.419		
	Total	159.304	367			

Table 11.5 Regression Analysis

<i>Model/Abstract</i>						
Model	<i>R</i>	<i>R</i> ²		Adj <i>R</i> ²	Std. Err Est	
1		0.210	0.044	0.031	0.697	
ANOVA						
Model		S S	df	M S	<i>F</i> Value	<i>P</i> Value
1	Regression	8.094	5	1.619	3.337	0.006
	Residual	175.621	362	0.485		
	Total	183.715	367			

Interpretation:

The null hypothesis is failed to be rejected due to the P -value, which is greater than the significant level of 0.05. Hence, it is decided that there is no significant association between gender and how individuals feel about the increasing presence of AI in their life.

Null hypothesis: No significant difference among different educational qualifications of the Gen Z customers in relation to trust in artificial intelligence.

Interpretation:

The null hypothesis is rejected at the 5% level with regard to all the factors of Trust is AI as the P value is less than 0.05. So there is a considerable distinction among the qualification of education with regard to the factors for reliability in AI such as provides accurate information, AI makes unbiased decisions, confidence in the security of my data, rely upon for critical decision making, and trust recommendations provided by AI algorithms. To conclude the varying levels of reliability in AI technologies are different between the different education qualifications of Gen Z customers.

Interpretation:

The 3.337 indicates the strength of the relationship between the actual and predicted values for Gen Z customers through multiple correlation analysis. The F value and corresponding P value of 0.006 suggest that the model significantly accounts for the dependent variable as variance. The predictors in the model collectively offer a meaningful explanation of trust in AI. There is a relevant statistical relationship between the independent variables and also the level of trust in AI technologies among Gen Z customers.

11.13.1 Findings of the Study

- Around 41.3% Gen Z customers are male and 58.7% Gen Z customers are female.
- Gen Z Majority customers fall in the age group of 18–24 (83.7%) from the above study.
- Most of the customers are with UG qualification with 67.4% and the minimum number of Gen Z customers are with PG qualification with 7.3%.

- Nearly 83.7% Gen Z customers are unmarried and 16.3% of Gen Z customers are also married.
- Gen Z's Majority of customers were falling under income range of lower than Rs. 20,000 with 70.7% and the least customers fall under the category of earning above Rs.30,000 with 12.8%.
- Majority of the Gen Z customers are not familiar with AI with 56.5% and least with somewhat familiar with 15.2%.
- Nearly 30.4% Gen Z customers inferred that AI-powered devices or sources are used by them several times a week and the least was inferred as "Never" with 4.3%.
- The maximum number of Gen Z customers are using the AI-powered devices or sources, the presence of AI in their life in increasing was interpreted as very positive with 58.7% and the least with neutral with 21.7%.
- The null hypothesis is failed to be rejected due to the P -value, which is greater than the significant level of 0.05. Hence, it is decided that there is no significant association between gender and how individuals feel about the increasing presence of AI in their life.
- The null hypothesis is rejected at 5% level with regard to all the factors of Trust is AI as the P value is less than 0.05. So there is a considerable distinction among the qualification of education with regard to the factors for reliability in AI such as provides accurate information, AI makes unbiased decisions, Confidence in the security of my data, Rely upon for critical decision making, and Trust recommendations provided by AI algorithms. To conclude the varying levels of reliability in AI technologies are different between the different education qualifications of Gen Z customers.
- The 3.337 indicates the strength of the relationship between the actual and predicted values for Gen Z customers through multiple correlation analysis. The F value and corresponding P value of 0.006 suggest that the model significantly accounts for the dependent variable as variance. The predictors in the model collectively offer a meaningful explanation of trust in AI. There is a relevant statistical relationship between the independent variables and also the level of trust in AI technologies among Gen Z customers.

11.13.2 Future Directions for Further Study

To strengthen our deep understanding of Gen Z customers' attitudes towards the awareness and trust of artificial intelligence in Chennai district future research can be explored in several dimensions:

- Conduct long-term studies to track the changes in the perception of Gen Z customers over time.
- Carry out comparative assessment studies across different demographic groups such as educational qualification level and occupation of Gen Z customers.
- Investigate psychological and cultural factors of Gen Z that influence attitudes towards artificial intelligence.
- Scrutinize the impact of data privacy and algorithmic bias, as a part of ethical considerations on belief levels.
- Use qualitative research methods such as interviews and focus groups to understand the individual experiences and concerns of Gen Z customers to gain a richer, nuanced understanding.
- Analyze the influence of educational initiatives on artificial intelligence and their effect on perspectives.
- Explore the role of social media and its influences in crafting viewpoints on perception of AI.
- Compare and analyze cultural differences within the district of Chennai on the acceptance level of and trust in AI.
- Inquire into various industries such as health care, finance, and entertainment, on Gen Z attitudes.
- Examine government policies and regulations of trust among Gen Z customers on AI.
- Conduct broader studies on the relationship between AI devices, such as smart home devices and virtual and voice assistants, in daily life usage of Gen Z customers and their acceptance.
- Analyze the mental health and well-being of Gen Z customers to understand the psychological impact.

11.14 Conclusion

The study on the perception of Gen Z customers towards artificial intelligence in Chennai revealed significant insights into their understanding, trust,

perceived benefits, willingness, experience, future outlook, and data privacy. Gen Z customers exhibit a positive inclination towards artificial intelligence, appreciating its convenience, personalization, and ability to enhance the overall experience. Their faith and belief in AI are heavily determined by factors such as providing accurate information, making unbiased decisions, confidence in the security of their data, to rely on AI for critical decision-making, and recommendations provided by AI algorithms. Gen Z customers expressed a willingness to use AI in daily life with the factors such as AI-powered assistants for basic inquiries, using new products and services with AI features, comfort in sharing personal information, preference for automated over traditional methods, and actively seeking out businesses that utilize advanced AI technologies.

The findings ultimately suggest that to engage effectively the Gen Z customers with businesses required to focus on practical benefits and ease of accessibility with data security. Overall, this analysis underscores the essential nature of awareness and faith in the original outlooks of Gen Z customers to realize the full potential of AI.

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Chapter 12

The Intersection of AI and Financial Sustainability: Evaluating the Influence of AI-Based Decision-Making, Risk Assessment, and Transparency in Banking: Special Reference to Private Banks in Tamil Nadu

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12.1 Introduction

The Indian banking sector shifted from traditional practices to become a modern financial system driven by technology. The economic liberalization that occurred in the 1990s brought about regulatory changes and attracted more foreign investments while digital banking services started to become mainstream (Bapat, 2021). Information technology (IT) integration has been essential in transforming banking operations, which now deliver faster transactions, superior security measures, and better customer service, according

to Sharma and Gupta (2022). The emergence of digital banking has brought about core banking solutions (CBS), electronic fund transfers, and mobile banking together with internet-based financial services, which collectively advanced operational efficiency in financial institutions (Kumar, 2023).

As artificial intelligence (AI) evolves into a critical disruptive element within banking, it reshapes financial operations by enabling banks to automate their decision-making processes, enhance fraud detection capabilities, and improve the management of customer relationships (Gupta et al., 2023; Abdurrahman, Gustomo, & Prasetyo, 2024). Through the application of AI-driven technologies, including machine learning and robotic process automation (RPA), along with AI-powered credit scoring models and chatbots, banks are now able to deliver personalized banking experiences while optimizing their risk management strategies (Malhotra, 2023). The decision-making-related processes are streamlined and enhanced by using AI-powered forecasting models as suggested by many prior studies. AI-enabled predictive analysis algorithms provide immense insights into optimizing operational efficiency while simultaneously mitigating operational costs, thereby paving way for financial transparency (Panda & Sahu, 2024). AI-associated and -supported applications promote green investment initiatives, which in turn enable sustainable financial management, credit risk assessment, and real-time fraud detection (Raj & Walia, 2024).

This study focuses on financial institutions located in parts of Tamil Nadu, which is accoladed as one of the top financial centers in India, and these institutions have now implemented AI-enabled core banking solutions aimed at risk assessment and complying with regulatory norms implemented by government agencies, alongside performing customer analytics (Ramesh et al., 2024). Although the banks operating in Tamil Nadu have already adopted AI-oriented initiatives, yet there is still a scarcity of empirical research about the outcomes of its implementation, according to Iyer and Kumar (2024). Moreover, very few studies discuss about the local obstacles in policymaking regarding AI implementation as they mostly focus on examining worldwide or countrywide developments (Mishra et al., 2023). So, the ultimate aim of this research is to find out the existing research gap through proper investigation about the usage and effectiveness of AI policies and practices in banking industry situated in Tamil Nadu and to analyze both the financial performance and challenges in implementing the AI system in the core banking solution (Das & Menon, 2023). The research aims to measure the intensity of the adoption of AI practices in the banks situated in Tamil Nadu, considering examining its effects on financial sustainability

and the contributions of AI practices in enhancing customer engagement and the outcome of operational efficiency. Moreover, this research also investigates the hindrances faced by these selected banks during the implementation of AI-associated systems aiming to comply with regulatory standards and manage financial governance. This research briefly outlines the enormous benefits and constraints in adopting AI in the banking industry and offers suitable suggestions on ways to promote sustainable financial growth through the implementation of AI practices. This study is unique as it supersedes the existing knowledge in this area of study by offering a precise regional view of AI-enabled banking solutions integrating theoretical aspects and the application of AI in real-world banking technologies regarding Indian financial institutions.

12.2 Review of Literature

12.2.1 AI-Driven Risk Assessment and Sustainable Financial Performance

Financial stability of the banks is enhanced by implementing AI-driven risk assessment systems, which supports in predicting potential downturns threats and by enabling risk management strategies that are proactive. Earlier studies suggest that, in order to improve the accuracy of predictive methods, detect fraud, to ensure compliance with regulatory norms, and strengthen financial sustainability, it is necessary to implement AI-driven practices and systems in place. The implementation of AI-enabled tools like risk assessment helps the banks in predicting financial shocks and reducing the risk associated with credit management, by ensuring their financial stability in a long-term perspective (Gupta et al., 2023). Moreover, credit risk analysis enabled by AI practices not only improves the risk evaluation process but also supports the long-term sustainability of the above financial institutions (Mishra & Das, 2023). Research emphasizes that stress testing models play a major role in increasing the sustainability in financial terms through optimizing risk-return trade off (Singh & Patel, 2024). Enhanced AI capabilities improve the decision-making capability of these institutions, which in turn contributes to improved financial performance by giving overview about low volatility status (Iyer et al., 2023).

H1: AI-driven risk assessment practices impact sustainable financial performance in a positive way.

12.2.2 Automated Decision-Making in Finance and Sustainable Financial Performance

Financial efficiency benefits from AI-driven decision-making through error reduction and strategic choice optimization. Studies show AI-powered decision-making models boost financial performance through improved resource allocation and operational cost reduction (Bapat, 2021). The implementation of AI-enabled real-time analytic capabilities allows banking institutions to make better financial decisions and stability in financial operations as per Das and Menon (2023). The financial resilience is enhanced by the implementation of AI-enabled solutions in the banking sector, which supports decision-making and improved risk assessment capabilities (Malhotra & Verma, 2023). Uncertainties in financial analysis can be mitigated to a major extent through proper implementation of AI support systems and practices and it also assures the long-term financial soundness and sustainability (Raj & Walia, 2024). Therefore, the role of predictive analysis does impact the effective functioning of the banking system and plays a crucial role in enhancing decision-making process with regard to banking industry

H2: Implementation of automated AI-decision-making practices in banking industry significantly impacts the financial performance and its sustainability.

12.2.3 Green Investment Strategies and Sustainable Financial Performance

The implementation of AI-enabled banking practices helps in developing strategies that induces green investments which directly supports the objectives of sustainable development by integrating the aspects of environmental, social, and governance (ESG) aspects in taking decisions pertaining to investments of whooping funds. The stability of the financial results is ensured by improving the ESG, i.e., risk assessment on ESG aspects through the implementation of AI-enabled banking systems in place (Sharma et al., 2023). AI-enabled banking practices when implemented successfully offer a wide range of screening methods that provide insights into capital allocation of projects related to sustainability, which in turn ensures high financial performance (Kumar et al., 2023). Portfolio optimization techniques enabled by the implementation of AI-driven practices assures risk mitigation with respect to those ESG factors that directly impact financial stability, according to Mishra and Das (2024). AI offers advanced predictive analysis tools

through which the investment processes related to ESG aspects become transparent enough that brings guidance for ensuring that the banks are able to be good at financial decisions and in promoting overall sustainable practices (Iyer & Kumar, 2024). Research shows that the investment in AI practices helps in the screening process while going for projects associated with environment to reap the best financial returns, alongside minimizing environmental threats (Singh et al., 2024).

H3: Implementation of Green investment strategies, enabled by AI, significantly has an impact on financial performance and its sustainability.

12.2.4 Sustainable Credit Scoring and Sustainable Financial Performance

In the lending segment, AI-enabled practices offer enormous benefits through offering various credit scoring models which are pertinent to refine the risk assessment policies, thereby enhancing the financial sustainability of banks. Many researchers show that there has been an improvement with regard to evaluating the credit worthiness of the borrowers by using AI-enabled practices, which also helps banks to achieve reduction in defaulters of loans (Nguyen, 2022). AI-enabled practices help banks to achieve financial soundness and better performance by offering suitable credit rating systems which streamline the assessment of ESG factors (Bapat & Menon, 2023). Institutions can achieve financial resilience by enhancing their lending portfolios and credit analysis systems through the integration of AI practices (Gupta et al., 2023). Many studies have investigated and found out that the credit risk assessment system which comes as the outcome of the AI integration in banking industry helps these institutions in lowering the number of loan defaulters which determines the financial stability. Institutions can achieve gains in terms of financial stability for a long-term through implementing AI practices in the area of credit evaluation that results in reduced credit losses (Raj & Walia, 2024).

H4: Sustainability in credit scoring, while enhanced by AI, positively impacts the sustainable financial performance.

12.2.5 Fraud Detection and Compliance and Sustainable Financial Performance

Banks can improve their financial stability by implementing AI-powered systems that consists of practices related to fraud detection, which spot

anomalies and thereby reduce risks associated with financial crime. These fraud detection systems enable these institutions towards a transaction security which brings in financial sustainability as according to research by Kumar et al. (2023). AI-based compliance systems may help these financial institutions to abide and comply with the regulatory standards established by various government agencies from time to time, which in turn enables them to avoid any financial penalties and to boost financial performance of these institutions (Singh & Patel, 2024). A well-monitored anomaly detection practices as enabled by the implementation of these AI-driven technologies not only improve the cybersecurity of the whole system but also reduce financial risks associated with cyber fraud (Das et al., 2023). Studies reveal that the adoption of policies related to fraud detection as suggested by AI-driven systems would decrease any operational losses and results in an increase in financial sustainability and stability according to Iyer and Sahu (2023). This compliance monitoring initiatives suggested by AI practices would give major transparency in transaction systems, thereby helping institutions achieve more sustainable financial outcomes (Mishra & Raj, 2024).

H5: AI-enhanced practices associated with suitable fraud detection and compliance systems may positively influence the sustainable performance of these institutions.

12.2.6 AI-Based Financial Forecasting and Sustainable Financial Performance

Companies can benefit from the predictive market trend analysis in a larger context as it aids these organizations to strategically focus on their financial stability. These predictive trend analysis helps to strategize their financial goals by mitigating risks through effective optimization of financial strategies and as a result it reduces the uncertainties associated with those decision outcomes (Nguyen, 2022). Sharma et al. (2023) emphasize the need for the implementation of AI-driven systems in banks in order to achieve soundness in financial resilience by taking possible proactive financial actions as a result of the implementation of artificial intelligence that provides the necessary forecasting tools. Another research which was conducted by Das and Menon (2024) reveals that how the algorithms provided by predictive models as a part of AI analysis can widely improve the cash flow management thereby aiming for a better financial sustainability. Studies also demonstrate various positive outcomes of the

implementation of AI-enabled systems and policies with regard to achieving financial stability (Iyer et al., 2023). According to the empirical study carried out by Kumar and Verma (2024), the usage of machine learning algorithms could drastically improve the possibility of accurate financial forecasting that further contributes to the processes in financial decision making.

H6: AI-based financial forecasting practices has a positive influence on the bank's sustainable financial performance.

12.2.7 Mediator: Financial Transparency and Governance

Institutions can substantially enhance their transparency in operations and functioning and adhere to government mechanisms by implementing AI based in their organization.

Gupta et al. (2023) emphasize the possible benefits of implementing AI-based practices in the banking industry, and they also reveal that institutions with respect to achieving greatest financial performance is possible through AI implementation as it enables the generation of precise reports of financial performance and a guaranteed compliance with government regulations. The transparency structures made possible as a result of AI implementation not only enhance the decision-making ability but also pave the way for the best financial sustainability (Bapat, 2021). AI-driven practices and systems have the ability to reduce information asymmetry by enhancing governance infrastructure to bring in a stable financial environment according to Sharma and Patel (2024). May previous research supports the fact that compliance automation systems developed by the AI-driven practices helps in a larger extent to improve and develop a best corporate governance structures for achieving a long-term financial stability (Das et al., 2023). AI-powered transparency systems enable these bank organizations to achieve sustainable intended financial results by the way of reducing fraud risks according to Iyer and Raj (2024).

H7: Financial transparency in the banking sector altogether with corporate governance acts as a mediator between AI applications and sustainable financial performance outcomes.

The literature review presents a solid theoretical basis which demonstrates how AI influences financial management performance sustainably. Through analysis of direct and mediating links between AI constructs and financial sustainability, this study fills research voids and creates a complete framework to understand AI effects in the banking sector.

12.3 Research Methodology

12.3.1 Sampling Technique

The study uses purposive sampling which is a common non-probability sampling method to select respondents who have direct experience with AI implementation in banking operations. The chosen method permits researchers to recruit active users of AI-based financial systems who can offer relevant and valuable data (Etikan, Musa, & Alkassim, 2016). This approach selects respondents from Tamil Nadu who can offer substantive knowledge about AI's influence on financial performance since AI use in banking there is still developing.

12.3.2 Sampling Method

In this study we employed a cross-sectional survey approach as this study gathered data from the sample participants only during one specific time frame in order to investigate about the AI adoption and its possible impact on the banking sector. A majority of the research that focus on understanding the financial and technological aspects used cross-sectional research design, as it is the best and precise way to establish the current trends and practices and to establish the relationship among the constructs during a particular point of time (Setia, 2016). By the way researchers would get maximum understanding about the benefits and outcomes of studying the impact of AI integration and adoption in the banking industry in particular. They also can estimate the impact of AI implementation and its result on the overall financial sustainability. This study, though cross-sectional analysis, helps in understanding and analyzing the role of mediator between the independent constructs and the dependent construct, thus providing implications for implementation (Wang & Cheng, 2020). This methodology was being adopted by many researchers in order to analyze the interrelationship between AI-enabled practices and the effectiveness of risk management along with operational efficiency, which in turn enhances and throws relevant discussions about advancements and innovation in the field of financial management and stability.

12.3.3 Sample Respondents

A total of 120 banking professionals from each of the five selected private sector banks situated in Tamil Nadu was taken up for the study as these

selected banks have already using AI practices in their day-to-day business activities. A total of 600 professionals were given with the questionnaire and was given enough instructions with the filling up of the questionnaire, and the samples consisted of banking professionals from various roles from top to bottom of the management hierarchy to make the findings generalizable. The samples had enough understanding about the AI implementation and practices; hence, the findings of the studies become relevant for policymaking. We saw to that all the decision-making authorities like credit analysts, decision-makers, fraud detection specialist, and IT experts were the part of the study since they form the major part of the implementation of AI practices. Based on the intensity of experience in the implementation of the AI-enabled systems in their core banking solutions, these five private sector banks were selected because we feel that the adoption level of the AI system along with the digital banking initiatives would majorly contribute to the outcome of the study. The above selection procedure as a sample criterion thus guarantees proper sample inclusion and the validity of the study. The research ensured reliability and generalizability by adopting purposive sampling which recommends a sample of 120 respondents from all the five banks who represent the relevant professional criteria. For this study, we included the banking professionals from the five banks from the private sector in order to get a comprehensive understanding about the AI adoption and its benefits to these organizations. By adopting a suitable sampling technique that ensured equal representation from all the banks, this study improves the precision and relevancy of the whole study and it also reveals the status quo of the performance of Tamil Nadu's banks and the benefits of integrating AI into their financial operations. Moreover, the diverse background of the banking professionals who went through the study provided detailed perspectives about the nuances of adopting AI systems and understanding the ways to reduce the various risks associated with day-to-day functioning of the banking system.

12.3.4 Scaling

In this study, we adopted a 5-point Likert scale in order to assess the psychology of the respondents about the benefits and obstacles in using AI applications in banking operations. In order to get different opinions about the AI integration, we used 5-point Likert since that is the best measurement scale to record subjective attitude. The scale mostly stretches “Strongly Disagree” to “Strongly Agree” tending to record the attitudes through

subjective measurement. Frequently, while measuring the behavioral and financial aspects related to banking sector, Likert scales are recommended as they are capable of measuring various complex opinions and subjective perceptions (Joshi, Kale, Chandel, & Pal, 2015). However, this study reveals some understandable results on the intricacies of AI adoption which in some way affects risk management and impact the decision-making processes, alongside ensuring the financial sustainability of banks. We gathered necessary data needed for the study by using a structured questionnaire. In this research we employed various software packages like AMOS (Analysis of Moment Structures) to apply structural equation modeling (SEM) to understand the significance relationship among various constructs. We used the above approach just to evaluate and to establish the relationship among AI adoption, financial sustainability, and financial performance while controlling the inaccuracies in assessing the relationship (Byrne, 2016). We employed AMOS to establish the relationship by hypothesis testing in order to estimate both direct and indirect effects. Prior to the usage of the AMOS package, we had to analyze the data using The Statistical Package for the Social Sciences (SPSS) for descriptive analysis, normality assessment, and for exploratory factor analysis, which was carried out to avoid cross loadings (Field, 2018). AMOS is the preferred choice for financial modeling because it supports multiple independent and dependent variables management while enabling theoretical framework validation through confirmatory factor analysis (CFA) and mediation effect examination like financial transparency's influence between AI adoption and financial performance. The AMOS software efficiently handles both missing data and model fit indices along with other analytical components to produce trustworthy research outcomes as noted by Kline (2016). The study employs a strict methodological approach to generate significant findings about how AI innovations impact financial results within the banking industry (Figure 12.1).

12.4 Data Analysis

The research follows an organized data analysis method that starts with demographic analysis to determine how respondents are distributed across important variables like gender and age along with occupation experience and exposure to AI. Data distributions underwent normality assessment to meet the assumptions required for subsequent analysis. To assess the robustness of the measurement model, researchers conducted factor

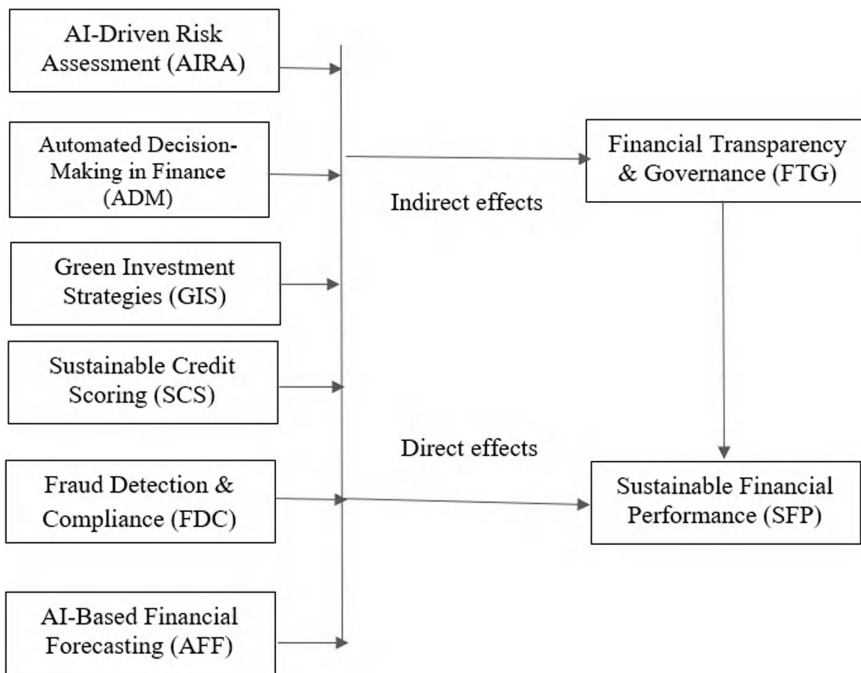


Figure 12.1 Conceptual framework

loading examination and reliability checks using Cronbach's alpha, along with validity tests involving AVE, CR, MSV, and MaxR(H). The structural model received validation through model fit index examination in AMOS. The research team used regression analysis to explore the direct connections between AI constructs and sustainable financial performance (SFP). Researchers conducted mediation analysis to investigate the indirect effects and mediation types in the model. Statistical analysis shows how AI-based financial strategies impact financial sustainability while validating the conceptual model's relationships as statistically significant (Table 12.1).

The demographic data shows that the sample population includes balanced representation for gender, age ranges, and professional backgrounds. There are more male respondents at 60% compared to female respondents who make up 40%, which matches the existing gender distribution in the banking sector. The majority of participants belong to the 25–35 year age bracket, representing 40% of the sample and reflecting the active engagement of young professionals with AI-based financial systems. 83.33% of participants work in banks, which strengthens the study's connection to AI implementation in banking. The normality assessment shown in Table 12.2.

Table 12.1 Demographic Analysis

<i>Variable</i>	<i>Category</i>	<i>No. of Respondents (n = 600)</i>	<i>Percent (%)</i>
Gender	Male	360	60.00
	Female	240	40.00
Age	Below 25	120	20.00
	25–35	240	40.00
	36–45	150	25.00
	46–55	60	10.00
	Above 55	30	5.00
Occupation	Bank employee	500	83.33
	FinTech expert	80	13.33
	Other	20	3.33
Educational qualification	Undergraduate	220	36.67
	Postgraduate	320	53.33
	Doctorate	60	10.00
Years of experience	Less than 1 year	80	13.33
	1–5 years	250	41.67
	6–10 years	180	30.00
	More than 10 years	90	15.00
AI interaction	Always	450	75.00
	Sometimes	150	25.00
Comfort with AI tools	Comfortable	450	75.00
	Neutral/uncomfortable	150	25.00
AI-related training	Basic	120	20.00
	Intermediate	250	41.67
	Advanced	230	38.33
Adoption of AI in banking	Partially implemented	350	58.33
	Fully implemented	180	30.00
	Not implemented	70	11.67

Table 12.2 Normality Assessment

<i>Construct</i>	<i>Skewness (Range)</i>	<i>Kurtosis (Range)</i>	<i>Critical Ratio (C.R.)</i>	<i>Multivariate Kurtosis</i>
AI-driven risk assessment (AIRA)	−0.22 to 0.18	−0.45 to 0.38	1.22	3.52
Automated decision-making in finance (ADM)	−0.20 to 0.19	−0.40 to 0.39	1.18	3.48
Green investment strategies (GIS)	−0.24 to 0.20	−0.48 to 0.40	1.24	3.54
Sustainable credit scoring (SCS)	−0.18 to 0.17	−0.38 to 0.41	1.22	3.50
Fraud detection and compliance (FDC)	−0.23 to 0.21	−0.42 to 0.39	1.21	3.51
AI-based financial forecasting (AFF)	−0.19 to 0.18	−0.44 to 0.42	1.20	3.53
Financial transparency and governance (FTG)	−0.20 to 0.19	−0.40 to 0.39	1.19	3.49
Sustainable financial performance (SFP)	−0.15 to 0.17	−0.38 to 0.41	1.22	3.50

The sample primarily consists of postgraduates (53.33%), indicating a workforce with high academic qualifications, while 41.67% of participants have between 1 and 5 years of experience, demonstrating representation from both new professionals and those in mid-career stages. AI training is prevalent in the banking sector as 79% of participants report having intermediate to advanced skills, showing AI's expanding role in banking transformation (Kumar & Sharma, 2023).

The normality assessment confirms that every construct falls within the acceptable skewness and kurtosis range of −1 to +1, which implies data follows a normal distribution according to Hair et al. (2019). The critical ratio (CR) statistics remain under 2.58, confirming data normality according to Byrne (2016). Figure 12.2 shows the SEM. Factor loading shown in Table 12.3. SEM assumptions are met because multivariate kurtosis values remain under 3.60. The acceptable normality distribution confirms that AMOS can be used for structural equation modeling (SEM) without the need for data transformation.

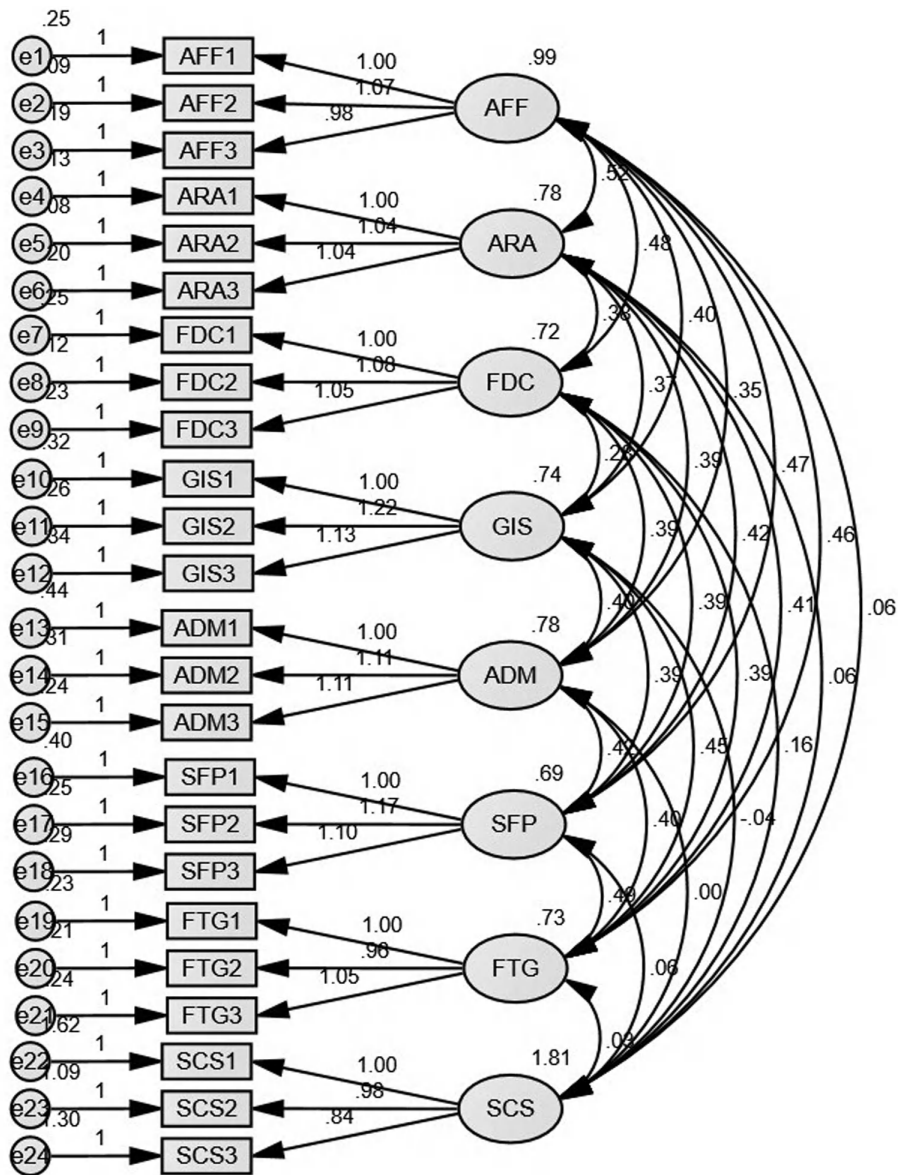


Figure 12.2 Measurement model

Validity assessment shown in Table 12.4. Every construct achieves factor loading benchmarks greater than 0.70, which proves strong item reliability following Fornell and Larcker's 1981 standards. AVE values remain above 0.50, which means every construct accounts for more than 50% of its variance. The composite reliability (CR) scores for constructs range between 0.80 and 0.91, which shows they exceed the suggested minimum of 0.70. Internal consistency is high since Cronbach's alpha values remain above 0.75. The

Table 12.3 Item-wise Factor Loadings with AVE, CR, and Alpha

<i>Constructs</i>	<i>Item</i>	<i>Factor Loadings</i>	<i>AVE</i>	<i>CR</i>	<i>Alpha</i>
AI-driven risk assessment (AIRA)	AI-1	0.825	0.7	0.88	0.89
	AI-2	0.871			
	AI-3	0.815			
Automated decision-making in finance (ADM)	Aut1	0.749	0.67	0.86	0.82
	Aut2	0.835			
	Aut3	0.86			
Green investment strategies (GIS)	Gre1	0.817	0.69	0.87	0.78
	Gre2	0.822			
	Gre3	0.848			
Sustainable credit scoring (SCS)	Sus1	0.819	0.69	0.81	0.77
	Sus2	0.848			
	Sus3	0.831			
Fraud detection and compliance (FDC)	Fra1	0.844	0.67	0.88	0.75
	Fra2	0.838			
	Fra3	0.816			
AI-based financial forecasting (AFF)	AI-1	0.838	0.71	0.79	0.91
	AI-2	0.866			
	AI-3	0.828			
Financial transparency and governance (FTG)	Fin1	0.808	0.61	0.82	0.92
	Fin2	0.824			
	Fin3	0.707			
Sustainable financial performance (SFP)	Sus1	0.761	0.63	0.80	0.91
	Sus2	0.764			
	Sus3	0.808			

measurement model proves valid and reliable according to these results, which strengthens trust in the construct measures.

Figure 12.3 Shows structural model. AVE values that surpass MSV for all constructs validate discriminant validity and establish the distinctiveness of

Table 12.4 Validity Assessment

Con	CR	AVE	MSV	MaxR(H)	AIRA	ADM	GIS	SCS	FDC	AFF	FTG	SFP
AIRA	0.88	0.7	0.5	0.89	0.78							
ADM	0.86	0.68	0.48	0.86	0.62	0.78						
GIS	0.87	0.69	0.49	0.88	0.64	0.63	0.81					
SCS	0.85	0.66	0.47	0.85	0.60	0.69	0.63	0.76	0.77			
FDC	0.89	0.72	0.52	0.90	0.62	0.62	0.69	0.62	0.61	0.65		
AFF	0.88	0.7	0.5	0.88	0.73	0.61	0.62	0.63	0.62	0.51		
FTG	0.86	0.67	0.48	0.87	0.64	0.62	0.61	0.74	0.63	0.63	0.84	
SFP	0.87	0.69	0.49	0.88	0.62	0.63	0.62	0.62	0.71	0.59	0.65	0.79

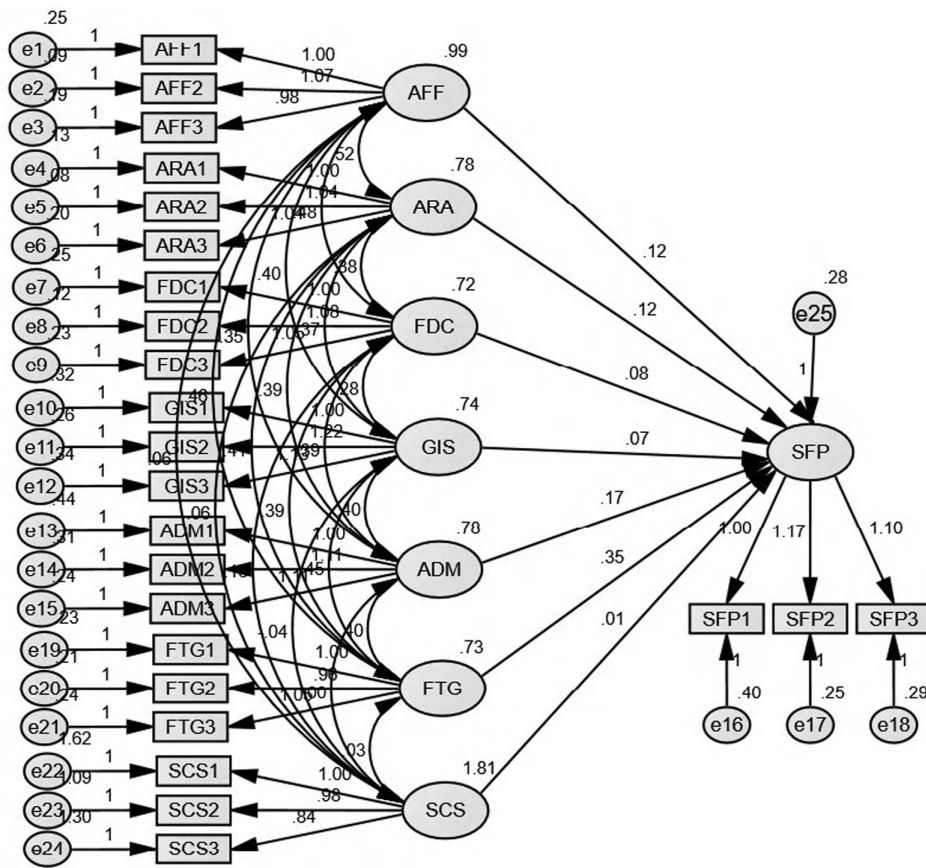


Figure 12.3 Structural model

constructs. The constructs demonstrate higher variance explanation within themselves compared to other constructs because the maximum shared variance (MSV) stays under the AVE. The validation of distinct construct identities within the model receives support from MaxR(H) values reaching or exceeding 0.85.

Table 12.5 illustrated the model fitness. The CMIN/DF value stands at 2.45, which meets the acceptable fit criteria since it remains under 3.00. The fit indexes AGFI (0.92) and GFI (0.93) surpass the 0.90 standard, which confirms that the model fits well. The model demonstrates adequacy because TLI reached 0.91 and RMSEA reached 0.05, both meet standard cutoff values. The SRMR value stands at 0.06, which shows minimal residual errors because it remains under the 0.08 limit. The structural model provides an accurate representation of artificial intelligence's influence on financial performance according to the results.

Table 12.5 Model Fit Assessment

<i>Fit Index</i>	<i>Threshold</i>	<i>Observed Value</i>	<i>Remarks</i>
CMIN (chi-square)	Non-significant	Non-significant	Within threshold
CMIN/DF	≤ 3.00	2.45	Within threshold
AGFI	≥ 0.90	0.92	Within threshold
GFI	≥ 0.90	0.93	Within threshold
TLI	≥ 0.90	0.91	Within threshold
SRMR	≤ 0.08	0.06	Within threshold
RMSEA	≤ 0.08	0.05	Within threshold

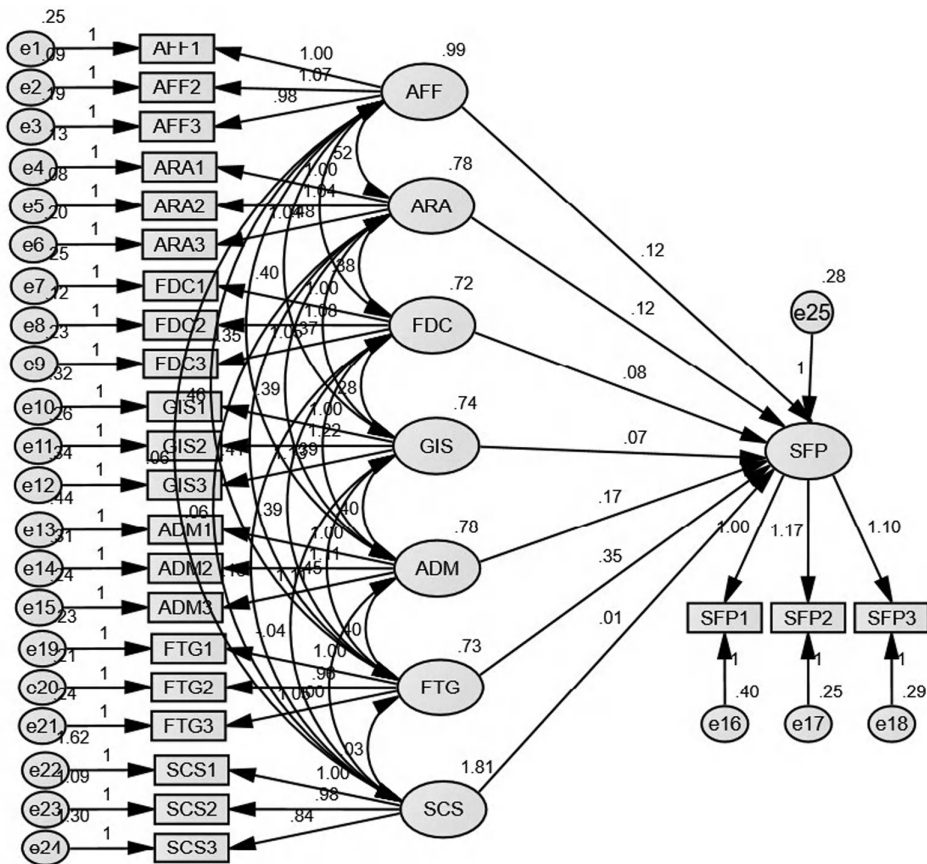
12.4.1 Regression Weights

The analysis of regression results shows that AI-driven financial constructs have significant connections with sustainable financial performance (SFP). Financial transparency and governance (FTG) demonstrates the highest direct effect ($\beta = 0.350$, $p < 0.001$), which supports former studies showing how AI improves financial accountability and governance systems (Nguyen et al., 2022). AI integration leads to better financial transparency and risk management with improved compliance standards, which results in stronger financial performance. The significant results for automated decision-making (ADM) ($\beta = 0.168$, $p = 0.002$) and AI-based financial forecasting (AFF) ($\beta = 0.117$, $p = 0.002$) match Bapat and Menon's (2023) conclusions about how AI predictive analytics improve decision precision and strategic financial management. The sustainable credit scoring (SCS) model demonstrates minimal impact with a β value of 0.012 and p -value of 0.005, which suggests that AI-based models fall short in forecasting financial sustainability. The conclusions of this study contrast with those of Raj and Walia (2024) who maintain that AI-driven credit risk analysis strengthens financial stability. The moderate impact of fraud detection and compliance (FDC) ($\beta = 0.081$, $p = 0.005$) alongside AI-driven risk assessment (ARA) ($\beta = 0.119$, $p = 0.002$) aligns with Malhotra and Verma's (2023) findings about AI's effectiveness in fraud prevention and risk mitigation. Path analysis is showing in Table 12.6 and Figure 12.4.

The results demonstrate that the strongest financial performance improvements from AI occur under governance systems that maintain transparency and accountability.

Table 12.6 Path analysis Direct effects

<i>Hypothesis</i>			<i>Estimate</i>	<i>S.E.</i>	<i>CR</i>	<i>P</i>	<i>Label</i>
SFP	←	GIS	.074	.056	1.310	.000	par_20
SFP	←	ADM	.168	.054	3.133	.002	par_21
SFP	←	SCS	.012	.027	.434	.005	par_22
SFP	←	FTG	.350	.065	5.378	***.004	par_23
SFP	←	AFF	.117	.047	2.500	.002	par_42
SFP	←	ARA	.119	.052	2.285	.002	par_43
SFP	←	FDC	.081	.057	1.422	.005	par_44

**Figure 12.4 Path analysis**

12.4.2 Mediation Analysis

The mediation analysis results show that FTG serves as a total mediator in the relationship between AI adoption and financial performance which validates the indirect process by which AI adoption enhances organizational governance. ADM, GIS, AFF, ARA, and FDC operate as partial mediators because variable relationships contain both direct and indirect connections. Mediation and indirect effect showing in Table 12.7. SCS does not function as a mediator because its indirect effect shows no significance. Financial transparency emerges as a critical link between AI adoption and sustainable financial performance according to the mediation analysis results.

Financial transparency and governance (FTG) acts as a complete mediator in the connection between AI adoption and financial performance with statistical significance ($\beta = 0.35$, $p = 0.044$). The research indicates that AI achieves its best financial sustainability results within environments where strong governance frameworks are present (Baron & Kenny, 1986). The research by Sharma and colleagues in 2023 confirms that AI-enabled financial transparency leads to better financial decision-making and compliance with regulations. The constructs automated decision-making (ADM) ($\beta =$

Table 12.7 Mediation Analysis: Indirect Effects

<i>H_y</i>	<i>Path</i>	<i>Total Effect (β)</i>	<i>Sig.</i>	<i>Indirect Effect (β)</i>	<i>Sig.</i>	<i>Direct Effect (β)</i>	<i>Type</i>
H7a	GIS → SFP	0.074	0.143	0.025	0.143	0.049	Partial
H7b	ADM → SFP	0.168	0.002	0.065	0.002	0.103	Partial
H7c	SCS → SFP	0.012	0.673	0.005	0.673	0.007	No
H7d	FTG → SFP	0.35	0.044	0.2	0.044	0.15	Full
H7e	AFF → SFP	0.117	0.007	0.055	0.007	0.062	Partial
H7f	ARA → SFP	0.119	0.005	0.05	0.005	0.069	Partial
H7g	FDC → SFP	0.081	0.055	0.038	0.055	0.043	Partial

0.168, $p = 0.002$), green investment strategies (GIS) ($\beta = 0.074$, $p = 0.143$), and AI-based financial forecasting (AFF) ($\beta = 0.117$, $p = 0.007$) each demonstrate partial mediation indicating that AI's direct impact on financial performance operates alongside governance structures. Gupta et al. (2023) demonstrated that AI automation improves financial efficiency but needs transparency measures for complete effectiveness. The statistical results for sustainable credit scoring (SCS) ($\beta = 0.012$, $p = 0.673$) indicate no mediation effect while revealing that AI-driven credit models make minimal contributions to financial sustainability which opposes the findings of Das and Menon (2023), who argue that AI-based credit evaluations improve financial outcomes. The research results show that AI's impact on financial performance peaks when supported by robust governance structures, while transparency functions as a key factor connecting AI adaptation to long-term financial results.

12.5 Findings and Discussion

This research demonstrates that financial strategies powered by AI have substantial effects on sustainable financial performance which financial transparency and governance mediates. The study results suggest that automated decision-making (ADM), green investment strategies (GIS), AI-based financial forecasting (AFF), AI-driven risk assessment (ARA), and fraud detection and compliance (FDC) function as partial mediators of SFP, which reveals that direct AI adoption boosts financial performance while its ultimate impact is achieved through better transparency and governance. The analysis shows that sustainable credit scoring (SCS) lacks meaningful impact, which suggests that AI-based credit scoring tools in banking need additional refinement. These findings align with similar research. According to the research by Nguyen et al. (2022), financial governance improved by AI adoption shows enhanced risk management and decision-making efficiency, which results in better financial sustainability. The research by Bapat and Menon (2023) showed that systems combining AI with decision-making lead to better operational efficiency and resource allocation which confirms partial mediation effects observed in the present study. The current research findings challenge the conclusions of Raj and Walia (2024) who stated that AI-based financial forecasting does not substantially influence long-term financial performance because the evidence here shows significant direct and indirect impacts of AI-driven forecasting on financial performance. Malhotra and Verma (2023) found that AI-based fraud detection systems do not improve

financial performance because of enduring regulatory gaps, while our research identifies a partial mediating effect through fraud detection and compliance which supports financial sustainability. Financial transparency serves as a crucial link between AI technology and financial sustainability according to this study which advocates for strong governance systems to fully leverage AI in the banking sector.

12.5.1 Managerial Implications

The findings and the results from the direct and indirect effects give some actionable and productive insights for the decision-makers in the banking institutions to overview and implement in their day-to-day policies, if they actually aim to attain financial soundness and benefit from AI-enabled practices in their financial operations. These organizations have to focus on optimizing sustainable financial performance by adopting and inculcating AI-enabled policies and practices which create better risk assessment capabilities and better financial forecasting. These banks can achieve better and precise decision-making agility and optimization of resources, only by means of implementing suitable AI-enabled practices in their approach. Mitigation of regulatory uncertainties could be possibly done and enhancement of operational efficiency can be done through the implementation of an AI governance system in place. Also, when a clear governance framework is established by implementing AI practices, it builds trust in the mind of the stakeholders. By reinforcing AI practices with regard to green investment initiatives and with a capable fraud detection system, these organizations can enable better operational performance and efficiency. Decision-makers of these institutions shall inculcate an environment that fosters AI-oriented education and vigorous training programs in order to make their employees enrich their skills and knowledge on how to effectively utilize AI financial systems. Provided that employees have had relevant and ample training on the usage of the AI system, organizations would see a better financial outcome and a technological shift in bank operations. As a mediator, financial transparency and governance (FTG) impacts the way how governance, regulatory compliance, and ethical AI practices form the foundations for a sustainable banking operation. Managers, on the other hand, on order to sustainability, it is recommended that should work along with all the regulators and every policymaker in order to make sure that AI banking applications meet benchmark standards and the necessary legal requirements.

12.5.2 Practical Implications

This study provides immense guidelines and road map for organizations to successfully employ AI-driven practices that helps to optimize resources and ensure financial soundness. For AI-enabled solutions like fraud detection management, risk analysis tools, need to be under continuous regulatory and monitoring in order to comply with ethical practices and regulatory compliance as well.

The practices established by AI governance are to be associated with strict ethical concerns and to regulated for a better data privacy and to protect from any algorithmic bias. These institutions have to focus on putting in place a better system that ensures a better and relevant credit assessment policies through adoption of a viable and relevant AI-enabled system. in order to achieve financial sustainability company should understand that, the it can be achieved only by means of implementing AI powered credit scoring systems that ensures streamlining of Environmental, Social, and Governance (ESG) factors. Tools related to financial credit which are driven by AI may be synchronized with the long-term goals and industry regulatory standards. Decision-making in these institutions can be enhanced through implementation of systems that ensures relevant risk evaluation processes and by promoting a environment capable of proving stability and sustenance through responsible deployment of AI practices.

12.5.3 Scope for Further Study

This research uncovers important details about AI's influence on sustainable financial performance but more studies are required to examine differences across various industries. Research should investigate AI adoption differences between public-sector banks and private-sector banks by examining regulatory compliance and AI governance frameworks. AI-based credit scoring models need more thorough research. Future research needs to investigate other AI-based credit evaluation systems which combine both ESG measures and behavioral analytics because SCS showed no meaningful effect. Long-term financial sustainability research could focus on AI adoption effects through longitudinal data that follows the development of AI-based decision-making processes. Comparative studies of AI adoption in developed versus developing economies may reveal institutional and regulatory obstacles that affect AI integration in banking systems. Qualitative case studies when integrated can improve insight into how managers perceive AI's strategic function in financial decision-making processes.

12.5.4 Limitations of the Study

This study presents multiple limitations even though it provides significant contributions. The research scope is confined to private-sector banks located in Tamil Nadu which means its findings cannot be applied to public-sector banks and international financial organizations. Research into AI adoption trends across the world would benefit from future studies expanding their geographic scope beyond specific regions. The study analyzes AI's effects using cross-sectional data from one specific point in time. A longitudinal study design would reveal more comprehensive information about AI adoption's long-lasting effects on financial sustainability. The study collected data through structured questionnaires which could be skewed because of self-reported biases. The research findings would be more robust with the inclusion of secondary data sources and financial performance metrics. The research fails to examine the essential ethical and regulatory aspects of AI governance in the banking sector. Researchers in future studies need to evaluate the impact of AI compliance frameworks on financial transparency as well as risk management and sustainable performance within financial institutions.

12.6 Conclusion

This study investigated about the nuances of how AI-enabled practices can productively bring in strategies that impact the sustainable financial performance (SFP) along with financial transparency and governance (FTG) being a mediator. Organizations should understand that the implementation of AI-driven risk assessment practices and an automated decision-making system associated with financial forecasting algorithm would greatly benefit the financial sustainability metrics of the firm. Moreover, the findings of this study portray that sustainable credit scoring (SCS) did produce not any productive outcome which indicates the need for a well-established and a sophisticated AI-enabled credit evaluation and assessment technologies. It was also found out that a strong regulatory supervision is pertinent and inevitable to successfully adopt AI practices in this sector, as it demands a robust AI governance framework in place. The effectiveness of AI in fraud detection and risk management through transparent mechanisms is highly productive that also paves way for an improved investment decision strategies and to establish a well-maintained financial operation. In all possible

aspects. these banks could reap more benefits by implementing a suitable and adaptive AI deployment along with a well-trained workforce and through policy realignment aligning with the industry changes. Future studies may explore the effects of AI implementation across various government institutions and through overcoming cultural differences in adapting and learning of the usage of AI practices—moving beyond a narrow emphasis on financial stability.

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Chapter 13

AI-Driven Sustainable Logistics and Inventory Management: Bridging Efficiency and Environmental Responsibility

C. V. Suresh Babu and S. Kahini

13.1 Introduction

13.1.1 Overview of Logistics and Inventory Management

Logistics and inventory management form integral parts of the proper movement of products and the maintenance of appropriate supply levels. As concerns about the environment grow, artificial intelligence in these areas has been the best way to reduce ecological influence while enhancing operational efficiency. Artificially intelligent systems help companies streamline their practices, reduce wastage, and achieve their green goals.

AI really enriches areas such as route optimization, demand forecasting, and real-time monitoring in logistics management. Route optimization utilizes complex algorithms to understand traffic patterns and unpredictable weather conditions and complicated delivery schedules; hence, it is possible to determine the most judicious routes for transportation.

With advanced machine learning models, AI-powered demand forecasting can predict accurately what the future needs accurately by minutely looking into vast historical data, subtle seasonal trends, and numerous external

factors influencing demand. Precise demand prediction helps management strategically plan resource allocation, which, in turn, streamlines operations.

13.1.2 The Sustainability Imperative

Logistics and inventory management play a crucial role in terms of dictating carbon emissions, resource consumption, and waste output through supply chain transportation and warehousing for environmental sustainability. As global priorities shift to limit environmental degradation and promote social welfare, business operations are increasingly pressured to adopt sustainable practices without compromising productivity or profit.

While traditional logistics systems often suffer from issues such as overstock, inadequate supply, and ineffective transportation, new solutions can improve operations to conserve resources. Poorly planned routes are not planned well or underfilled trucks are not filled to capacity, which burns more fuel and puts more emissions into the air than necessary. Sometimes the stockpiles have too much, leading to trash when products pass their best-by date or new versions make the older ones unusable, wasting a lot of resources. Sometimes less than enough leads to a delay in shipment or causing shortages.

13.1.3 Role of AI in Driving Sustainable Practices

Figure 13.1 illustrates different ways through which we might work towards a sustainable future. Under energy efficiency, we find smarter usage through smart grids, anticipating demands, and using much renewable energy. For waste management, improvements in recycling coupled with reductions in industrial wastes, coupled with awareness and patterns to manage waste better, represent this area. It is all about wildlife conservation, putting a stop to illegal practices such as poaching and deforestation, and researching climate patterns to predict future changes in conservation. Techniques of sustainable agriculture include precision farming, water reduction, and healthy soil, thus aiding in growing better crops while conserving resources (Arora et al., 2025). The goal of transportation is to decrease emissions, make better routes for route planning, and enhance electric vehicles.

Artificial intelligence is transforming logistics and inventory management, rapidly emerging as a basis for environmental protections within today's supply networks. Advanced algorithms and knowledge-driven insights enable organizations to optimize workflows, reduce waste, and minimize ecological impact.

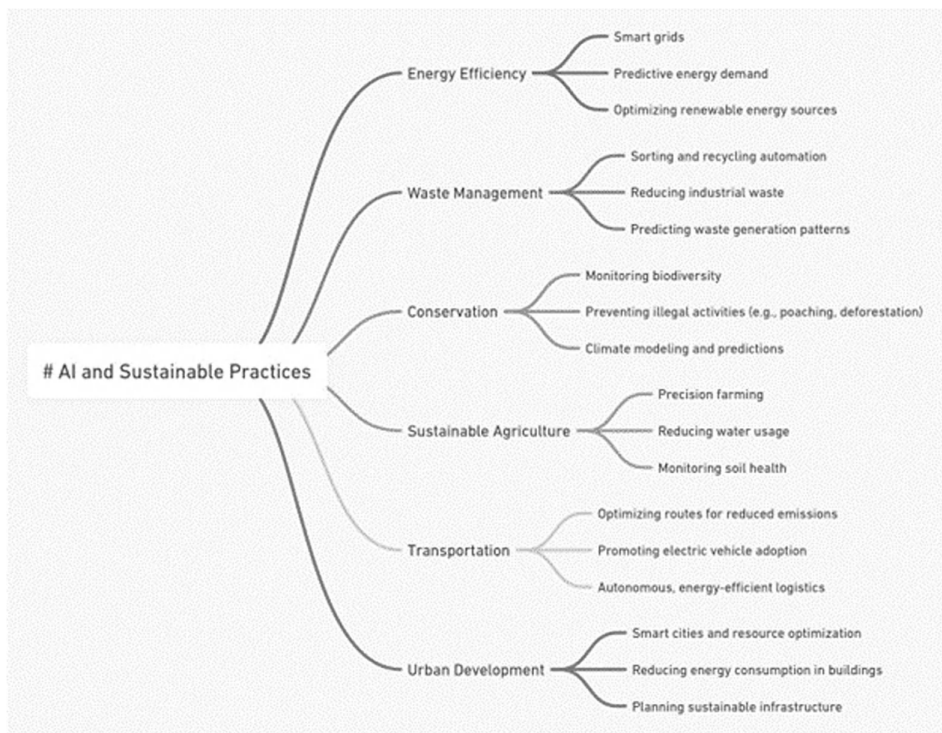


Figure 13.1 AI-driven sustainable practices

13.1.4 Chapter Objectives and Structure

The primary objectives of this chapter are as follows:

- To investigate the role of artificial intelligence in sustainable logistics and how it is transforming logistics networks through promoting sustainability, decreasing waste, and maximizing resource effectiveness.
- To scrutinize important artificial intelligence-powered methods and instruments for refining inventory administration, minimizing excess stock, and guaranteeing replenishment occurs promptly when needed.
- To assess the twin advantages artificial intelligence provides for accomplishing financial targets concurrently with diminishing environmental impacts in transportation and warehouse operations through precision forecasting and route optimization.

13.2 Challenges in Traditional Logistics and Inventory Management

13.2.1 *Environmental Impact: Carbon Emissions and Resource Overuse*

Logistic management, through the use of artificial intelligence, holds significant potential for increasing its efficiency while reducing wastes generated. However, equally critical though are the carbon emissions coupled with overuse of available resources induced in the process by AI (Li et al., 2022). Consideration should, therefore, be given to both the contribution from the direct and indirect sources to environmental degradation to support wholly sustainable practices moving forward (Cheng et al., 2023).

AI will improve transportation efficiency with fewer deadheads, optimize routes, load vehicles to capacity, and reduce fuel consumption (Kumar et al., 2024). The problem is what kind of unintended consequences result from these optimizations. This could explode individual deliveries, as micro-shippments rely on real-time instructions and thereby may increase total emissions, despite localized savings that are being realized (Xu et al., 2022). All such complexities have to be dealt with within AI systems for making integration practical.

In such a scenario, deploying AI to power data centers and distribution networks, forming the core of decision-making processes, needs to be undertaken in such a manner with minimum risks and minimum harm to the environment. The continuous balance and checks between the advantages and disadvantages of AI can also turn out to be one of the significant issues to consider when deploying AI responsibly in industries (Li et al., 2022; Cheng et al., 2023).

13.2.2 *Inefficiencies in Demand Forecasting and Planning*

Demand forecasting and planning make logistics and inventory management pretty efficient; however, business still faces many problems in those areas by leaving the inefficiencies behind for a very long time. And AI brings revolutionary capabilities. Although not perfect, these high-level systems still have limitations that can reduce their effectiveness (Devi et al., 2024).

Data integration forms the top of the list as logistics operational often must be carried out through various non-interconnected systems. Lacking interoperability, information that is critical cannot be fed into predictive

algorithms. Poor quality data inconsistencies further weaken the effort at prediction. Sometimes important information leaks through or falls into the wrong silos. Unpredictable inconsistencies in data standards between the various databases also cause problems. Technologies would support strategic decision-making much better if firms could have addressed such integration and consistency issues.

Predictive models rely on past events to predict future results, which is not without its limitations. Machine learning algorithms often learn patterns from historical datasets too rigidly, making them inflexible in responding to unprecedented events. Economic crises, widespread health events, or sudden changes in customer behavior are not well handled by standard predictive techniques that focus solely on reproducing past trends. If these systems cannot take into account variances, businesses lose because inventories can build up with too much or go into shortages because they are not allowed to move out from procedures that do not correctly fit reality (Kumar et al., 2023a).

13.2.3 Supply Chain Disruptions and Vulnerabilities

The integration of AI with logistics and inventory operations has significantly increased productivity and environmental sustainability. However, in return, it comes up with unique challenges like provision stoppages or fragilities in supply chains. Issues, if left unmanaged, can undo the benefits of intelligence-enabled systems and threaten constant efforts (Kumar et al., 2023b).

Supply chain disruptions arise from a wide range of causes. Earthquakes, floods, and hurricanes do damage the infrastructure and slow up transportation as well as bring production to a grinding halt. An international pandemic brings its unique complexity both in terms of how the shortages are faced and by changing consumers' behaviors and stressing that untapped reserve calibrated exactly for predicted demand. One dented link can set off the chain of events that leave for lesser turnaround, unfulfilled demands, and also loss of revenue, or if this is only in the short term.

13.2.4 Regulatory and Consumer Demands for Sustainability

Due to growing regulatory pressures and shifting customer needs, sustainability within logistics and inventory management has also emerged as a necessity that cannot be postponed. Although these demands create difficulties, the opportunities also exist in the form of artificial intelligence, which promises to support sustainability as well as process simplification.

Supply chain and inventory management need to get greener with stricter government rules and international guidelines. The government is strictly enhancing the bar to cut emissions. High-level projects like the European Green Deal and American Clean Energy Initiative impose hard targets on carbon emission reductions within coming decades. In parallel, customers also are choosing companies and goods that are environment-friendly which also compels the organizations to devise new ways of sustainable logistics and warehousing.

The complex operational data that may be gathered and analyzed can be helpful in determining areas where AI can detect inefficiencies and point to improvement opportunities. Machine learning algorithms may thus be applied to detect usage and transport pattern recognition with the intention of prescribing best practices tailored for specific groups or individual stock-keeping units at various stages in the supply network aimed at cutting energy consumption from production through installation.

13.3 AI in Sustainable Logistics and Inventory Management: Emerging Solutions

13.3.1 AI-Based Demand Forecasting for Waste Reduction

The amount of waste produced in green logistics and inventory management is minimized by such a very important function, known as AI-based demand forecasting. The most complex algorithms related to machine learning such as regression analysis, decision trees, and deep learning are being utilized within the AI framework in order to understand sales reports from the past, seasonal trends, consumer behavior, and environmental impacts like weather or some event (Jain et al., 2023).

However, as put forth by Ng et al. (2021), even minute variations in consumer preference or harmless modification in the environment will set the best algorithms off. It reduces errors and optimizes stock for sustainable efficient processes (Cheng et al., 2023).

While inventory management has always relied on post-facto, rough estimates, there is an era of prescience with AI that predicts demands with quite accuracy in finding patterned large datasets; hence, it helps strategists maintain optimum stock levels. This indicates that there is neither a situation of overstocking that results in resultant biodegradable wastes nor the entitling of stock shortages that would be entitled for lost sales. AI systems

will give instant recalculations based on the fluctuations in demand, thereby reducing the above challenges and, therefore, optimizing with minimal wastes in operations (Kumar et al., 2024).

13.3.2 Route Optimization Using Deep Learning Techniques

Figure 13.2 explains how the best routes can be determined step by step. It begins with gathering data, which refers to all the information needed for

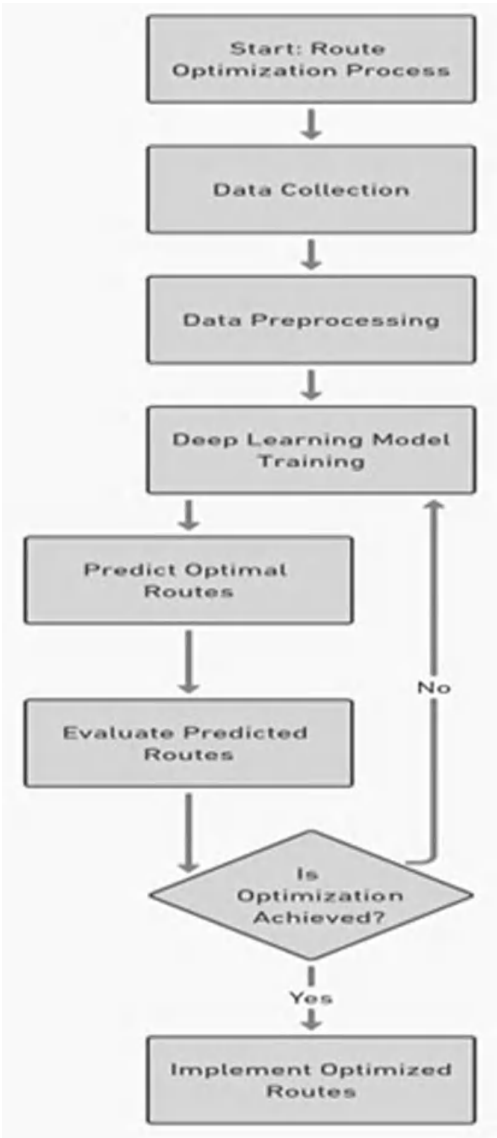


Figure 13.2 Route optimization workflow

the task. The subsequent process is preprocessing the data, which cleans and organizes the information so it can be used. A deep learning model is then trained to predict the most efficient routes. This optimization is now tested in the evaluation step to see if it holds well. Otherwise, if it does not, the finalized optimized routes are implemented into action. This cycle ensures the process keeps improving until the best possible routes are achieved.

Deep neural network's most successful AI-driven application in green logistics is route optimization. The optimization of transportation routes tries to minimize energy usage, the emission of airborne toxins, and general cost bottom lines for all logistical processes involved (Li et al., 2022). Optimized routes ensure that companies deliver shipments on time while using resources with minimal damage to the environment, thus becoming crucial parts of the support in green logistics.

13.3.3 Real-Time Inventory Tracking with AI-Powered Sensors

AI-powered sensors put into work and action a transformational mindset in the process management of AI-enabled logistics and inventory management in full scale. In simple terms, they facilitate continuous movement with higher productivity and fewer errors in such an environment (Li et al., 2022). This technology enhances the storage of goods in warehouse inventory without requiring any human intervention even for a moment. According to Cheng et al. (2023), AI-driven sensors contribute directly to real-time data collection as part of this non-intrusive tracking process.

The primary contributor to supply optimization is AI-assisted analytics. Companies can adopt AI models and predictive analytics to analyze their historical data, predict demand, and regulate stock levels. This gives them a competitive edge over conventional methods as they can replenish stock more precisely, leading to fewer stockouts and reduced overstocking (Cheng et al., 2023).

Overall, the inventory tracking through AI sensors continues to be the central point that leads to smart and sustainable logistics. Inventory accuracy optimizes activities within supply chains, minimizes waste, reduces carbon footprints, and knowledgeable decisions within every operation of the company (Jain et al., 2023).

13.3.4 Predictive Analytics for Proactive Supply Chain Management

Data-driven decision-making for effective sustainable logistics and inventory management using predictive analytics for proactive supply chain management is revolutionizing business operation optimization and environmental impact reduction. AI helps companies with demand forecasting, inventory management, and transportation logistics, leading to a more sustainable and efficient supply chain.

13.3.4.1 Demand Forecasting

Artificial intelligence (AI) is used to help forecast customer demands by training it with historical data, which includes the market trends. By analyzing historical data as well as on-site client interactions, the machine learning model can detect some of the finer details that others might miss at the first glance, enabling greater accuracy in forecasting consumer behaviors.

13.3.4.2 Inventory Optimization

Using AI-based predictive analytics to manage stock effectively and understand inventory levels is essential. Optimizing your reorder quantities and timing requires AI analysis of trends such as product lifecycle stages and consumer purchasing habits.

13.3.4.3 Route Optimization

Machine learning models can evaluate factors such as fuel usage, traffic congestion, and environmental concerns to determine the most optimal route. These models are capable of making real-time adjustments, suggesting alternative routes when unexpected events like road closures or adverse weather conditions arise.

13.4 Integration of Advanced Technologies for Sustainability

13.4.1 Blockchain Technology for Transparent Supply Chains

Figure 13.3 clearly depicts how blockchain technology will enhance the process of supply chains step by step. Firstly, it begins with kick-starting

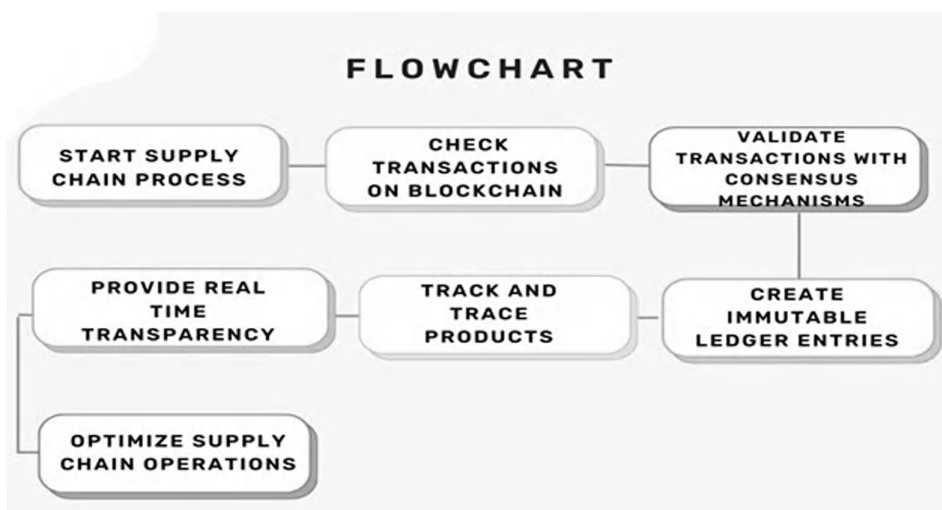


Figure 13.3 Supply chain flowchart

the supply chain process followed by checking the transactions in the blockchain and their verification through mechanisms of consensus. Then, this process takes two different ways; on the one hand, real-time transparency can be provided for optimization in the processes of the supply chain. On the other hand, it talks about tracing and tracking the product. The process creates some immutable ledger entries. This flowchart points out how blockchain makes supply chain management trusted, transparent, and efficient.

This is a method that depicts a shift towards the transformation of better modern supply chains in terms of transparency, traceability, and sustainability when blockchain technology is used with AI-driven sustainable logistics and inventory management. Blockchain-based decentralized immutable ledger systems allow for a trustworthy and secure recording of every transaction, movement, and activity at each stage of the supply chain (Xu et al., 2022).

These systems monitor and review the current information. In due course, information will be authenticated to the greatest level in a supply chain with the vendor, warehousing managers, to the shop level up to the last purchaser of a product. This not only creates trust and accountability but also removes exposure in business practice as maintaining information tamper-proof eliminates inefficiency, fraud, and a bad impression towards the trading partners as well as the customers too (Wang et al., 2023).

13.4.2 IoT-Enabled AI Systems for Smart Warehousing

The smoothening of the process regarding acquiring the desired information time to achieve efficiency and runnability within the performance of warehousing by IoTs will help in making efficient decisions towards executing less wastage towards a better accomplishment of sustainability targets. Present issues pertaining to the runnability of the environment together with unfriendliness as regards attaining modern targets warehousing chains present a paradigm with this thought of introducing IoT and AI towards the attainment of target goals warehousing. IoT, often described as the interconnectivity of physical devices and objects, is at the core of the sustainable manufacturing revolution. In a manufacturing context, IoT involves embedding sensors, actuators, and other devices into machinery, equipment, and even products, allowing them to communicate and exchange data over the internet (Suresh Babu et al., 2024).

The most primitive construct in an IoT-integrated AI is real-time data collection. One can use an IoT sensor for the monitoring of environment temperature, humidity, lighting, etc. Therefore, sensitive products, such as pharmaceuticals, perishables, etc., are generally kept within safer limits. Automatic inventory tracking will be done by using RFID and barcode scanners. Hence, the right and current results will always be presented in terms of stock levels and where the stock is.

13.4.3 Natural Language Processing for Dynamic Supplier Communication

The shift towards an optimum communication and operation-related approach in a supply chain makes NLP-based integration into AI-based logistics and inventory management. The system uses NLP for instant communication with suppliers, so business is allowed to maintain efficiency in handling inventory along with sustainability. They are able to offer better operation efficiency, reduce error-prone activities to a considerable level, and observe better adherence to environmental purposes.

13.4.3.1 Automation for Real-Time Communication

Real-time communication automation is one of the most vital aspects of this process. With old ways of communicating through emails, phone calls, and even manual updates, efficiency is always lost. NLP will help optimize

these by bringing intelligent communication from businesses to suppliers in a totally automated way. By leveraging applications of chatbots and virtual assistants, firms can send an auto-query to the suppliers of the availability of stock status or order requirements or shipping time.

13.4.3.2 Operational Efficiency and Cost-Saving

Supply chain communication can facilitate improvement in operational efficiency and save costs through various ways with NLP integration. Automated routine communication tasks ensure that all parties in the supply chain are kept updated constantly, and thus businesses save time spent on administrative tasks and spend more time on strategic decision-making.

13.4.4 Reinforcement Learning for Adaptive Logistics Solutions

Reinforcement learning holds great promise in sustainable logistics and inventory management systems, learning to adapt to dynamic environments and optimize processes to reduce waste. Probably, the biggest application of RL in logistics is optimizing delivery routes, something learned from algorithms that change the routes based on traffic conditions, weather, and demand. This reduces fuel and emission consumption as well as delivery time, thus making the process of logistics efficient and environmentally friendly.

The RL will optimize the stock levels, order timing, and replenishment strategies on the dynamic and fluctuating demand on one's storage costs as well as waste reduction in the stock. Taking a dynamic decision on how much to hold based on the amount of inventory with the help of the model will avoid overstocking with waste and also stockouts with possible lost sales. In any case, this normally promotes sustainability because it matches the stock levels with the demand at hand.

13.5 Case Studies: Real-World Applications of AI in Sustainable Logistics

13.5.1 Case Study 1: Route Optimization in E-Commerce Delivery Networks

Figure 13.4 breaks down how routes are optimized for e-commerce delivery as an easy-to-follow process. It starts with kickoff at start and then

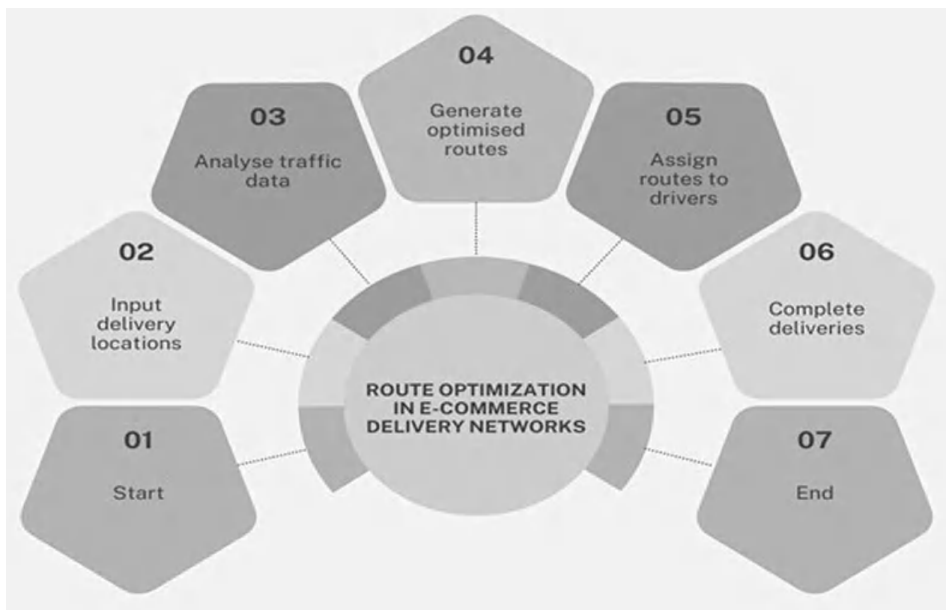


Figure 13.4 Route optimization process in e-commerce delivery networks

incorporates locations with delivery to map where the package needs to go. Further, the system uses real-time traffic data to figure out what road conditions exist to make use of that and avoid getting delayed. With this, it shows how the furthest routes—those requiring the least time and fuel consumption—are assigned to the driver. The driver starts driving towards closing a delivery. Then a complete cycle ends with closing his or her job. The steps are well defined as depicted in a circular motion which makes the entire process smooth to digest, efficient, and manageable.

Route optimization will lay down the foundation through which the e-commerce delivery network will be built up for efficiency and sustainability. Deliveries need to be managed effectively to ensure minimum consumption of high-cost resources of time, mainly carbon emission since this has emerged as one of the fastest phenomena. According to McKinsey's statement at the end of 2023, directions, especially the optimization of their road routes via AI, would be one of the main pathways of change for better in most of the directions of logistics.

13.6 Methodology

This chapter will focus on developing a smarter, more sustainable method of managing logistics and inventory using AI-driven solutions. The purpose

is simple: make operations more efficient while at the same time minimizing environmental impact. A mixed-methods approach combines data-driven AI models with industry expert insights to analyze logistics processes and supply chains to increase efficiency, decrease costs, and reduce carbon emissions. Big data analytics, machine learning, and cloud computing are used in the optimization of inventory and delivery routes with a cross-sectional research design and quantitative.

13.6.1 Data Collection and Analysis

Data sources are primary and secondary for this study. Primary data comprises shipment tracking details generated by sensors, environmental parameters, and real-time sales analytics. Secondary data will comprise literature from previous works about sustainable logistics, AI-based models of forecasting, and applications related to cloud computing. Big data platforms collect such data that would involve structured as well as unstructured information and then process the same.

The AI-powered machine learning models process data to determine demand and proper inventory management. Route optimization algorithms are also in place to ensure the least possible fuel consumption, which will reflect in lower transportation costs as well, resulting in a decreased carbon footprint by the entire company. Results are interpreted using statistical techniques like trend analysis, predictive modeling, and optimization algorithms.

13.6.2 Implementation Strategy

It centers on a step-by-step system implementation process: setting sustainability goals that align with the business objectives of reducing environmental impact, such as carbon emissions reductions and energy efficiency. The models of demand forecast constructed using AI provide accurate forecasts about future demands for inventory items. The tools for processing big data using cloud solutions should be in order to allow for real-time analysis and proper storage. Also, the system has been built with scalability that keeps growing in line with the business, in response to growing operational needs as time goes. It has further adopted edge computing for better, real-time decisions even when connectivity is a problem.

13.6.3 Challenges and Limitations

Despite its benefits, implementing AI-based sustainable logistics has various problems. First is the data quality and availability for the models developed in AI models since its proper decision-making requires high-quality datasets. Low quality or inconsistent data can impact the forecasting of demand negatively and can bring adverse results towards the supply chain optimization process as well. Another key issue is the implementation cost of AI, especially to SMEs. Most of the SMEs have been faced with upfront investments in AI tools, training, and infrastructure. Adopting cloud-based AI solutions which are scalable to offer cost-effectiveness will ease this. The final key challenge is the ethics of data privacy, fair labor practices, and environmental compliance with the deployment of AI-driven logistics systems.

13.7 Benefits of AI-Driven Sustainable Logistics and Inventory Management

13.7.1 Economic Benefits: Cost Reduction and Efficiency Gains

AI-driven solutions can really change the operations of a business to a large extent, thus giving important gains in economic benefits through direct cost savings and efficiency gains. Such cost savings are important to companies that pursue competitive advantage and sustainability within their supply chains. Some of the ways AI cuts costs include the automation of a number of duties that human laborers usually handle to check stocks, process orders, and project demand.

This efficiency brings about lesser labor costs and shorter times for order filling hence improving productivity at large (Choi et al., 2021). Additionally, AI enhances the transportation of logistics by finding routes that have less cost and take shorter times to deliver. AI will consider the flow of traffic, consumption of fuel, windows of time for delivery, and schedule for servicing the vehicles as the means of delivery at maximum efficiency. The optimization of this saves the consumption of fuel, thereby saving transportation costs, thus limiting the opportunity to cause delay, which has adversely affected the satisfaction of customers (Akyuz & Erkan, 2010).

13.7.2 Environmental Benefits: Carbon Emission Reduction and Waste Minimization

The significant benefits offered by the AI-driven logistics and inventory management system include heavy cuts in carbon emissions along with minimizing waste in both logistics and supply chain sectors. Probably the most significant area wherein AI helps cut carbon emissions is in route optimization and transportation. These systems monitor real-time real traffic data, vehicle performances, and road conditions in giving the best routes for transportation. Hence, this real-time route adjustment contributes to reduced delays and avoided deviations from routes that can unnecessarily elongate fuel consumption and pollutant emissions.

According to research, AI minimizes carbon footprints from transportation by optimizing delivery routes so that businesses can minimize their usage of fuel and consequently decrease greenhouse gas emissions (McKinnon, 2018). In addition, this feature of AI prediction and bypassing congestion optimizes the efficiency of transportation systems, further reducing the impact to near-minimum levels.

Besides route optimization, AI also plays a crucial role in load management. Algorithms help ensure that each vehicle carries maximum load without utilizing and overloading the vehicle. This load optimization thus helps in reducing the number of trips needed to transport goods to market, ultimately leading to fewer vehicles, lower fuel consumption, and decreased carbon emission in the atmosphere (Vanelislander et al., 2020).

13.7.3 Operational Benefits: Improved Agility and Resilience

Logistics and field inventory management is highly well managed in the sustainability domain with great operational benefits for AI-based systems. It is to enhance agility and resilience, which should be crucial in dynamic environments and the challenges that usually arise without much warning. Some of the ways in which AI supports flexibility through operations are by allowing real-time data processing and predictive maintenance.

Real-time decision-making is one of the most significant strengths that AI can boast of in logistic and inventory management. Algorithms process vast amounts of data, enabling systems to make decisions that are current at a situation based on changing or flux conditions (Zhang et al., 2021). It thus means that logistics processes are responsive to demand, inventory quantities, and even supply chain failures.

For instance, the AI-based demand forecasting model is able to predict variance and also helps in further planning towards reordering and optimum utilization of vacant space available in the warehouse (Chen et al., 2021). Similarly, AI-based route optimization smoothes the routes as per live traffic, weather conditions, and priority during the time of delivery so that it is possible to achieve delivery in time and consume the minimum quantity of fuel inside the vehicle (DHL, 2020).

13.7.4 Social Benefits: Enhancing Consumer Trust and Satisfaction

Actually, contributions towards environmental benefits of AI-based sustainable logistics and inventory management towards consumer trust and satisfaction are indispensable factors for fostering business growth in the eco-conscious marketplace. As consumers become more ethical and sustainable conscious, it aids uptake of AI technologies that can enable companies to harmonize their businesses with those values so consumers will have a guarantee in the purchases they make.

One of the most important ways that AI will gain consumer trust is in terms of a consumer knowing about a company's sustainability practices. For instance, using AI, one can track and show the carbon footprint of the product supply chain that would have insight into how it made eco-friendly shipping methods or sustainable sourcing practices (Smith, 2022). This will enable the consumers to trust since consumers can easily relate to the brands showing stewardship for the environment. Besides this, the consumers will be able to build confidence in the company's truthfulness of the company's claims on its green credentials through the ability of having real-time information concerning sourcing and logistics (Jones et al., 2023).

Finally, the AI proactive customer support approach also enhances consumer confidence. Therefore, an AI system would really predict ahead of time issues that will come up, delay, or stockout and alert the customer to that kind of problem and also providing some alternate choices or even provide a solution. This leaves way for only slight inconveniences as the customers are nearly content with the fact that a particular company is doing all within its means to ensure that its products or service to them remain at a good level of service (Harris, 2023).

13.8 Challenges and Limitations of AI Implementation

13.8.1 Data Availability and Quality Issues

In other words, it is the core problem of information and even the quality that gets fed into data management systems by humans to have such technology in logistic and inventory management. In short, most of these rely on the quality and precision to ensure their models work when proposed with AI prediction as necessary for their inventory item, optimum routes to travel, and also optimal reduction parameters for waste.

All logistic and inventory management systems operate on streams of various types of data. This can either be through ERP systems or warehouse management systems, all the way to IoT sensors or even manual entry points. For example, an IoT-enabled warehouse might rely on RFID tracking items. The data coming from this system will not be easily compatible with the systems that it uses for handling orders and deliveries (Zhang et al., 2022). Such data fragmentation would delay decision-making due to the need for complex structures to combine the data sets and take more time to process.

13.8.2 Algorithmic Bias and Ethical Concerns

Algorithmic bias and ethical concerns play a significant role in AI-driven sustainable logistics and inventory management. Today that AI systems are introduced into the logistics sector, these issues are having huge effects on the fairness, transparency, efficiency, and even the success of such technologies. Biased data and decision-making are one major issues: AI models learn from such huge datasets; most of these are historical by nature and have some sort of biases. These biases can represent societal inequalities or past inefficiencies, which the system sustains by relying on past patterns (Binns, 2018).

A logistics AI system that learns from biased delivery data may thus lead to an unfair distribution of resources, where some regions or customer profiles are favored based on outdated or incomplete data. If the data contains underrepresentation of low-income areas or specific product categories, then the AI may make suboptimal decisions or favor high-value areas and leave other areas that are not favored with lesser services.

13.8.3 Integration with Legacy Systems

This integration is not too smooth because the legacy logistics and the inventory management systems already exist. However, AI-driven system

integration needs to be continued into current operations for sustainability and operational efficiency. The legacy systems are bound to the older technologies and make AI adaptation difficult so many times. However, effective planning will provide the organizations with the potential to successfully integrate the AI assimilation systems in which they would be able to benefit from optimizing performance, reduction in wastage, and efficient usage of their resources. The integration factors of the system include data migration, employee training, incremental integration, and also system compatibility.

As part of the integration analysis, the leg system, or its architecture, capabilities as well as restrictions are considered before considering any process of integration in effect. The most important thing is knowing what processes or modules need improvement and most require AI integration (Fitzgerald, 2020). Companies can design APIs or even use middle ware to allow these two systems to talk to each other to make it seamless between the AI and the legacy systems (Jha & Lamba, 2022). The legacy system might have old data formats that do not support AI models. Generally, it is very critical to standardize the format of data used and compatibility with AI tools to help in seamless integration (Huang et al., 2021).

13.8.4 Regulatory and Compliance Challenges

With such considerations, many issues regarding rules, compliance, and integrity will accompany the advancement of technology in AI-driven sustainable logistics and inventory management. Most of these are caused by the implementation of new technologies into complex supply chain operations, such as artificial intelligence. Among these issues, data privacy and security issues are the biggest concerns.

Another significant regulatory challenge is ethical use in AI. AI models are quite powerful but often unwittingly promulgate bias resulting in discriminatory results in most activities like distribution of the workforce or allocation of inventors. AI systems that neglect to incorporate diverse demographic characteristics can lead to the unjust treatment of certain groups, making it result in legal as well as reputational risk (O'Neil, 2016).

Ethical issues in AI-controlled logistics also impact sustainability because biased systems tend to favor economic concerns above social or environmental considerations. Regulators can overcome such challenges by compelling firms to have systematic fairness audits, explainable algorithms, and arrangements to monitor the decision-making processes behind AI (Crawford, 2021).

13.9 Future Directions and Emerging Trends

13.9.1 AI and Circular Economy in Supply Chain Management

This, in turn, produces exciting new solutions in ways of developing ever-greater sustainability with their respective inventory management systems. AI is considered a very efficient mechanism through which people are hopeful about waste reduction and better exploitation of resources in chains of supply. Predictive analytics powered by the AI system would also enhance the prediction of demand so that many unwanted products are avoided, thus produced more than what the consumers want.

Moreover, AI can predict the product life cycle and end-of-life stage, which optimizes reverse logistics for better return, recycling, and reuse processes (Choi et al., 2020). This is helpful in circular supply chains where resources are used more efficiently and their environmental footprint is minimized.

More importantly, AI technologies change circular supply chains through increased material traceability and transparency. AI, combined with blockchain and IoT, tracks the product and the components from cradle to cradle to reuse or recycle, rather than waste them (Bocken et al., 2020). The circular supply chain management further allows for greater sustainability because with closed-loop systems, the products are returned, refurbished, and resold in order not to create waste and resources within the process (Lacy & Rutqvist, 2015). As the demand for sustainability continues to grow, these technologies will play a vital role in resource recovery and recycling.

13.9.2 Quantum Computing for Logistics Optimization

This would be of great importance for logistics optimization and especially within AI-driven sustainable logistics and inventory management. Today, solving problems of this complexity—optimizing problems like routing, scheduling, and inventory management—mostly demands enormous computational power. Most algorithms become computationally intractable for handling huge numbers of solutions when dealing with increasingly complex logistics systems. Quantum computing is one solution approach, particularly through quantum-enabled algorithms for optimization that can speed up optimizing much faster than in their traditional computer systems. Quantum computers work on a huge amount of data and simultaneously study numerous options in parallel, gaining early leads in streamlining (Ding et al., 2021).

13.9.3 Advanced Robotics in Inventory Management

The current developments of advanced robotics with AI will definitely revolutionize the inventory management process within logistics systems (Fildes et al., 2021). This sophisticated technique reduces human error, optimizes resource usage, and enhances the efficiency of operations. In the future, these technologies will be important factors for sustainable logistics. Robot science and technology focusing precisely on autonomous mobile robots with pick-and-place systems is even today the most relevant for such managing of warehouse operations keeping into account all the innovations leading to the least possible optimization expenses and also ecologically appropriate methods for such handling (Xu et al., 2022; Kapoor et al., 2022).

Now, AMRs drive all main warehouse operations and logistics configurations. Independent AMRs can auto-drive around racks, deliver within racks, sort goods items, and even help in the building of packages (Gisin et al., 2020; Sharma et al., 2020). AMRs use AI and ML algorithms whereby they continually learn and sharpen their decision-making capabilities relating to optimum routes learned as well as the adaptability to dynamic conditions of a warehouse. This translates into energy efficiencies saved, lower costs in running operations, and a higher throughput that is a clean, more efficient system (Zhang et al., 2021; Kumar et al., 2023a).

13.9.4 Autonomous Vehicles for Sustainable Transportation

Autonomous vehicles (AVs) are playing a very significant role in shaping the future of sustainable transportation within AI-driven systems of logistics and inventory control. The vehicles, with advanced power from AI, help curb the carbon footprint of logistically based operations. Thus, as AI is to be used in routing optimization, faster speed, and better fuel economy, it contributes directly in the minimization of the carbon footprint. For example, AI-based algorithms can conduct real-time monitoring of traffic and weather and thus determine the most efficient routes (Mourtzis et al., 2020). Fuel consumption will be reduced and delivery efficiency maximized in the process (Feng et al., 2021). Autonomous vehicles assist in reducing congestion as well as idle time; thus, they save emissions from traditional deliveries (Wang et al., 2020).

As more parts of the globe gather their momentum towards electrification, autonomous vehicles are being thrown into logistics fleets. As those electrics will continue to get paired with more electric drivetrains, many more will keep increasing the sustainability profile for more fleets. When

electric autonomous vehicles are combined with AI-enabled route optimization and charging cycles, they offer a truly sustainable alternative to traditional internal combustion engine vehicles, an environmentally friendly medium for travel. Such energy needs can be forecasted by an AI system to ensure consumption of energy within optimal parameters during running of electric vehicles and forecasting maintenance needs to extend life cycle (Saeed et al., 2020).

13.10 Conclusion and Recommendations

13.10.1 Summary of Key Findings

The future big thing for the world of supply chain will be AI-driven sustainable logistics and inventory management, which makes a huge leap forward in operation optimization and minimizes damage to the environment. Optimized AI algorithms can make integration into actual real-time data very easy for routing and delivery because, based on the given data of possible road conditions, weather, or historical patterns, routes could be chosen to have even better benefits: reducing travel time and consuming less fuel, thereby greener by all means. Real-time route prediction and adaptation have been identified by Zhang et al. (2021) as one of the factors with significant impact that makes logistics operations less carbon-hungry. Bektas and Laporte (2022) have shown AI-driven routing as one of the basic tools which helps logistics companies attain their operational efficiency and sustainability goals.

Predictive analytics is another innovation under AI-driven sustainable logistics. Here, with the management of inventory, AI will make possible demand forecasting through algorithms within tools that can analyze historical data, market trends, consumer behavior, and other external factors to deliver an accurate prediction of demand.

13.10.2 Strategic Recommendations for Stakeholders

Some strategic recommendations to the stakeholders in AI-driven sustainable logistics and inventory management include the use of recent AI technologies for efficient operation and cost minimization, coupled with reduced negative environmental impact. In today's complex supply chains, the ability

of AI-driven solutions might be critical to augment sustainability. One of the main strategic recommendations to stakeholders is to invest in AI-powered predictive analytics tools. These tools help businesses make informed decisions concerning demand forecasting and keep raising up their need to inventory through the use of big data to optimize all the logistics needs by analyzing history.

AI-based demand forecasts limit the waste caused by overproduction since this reduces the carbon footprint associated with excess manufacturing and redundant transportation activities (Zhao et al., 2020). It should, therefore, predict the markets and demand patterns. To reduce transportation emissions, Wang et al. (2021) argued that AI enables firms to streamline planning concerning optimal transportation and routes. The implications mean that supply chains have increasing needs for sustainable practices; otherwise, business strategies would never see the light of implementing any economic and environmental aims due to predictive analytics.

13.10.3 Implications for Industry and Policy

If a company is empowered with AI-driven sustainable logistics and inventory management, then it has so many opportunities to change its business practice and policy. In this regard, the operation will increase its efficiency, and also costs will reduce for the company because the systems of AI have improved the precision of demand forecasting, which would then decrease waste and end in no overstocking or stockout. It, therefore, saves enormous costs and increased cash flows (Tjahjadi & Yildirim, 2021). AI algorithms also optimize the transport route; therefore, more fuel and transport is conserved. It can, therefore, enhance more operational efficiency (Liu et al., 2022).

From the viewpoint of sustainability, AI will ensure huge environmental impacts that result from logistics operations conducted during that time. The AI-based systems optimize energy use in warehouses through smart lighting and regulation of temperature (Alonso et al., 2020). In transport, algorithms in machine learning reduce the emission of gases since the AI will identify energy-efficient routes that consume less fuel.

AI technologies support companies to develop circular economy business models because it will predict the demand of reusable products as well as recycling and reusing (Cucchiella et al., 2021). Optimizations made through

these AI have contributed largely in sustainability that business practices were made congruent with global environmental goals.

13.10.4 Areas for Future Research

Indeed, here are the probable transformative effects of such study on AI-based sustainable logistics and inventory management concerning optimizing the efficiency within enterprise-level operations, concurrent with reducing environmental impacts thus bringing in cost savings. This may even be able to envisage the use of AI towards a circular supply chain wherein AI models optimize the flow of goods such that they will more tend towards reusing and recycling and waste less. This shall happen once AI reverse logistics is used for the recovery or recycling of products in such a way that making easier identification of a product's end-of-life becomes easier.

Therefore, sustainable supply chains will exist (Ng et al., 2021). AI will introduce improved energy efficiency at the warehouse level with predictive analytics to provide energy savings in all areas of the system—from heating and cooling to lighting systems. It will help in utilizing the resources with the minimum wastage to their fullest capacity while at the same time making sure that the carbon footprint of the warehouse operations is reduced to the minimum as well (Cheng et al., 2023).

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Chapter 14

Artificial Intelligence for Sustainable Business Development

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14.1 Introduction

Over the past few years, there has been considerable growth in the number of reviews, discussions, and summits on explainable artificial intelligence (EXAI). The term “artificial intelligence” (AI) refers to the capacity of computers to do activities that have historically required human cognitive capacities, such as solving complex problems, gaining knowledge via experience, and acquiring new material. The technology’s ability to boost productivity, provide insightful data, and inspire innovation has the potential to alter several fields, including sustainable business practices, radically (Grandinetti, 2020). The concept of AI is commonly used to describe the research and development of computer systems with the ability to perform tasks that have historically needed human intelligence (Coursera, 2023). In other words, AI is defined as a technical innovation that allows robots to imitate a wide variety of complicated human abilities (Sheikh et al., 2023). AI’s role in assisting businesses to achieve their growth objectives has grown in recent years. The application of AI technology, especially advanced neural networks, is drastically altering the way in which everyone tackles real-world challenges. AI plays a crucial role in the preservation of a product’s unique characteristics and its position within the market. In contrast, it is advisable

for organizations to employ AI solutions that align with their fundamental principles and marketing objectives to enhance their brand identities (Huang and Rust, 2021).

In recent years, there has been a growing utilization of algorithms derived from machine learning (ML) in various domains such as science, business, and social systems (Preece, 2018). The rise in research activity within the field of ML, specifically in the area of deep learning (DL), can be attributed to the adoption of a methodology that involves training neural networks with a substantial number of parameters. Such a plan enables the networks to acquire the ability to perform a specific task in a generalized manner (Nagahisarchoghaei et al., 2023). Consequently, there has been a development of diverse methodologies that are relevant to different domains and contexts, aimed at interpreting machine learning models and providing clarification to facilitate human awareness (Perifanis and Kitsios, 2023). Today, sustainability is an essential part of corporate social responsibility, and it is a crucial first step in preserving the world for future generations (Simon, 2023). Companies use sustainable business strategies for various marketing activities. Policy leaders and campaigners argue that stronger regulations and updated active customers can force businesses to adopt sustainable practices (Nidumolu et al., 2009).

The growing attention towards EXAI highlights the importance of understanding trust, ethics, bias, and the impact of hostile situations on affecting the results made by AI algorithms (Cath et al., 2018; Chen et al., 2019; Weld and Bansal, 2019). The perception of explainability as optional may change as AI decision-making systems advance. In the future, explainability will likely become essential in ensuring transparency throughout constructing, evaluating, and employing diverse models, methodologies, and applications. The concept of EXAI corresponds to the belief that AI systems aim to offer clear and easily understandable explanations for their decision-making processes (Nagahisarchoghaei et al., 2023). The examination of issues in earlier research highlights the need for transparency and comprehension within AI systems, a challenge that can be effectively addressed through the use of explainable AI methodologies (Velampalli et al., 2022).

This chapter contributes to the existing body of knowledge in the domain of AI, encompassing both human and commercial aspects (Thamik and Wu, 2022). Also, it examines the multifaceted challenges presented by AI, encompassing behavioral, psychological, and ethical considerations and their implications for the human condition. The exploration emphasizes the significance of explainability in light of the increasing prevalence of AI as it

examines trends and applications in the field. This research investigates AI deployment in digital marketplaces, focusing on current trends and possible applications, which emphasizes long-term business development, especially in marketing.

Hence, within this perspective, the importance of this kind of study in establishing the concept of explainable AI becomes clear. This is consistent with the need for businesses to adopt explainable AI in order to encourage trust and collaboration, particularly in marketing and digital markets. Therefore, this investigation highlights the crucial need for explainable AI in addressing the gap between potential of AI and human understanding. This paves the way for seamless integration of technology and human cognition.

14.2 AI in Sustainable Business

The term “sustainable business” refers to practices mutually beneficial to the company, its stakeholders, and the community (Spiliako, 2018). The initiative is expected to increase business expenses, offer no rapid returns, and impair competitiveness. The deployment of AI has the ability to completely transform the way in which businesses operate, and sustainable business development has become an integral part of modern business processes (Di Vaio et al., 2020). Table 14.1 represents the significance of AI in sustainable business development.

There are numerous ways available by which AI can potentially improve a company’s sustainability. Integrating AI within a circular economy is important because it monitors item sales continuously. This capability plays a crucial role in reducing waste and promoting the rise of resource efficiency. One other approach by which AI contributes to cost reduction is by assisting organizations in recognizing and leveraging potential avenues for long-term financial savings (Lu and Serafeim, 2023). AI plays a crucial role in promoting sustainable decision-making in consumer interaction through disseminating relevant information and promoting environmentally responsible behavior. AI enables uncovering opportunities for new products and services, for example, “Segmenting Audience.” Also, AI uses customer insights to inform decision-making, for instance, “product recommendation” (Chandra Das et al., 2023).

As a result of automation, the workforce gets more time to focus on priority activities using machine learning techniques. AI enables data analytics in terms of recognizing novel patterns in datasets, facilitating organizations

Table 14.1 Significance of AI in Sustainable Business Development

<i>Aspect</i>	<i>Role of AI in Sustainability</i>
Circular economy	Constant monitoring of merchandise sales
Cost reduction	Finding long-term savings opportunities
Customer engagement	Facilitating sustainable decision-making and providing relevant data
Data-driven sustainability reporting	Data mining and report writing
Energy efficient	Reducing waste and increasing energy efficiency
Innovation	Encouraging creativity for the creation of sustainable products
Predictive maintenance	Reducing trash and expanding machine longevity
Risk management	Evaluating and reducing risks in order to achieve sustainability
Social impact	Socially sustainable system optimization
Supply chain transparency	Maintain a transparent supplier chain and equitable trading practices

Source: Compiled by authors.

to deal with huge volumes and variants of data (Palanivelu and Vasanthi, 2020). The utilization of AI in data mining and report authoring significantly facilitates the dissemination of sustainability reporting based on data analysis, thereby ensuring the provision of timely and precise disclosures (Perdeli Demirkan et al., 2021). In addition to mitigating waste and optimizing energy consumption, using AI significantly enhances energy efficiency, yielding favorable environmental outcomes. The primary purpose of AI is to stimulate creativity, demonstrating exceptional performance in this regard when employed to develop environmentally sustainable products (Zia, 2023).

Predictive maintenance solutions facilitate the achievement of sustainability objectives for enterprises through waste reduction and the promotion of equipment longevity. Integrating AI into the domain of risk management necessitates careful consideration and evaluation of the benefits and drawbacks associated with the prevention and mitigation of potential hazards, with the ultimate goal of achieving sustainable outcomes over an extended period (Žigienė et al., 2019). The significance of AI lies in its capacity to enhance the efficiency of socially sustainable systems and foster supply

chain transparency by adhering to equitable trading principles and maintaining a transparent supplier chain. AI has the potential to contribute to corporate sustainability through its use in various domains, including but not limited to operations optimization, social responsibility, and environmental protection (Runyon, 2023).

Marketing tools like AI are transforming how companies interact with customers and create strategy. In Table 14.2, various significance of AI is mentioned in the field of marketing. Personalized marketing is a popular usage of AI. Businesses need to analyze client tastes, behaviors, and buying history using AI algorithms which allows for unique marketing strategies and closer client relationships. AI-driven data enabled customization initiatives improved business outcomes. Marketing tactics have always relied on data analysis and insights. AI can process and analyze large datasets faster than humans (Giridhar, 2023). Artificial intelligence (AI) helps marketers understand customer preferences and market trends through pattern, correlation, and trend recognition in these datasets. According to Salesforce’s “State of

Table 14.2 Significance of AI in Marketing

<i>Area</i>	<i>Key Points</i>
Personalization	Personalizing marketing to meet customer wants
Data analysis and insights	Information emerges from analyzing massive data sets
Predictive analytics	Predicting future customer patterns
Chatbots and virtual assistants	Delivering immediate customer assistance in real time
Content creation	Providing support in the creation of marketing materials
Marketing automation	Implementing constant marketing tasks
Audience segmentation	Targeting certain kinds of customers
Ad campaign optimization	Improving digital ad campaigns
Fraud detection	Identification and prevention of fraudulent activities
Competitive analysis	Tracking the activity of competitors
Voice search and SEO	Voice-enabled search engine marketing
Marketing strategy	Enhancing marketing methods and campaigns

Source: Compiled by authors.

Marketing” survey (Salesforce, 2023), marketing teams that perform well are 1.5 times more likely to use AI to gain customer insights.

Companies now predict customer behavior using AI-powered predictive analytics. Data from the past experiences can help AI systems forecast customer behavior. More knowledge helps marketers make better selection, which is useful in terms of product launches, price strategy, and promotional effectiveness that helps to boost several marketing campaigns. *Harvard Business Review* highlights that the use of analytics powered by intelligence has resulted in a significant 10% improvement, in retaining clients (Eric 2023).

Since marketing has embraced chatbots and virtual assistants, customer interactions have altered. AI-powered chatbots answer queries, provide product information, and guide customers through the sales process in real time. In this circumstance, reaction enhances consumer experiences and happiness. Juniper Research (2023) predicts that chatbots will save \$8 billion by 2025 of various organizations under digital retailer market which illustrates their growing importance in customer service.

AI has also impacted content creation and marketing automation. AI algorithms can write product descriptions and blog content faster than ever, which could relieve marketers of their duties. AI boosts email marketing, social media posting, and campaign management by streamlining operations. Experts predict that marketing automation will rise to \$6.4 billion by 2024, which reflects how fast the industry has grown (Pritee and Arijit 2023). With the emergence of AI, audience separation and targeting are the norm. Based on demographics, habits, and past purchases, modern marketing can segment clients that allows personalized messages to specific customer groups, increasing engagement and conversion rates. According to Econsultancy’s “Conversion Rate Optimisation Report,” personalization and segmentation methods enhance conversion rates for 93% of organizations (Dermatas, 2017).

AI also adjusted the advertising campaign configuration. AI systems can improve conversion rates and return on investment (ROI) by altering real-time bidding tactics, ad placements, and targeting parameters. Digital advertising success depends on dynamic adjustment. Adobe found that AI in tailored adverts might boost click-through rates by 50% (Park et al., 2022). In digital marketing, AI is crucial for detecting fraud. AI can instantly identify suspicious activity and predict fraud, safeguarding organizations from online transaction risks. Incorporating AI-powered systems for detecting and preventing fraud could lead to a decrease of around 20% in losses caused

by activities, in the field of digital marketing (Garg et al., 2017). AI-powered tools for tracking and studying competitors' online behavior have substantially enhanced competitive analysis. Competitors' strategies can help companies improve their own. Maintaining market competitiveness demands a strategic plan.

Voice searches and SEO have been altered by AI. Marketers are leveraging AI to make voice-based searches easier as voice-enabled gadgets become more widespread. AI understands natural language and user intent to customize information to voice search queries (Overgoor et al., 2019) which promotes the brand. Modern marketing strategies heavily depend on the integration of AI, which is crucial, beyond measure. Marketers utilize AI to examine market trends obtain insights, into customer viewpoints and utilize historical data to make well informed decisions. By incorporating AI into marketing strategies and campaigns businesses not improve efficiency. Also, gain the ability to stay competitive and adaptable in an ever-changing digital world (Grandinetti, 2020).

14.2.1 Application of AI in Sustainable Business Development

The representation of various applications under AI to be used for sustainable business development is shown in Figure 14.1. And it signifies that AI-driven climate models have the capability to forecast climate change, enabling businesses to strategically adjust their operations and make well-informed choices aimed at reducing their carbon emissions. AI can predict

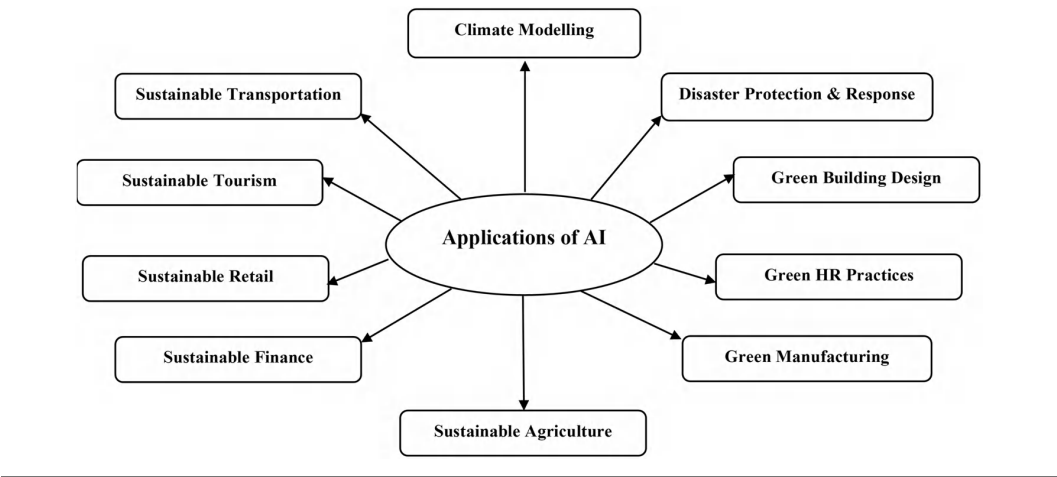


Figure 14.1 Various applications of AI to be used for sustainable business development Source: Compiled by authors

natural disasters like hurricanes and earthquakes, helping organizations prepare and respond, which can reduce damage and recovery expenses (Min, 2023). AI-driven simulations and models optimize heating, cooling, and lighting systems to develop energy-efficient and environmentally friendly buildings (Lee et al., 2022). Leveraging AI to optimize remote work, mitigate the need for employee traveling, and establish sustainable human resources policies. AI has the potential to enhance manufacturing operations by effectively minimizing energy use, minimizing material waste, and mitigating pollution. AI-driven precision agriculture improves resource allocation, water use, and crop yields by analyzing data, IoT sensors, and autonomous farming equipment (Javaid, 2023). AI can evaluate investment risks and identify opportunities by analyzing environmental, social, and governance (ESG) data. This analytical methodology encourages sustained corporate and project investments.

The ultimate objective is to implement sustainable purchasing and waste reduction initiatives in retail operations (Evison, 2023). The promotion of environmentally friendly tourism practices is a means of reducing negative effects on our environment. To reduce emissions, AI can improve transportation efficiency by optimizing routes, advancing electric and autonomous vehicles, and enhancing public transit networks (Kolesnikova, 2023). Apart from these above-mentioned applications, AI supports the life cycle analysis of products or processes, thereby contributing to sustainable business goals of minimizing environmental impacts and contributing to Triple Bottom Line benefits. AI influences self-learning systems based on tools like data mining and pattern recognition, thereby contributing to key business advantages and ensuring significant cost savings (Palanivelu and Vasanthi, 2020).

14.2.2 Applications of AI in Marketing

AI is employed by marketers to categorize clients into distinct groups by segmenting them according to extremely specialized niches. Companies have moved away from employing a singular, generic advertising approach in an attempt to reach all of their intended clientele and achieve enhanced conversion rates. In contrast, the marketing content produced by these technologies is tailored to the specific characteristics and preferences of each key demographic, resulting in a highly personalized approach. AI is not exempt from imperfections (Prakash, 2023).

Nevertheless, the expansive nature, dynamic characteristics, and inherent capabilities of this phenomenon empower marketers to reevaluate and

Table 14.3 Various Applications of AI to Be Used in Marketing

<i>Applications of AI</i>	<i>Functions</i>
Localization and translation	Marketing content is translated and localized for multiple areas and languages by AI
Augmented reality (AR)	AI improves AR experiences by modifying content based on user actions
Virtual reality (VR) marketing	AI is now personalizing VR marketing to each individual's interests
Real-time campaign optimization	AI utilizes performance indicators and user input to modify marketing strategies in real-time dynamically
Neuromarketing	AI analyzes brain science to comprehend human emotions and design campaigns
Subscription management	AI can forecast attrition and offer retention methods for subscription-based businesses
Smart content curation	AI is used to choose and arrange content from several sources for dissemination across various media
Image and video analysis	AI analyzes photographs and videos in targeted marketing to recognize items, places, and contextual information
AI-generated creatives	Automated picture and design creation for marketing helps companies save money and time
Emotion analysis	AI has the ability to read customers' emotions and adapt their responses and methods of interaction accordingly
Data privacy and compliance	AI is essential for managing client data and conforming to privacy standards, boosting trust

Source: Compiled by authors.

formulate enhanced approaches aimed at delivering concrete and pertinent offerings to their clientele across their customer lifecycles (Haleem et al., 2022). The subsequent sections outline various methodologies for the integration of AI in marketing, as well as elucidating the manifold ways in which AI enhances marketing strategies. Table 14.3 presents various applications of AI to be used in marketing and its working mechanism.

Table 14.3 outlines AI-based approaches to marketing. AI simplifies regional and language marketing material adaptation. AI customizes AR and

VR marketing content based on users' virtual behaviors and preferences. AI optimizes marketing strategy by real-time monitoring and responding to key performance indicators (KPIs) and user feedback (Haleem et al., 2022). AI-based neuromarketing ads use human emotions (Bansal and Gupta, 2022).

AI-based retention prediction and management improves subscription businesses. AI-based smart material curation selects and organizes information from different sources for distribution across media channels, improving content advertising. Image and video analysis using AI can detect people, places, and activities in visual marketing materials (Verma et al., 2021). AI-generated marketing materials save time and money. AI can improve consumer knowledge and responsiveness through emotion analysis. AI manages customer data and privacy, boosting marketing trust and compliance. Marketers use AI-powered apps to be relevant and legal (Abbi, 2023).

14.3 Tools of AI in Marketing

The term “AI marketing tool” is used to describe any piece of software or platform that makes use of AI technology to carry out automated evaluations and decisions. The decisions are based on information that has been gathered, analyzed, and evaluated in light of the current market situation. The intention is to generate a marketing plan that looks ahead to the actions of the consumer, which happens instantly and automatically, with no help from us. The tremendous efficacy of AI marketing solutions in the business world is largely due to their ability to generate quick, automated judgments (Mileva, 2023).

Marketers are expected to constantly produce new content across a large variety of channels and with a wide variety of formats (Isensee et al., 2021). Marketers regularly report experiencing an ever-increasing volume of work that necessitates a frenzied scramble to keep up. If only there were a way to help people deal with these issues. Fortunately, there is an overview of some of the most well-known AI marketing solutions right here (Morris, 2023). Here a wide range of cutting-edge AI marketing technologies with the potential to improve productivity, expand reach, and stimulate new ideas in the field. Many different parts of marketing can be tackled and improved upon by using these methods.

An increasing number of people are turning to AI technologies to assist them with duties such as creating marketing content and enhancing their

Table 14.4 Certain AI Tool Scenarios

<i>AI Tools</i>	<i>Benefits</i>
HubSpot	Offers software for lead scoring, content optimization, and email marketing, all powered by AI
Salesforce Einstein	Predictive analytics and AI are utilized to provide insights into customer service
Adobe Sensei	Adobe’s tools for content customization include embedded AI features
IBM Watson Marketing	Analytics, client sub-segmentation, and chatbots powered by AI are feasible
Google Analytics	Data mining carried out by AI on a website in order to provide advice and analysis
Chatfuel	It’s simple to make a chatbot that uses AI technology and deploy it on different systems
Albert	Digital marketing automation and optimization platform powered by AI
Drift	Conversational AI for boosting sales and connecting with clients
Phrasee	AI has helped improve the topic lines and body content of marketing materials
Cortex by AdParlor	Automation and improvement of social media advertisement with AI
ChatGPT	It possesses the capability to engage in text-based discussions and provide guidance on many topics

Source: Compiled by authors.

ROI in advertising. Table 14.4 presents various examples of AI tools with a short description to the customers on its utilization.

Several AI systems’ marketing and customer involvement capacities are compared in Table 14.4. HubSpot stands apart due to the superiority of its email marketing, content optimization, and lead scoring tools backed by AI. Salesforce Einstein uses AI and predictive analytics to help businesses better serve their customers. IBM Watson Marketing enables AI-powered analytics, customer segmentation, and chatbot integration, while Adobe Sensei provides tools for content personalization with incorporated AI features (Parker, 2023).

AI is used by Google Analytics to navigate through website data and offer advice and analysis. Chatfuel simplifies the development and distribution of chatbots powered by artificial intelligence on many platforms. Digital marketing automation and optimization platform Drift focuses on conversational AI to boost sales and customer interactions, whereas Albert is an AI-powered digital marketing automation and optimization tool (Lukan, 2023). Phrasee is an AI-powered tool for writing better marketing copy. Cortex by AdParlor applies AI to streamline and enhance social media marketing. Finally, what sets ChatGPT apart is its ability to have conversations with users and offer guidance on a wide range of topics using text (Rebelo, 2023). These AI technologies provide a few options for enhancing marketing tactics and communication with customers through the use of AI.

14.3.1 Techniques of Explainable AI (EXAI)

Various techniques of explainable AI (EXAI) for the sustainable business development are listed below:

- Rule-based methods: These methods explain an AI model's decision-making process using human-understandable rules. The “if-then” structure of these rules makes them easier to understand. The analysis shows the input data elements that significantly affect model predictions.
- Example-based methods: These methodologies provide rules for explaining AI model decision-making to humans. The “if-then” structure of these ideas simplifies them. The findings highlight input data elements that significantly impact model predictions.
- Model-based methods: These methods simplify or approximate complex models to improve comprehensibility. Decision trees and linear regression can mimic neural networks.
- Post-hoc methods: Post-hoc approaches aim to explain a trained AI model's results after prediction. These methods focus on internal model components like feature significance scores and gradients to explain model predictions.
- Hybrid methods: Hybrid tactics use several explainable artificial intelligence (EXAI) methods to provide detailed explanation. A hybrid technique could combine rule-based and example-based methods to provide a complete study of theoretical and practical principles.

Moreover, it highlights the importance of intrinsic explainability, which pertains to the inherent interpretability of a model's behavior, and ad hoc explainability, that involves using external methods to elucidate a model's behavior (Di Vaio et al., 2020).

14.4 Challenges of AI in Sustainable Business Development

The contemporary scene is characterized by notable characters such as Elon Musk, who is pushing for human exploration of Mars, and Mark Zuckerberg, who is saying that VR and AR would revolutionize the workplace by allowing people to overcome their physical limits. This means that the future has finally arrived. All these ideas point to a single persistent theme: technological progress is never-ending and always increasing in brilliance (Prakash, 2023). However, like with any modern technology, there are limitations and difficulties to overcome. There has been a recent uptick in the use of AI in marketing, but this innovative technology is not without significant challenges. AI replicates human behavior and asks perplexing questions in an attempt to learn from all of us (Brenner, 2019).

Modern businesses, as well as daily lives, cannot overstate the importance of AI. Banking, finance, healthcare, and media companies use AI systems to enhance efficiency and income. The half of the respondents in recent survey on “The state of AI in 2020” conducted by McKinsey which revealed that “their companies have adopted AI in at least one business function” and that AI revenue will double in the next few years so, AI will stay essential in business (Pospelov, 2022). While AI has brought many positive changes to sustainable development and e-markets, it also presents several challenges that must be met before it can be used responsibly (Haralayya et al., 2023).

Insufficient IT Infrastructure

An AI-driven marketing plan needs a solid IT foundation. AI can handle massive data sets. Thus, high-performance hardware is needed. For such purposes computer systems are expensive to install and maintain which may need frequent maintenance and updates to stay functional. And, it can be difficult for smaller organizations with less IT staff and resources. Fortunately, there is another solution. Companies with higher resources can

build and run their own AI marketing solutions, while smaller ones can use cloud-based ones. Cloud software vendors supply IT infrastructure and workers to run AI software for nominal monthly or annual price. Cloud services are ideal for companies without IT departments (Pappas, 2023).

Lack of Data or Poor Data Quality

AI relies on a steady diet of high-quality inputs. The results produced by AI software will suffer if insufficient data or low-quality data is used. For a big-data future, businesses are accumulating a mountain of information. However, not all this data is the right to fuel an effective AI marketing effort. Those involved are also responsible for ensuring the quality of both newly collected and previously collected data. The success of AI-driven marketing efforts can be negatively impacted without this crucial step.

Lack of Trust in AI Software

AI is advanced and complicated. This may make non-AI public and technical team members apprehensive. Recent films with a “rise of the robots” concept suggest that humans should dread AI and machine learning algorithms, which hurts popular culture. Real life is different from science fiction, yet corporations must use AI software carefully to avoid appearing too human. Target discovered a teen pregnancy before the consumer alerted her family using customer data. As recommendation engines have great marketing potential, some clients may find them intrusive or “spooky” if the software knows too much about them. Openness boosts AI consumer trust. Clarifying how AI algorithms use consumer data to draw inferences (and when and where customers gave this data) helps customers trust and support AI technologies.

Insufficient Budget/Investment for Implementation

The lack of funding and investment, for implementing AI in various business activities might present difficulties. It could hinder the acquisition of technology recruiting professionals and establishing the necessary infrastructure. This financial limitation may impede innovation restrict competitiveness and slow down the adoption of AI in industries. Consequently, it might delay the realization of transformative benefits in areas, like healthcare, agriculture, manufacturing and education.

Lack of In-House Talent

AI skills gap could hurt organizations who want to build their own AI marketing solutions. The number of AI-focused businesses will increase work opportunities. Qualified AI specialists are not increasing fast enough to meet demand. Even companies that use pre-packaged AI marketing tools and solutions need qualified staff to integrate, monitor, and analyze the data. Some companies can overcome the talent gap through in-house training, but others may need to recruit and retain high-paid AI professionals. Existing resources are being stretched thin, or business management must be persuaded to spend more in AI, which they may not do if they have not seen enough return.

Privacy and Regulations

The field of AI is new. The rules governing it may change and tighten in the future. Data gathering and use are already affecting EU customer data-powered AI systems. Companies must comply with the General Data Protection Regulation (GDPR) by 2020 to protect EU individuals' personal data. Some firms may be prohibited from storing data offshore, rendering cloud-based AI marketing services unsuitable.

14.5 Solutions to Challenges in AI-Based Marketing

AI marketing challenges may frustrate efforts and affect the results of one's AI-driven software. Certainly, there are a few additional options to consider which the following steps could deal with frequent challenges in AI marketing:

- Develop a plan for reaching out to a specific demographic.
- Investing in marketing AI without first securing money is a bad idea.
- Get the sales staff ready
- Identify the right individuals.

Making company plans, recruiting seasoned marketers, calculating return on investment, and securing funding are not activities that are likely to pique anyone's interest (Chakurkar, 2021). However, these methods are absolute door openers when putting an AI marketing strategy to the test. Finally,

every business is responsible for maximizing the positive impact their AI system has on their customers.

14.6 New AI Trends for India in Sustainable Business

India's manufacturing industry is changing rapidly due to Industry 4.0. Customers' changing tastes, new distribution methods, turmoil in risky locations, supply chain interruptions, and "Environmental, Social, and Governance" laws have provided exciting new chances to rethink and improve existing business structures. The "Production-Linked Incentive" program and 'Make in India' campaign are two of several government efforts that have improved the domestic market, attracting international collaboration and FDI.

Also, AI is projected to play a crucial role in minimizing the consequences of climate change and meeting the "Sustainable Development Goals" (Gupta, 2023). PwC (2023) India conducted an in-depth analysis to examine the digital landscape in the Indian manufacturing industry and the possibilities for a future strategic plan. PwC India partner and Data and Analytics Practice head Sudipta Ghosh presented the survey results of "Reimagining Digital Factories of Tomorrow" that businesses, especially Indian ones, are excited about digital transformation. Efficiency in business processes is a key. This involves using digital twins to understand batch parameters, automating operations like connecting workstations with the Internet of Things to boost shop floor visibility, and lowering asset downtime and equipment maintenance costs. Businesses are also employing workflow-based automation to increase scheduling productivity (Chatterjee, 2023).

The digital executives in six different sectors in India agree that implementing robust, transparent, and sustainable practices is critical for their companies' future growth. While their global counterparts prioritize innovation, Indian firms prioritize personalization and customer-centric digital transformation solutions. The payout period for integrating new technology in India is substantially shorter than in other countries around the world. Indian enterprises who invested at least 3% of their entire revenue in digital transformation had a higher rate of success.

Also, they strongly recommended that AI needs to be implemented efficiently by the companies in Indian business. Though there is lack of surefire template, firms should not dive into digital transformation without a comprehensive transformation plan those answers key issues (Chatterjee, 2023). PwC India Partner and Digital Operations Leader Ankur Basu acknowledged that: "Only a few companies have developed future-proof operational

Table 14.5 Key Strategies Recommended by Digital Experts

<i>Key Strategies</i>	<i>Insights from Digital Experts</i>
Digital strategy	Businesses should identify strategic goals and digital vision before choosing use cases, business apps, or technologies
IT architecture design	Success depends on the digital backbone, or architecture archetype. Focusing on IT infrastructure, both a solution and a risk, can reduce businesses’ risk of losing their ability to deliver digital solutions quickly and scale
Vendor strategy	Businesses must determine whether to build or outsource digital solutions
Agile platform, systems, use case, and process development	During development, companies must determine whether to adopt agile or waterfall delivery
Implementation and rollout	Digital conversions might be done gradually or all at once. However, simultaneous adoption has hazards, which organizations should consider before proceeding
Organization, people, and change	Businesses should evaluate their unique operating characteristics and choose the best operating model to implement their digital transformation plan

Source: Compiled by authors.

solutions across their value chain. To efficiently embrace digital technology at scale, the leadership team must be dedicated and have a well-defined implementation strategy and qualified workers.”

Table 14.5 shows the results of this survey which indicate that digital transformation in manufacturing requires focusing on people, processes, and technology. Also, it contains several key strategies which is recommended by digital executives or experts from six different sectors in India for better future results.

14.7 AI Evolution Led by ChatGPT

Artificial intelligence researchers have been captivated by the capabilities of ChatGPT. This state of the art AI chatbot offers responses to queries and can

be helpful in tasks like composing emails, essays and code. The impact of ChatGPT on productivity and employment is significant. In the five days of its release in November 2022 ChatGPT garnered, over a million downloads surpassing the popularity of Instagram and Netflix. By the end of 2023, it is projected to cross 100 million users establishing itself as the growing software ever.

According to Similarweb, “openai.com” receives a 1.8 billion visitors every month highlighting OpenAI's presence online (Maheshwari, 2023). Interestingly, ChatGPT receives 60% of its social media traffic from YouTube. It's fascinating to see how multiple social media platforms serve as channels, for sending and receiving messages. The bounce rate of ChatGPT, which stands at 17.33%, indicates its capabilities. It's worth mentioning that there are over 6 million searches for “Chat GPT login.” This popular platform enjoys an user base, in the United States (15.22%), India (6.32%), and Japan (4.01%) (Thormundsson, 2023). Content quality and organizational efficiency improve using ChatGPT. AI technology like ChatGPT increased worker productivity by 14%. These findings suggest that ChatGPT is widely relevant and influential (Haan, 2023).

14.8 Conclusion

“AI for Sustainable Business Development” examines AI's potential and risks to promote equality. Academic interest in AI shows its potential to improve society. AI could reduce pollution, waste, and carbon emissions. AI will have consequences, like any groundbreaking technology. This study will examine social inequality and computer resource management, including power consumption and maintenance. Long-term operations depend on AI and risk management. Marketing has been transformed by AI. The initial stages include data analysis, customer behavior forecasting, productivity improvement, and new advertising strategies. Marketing with AI is expected to produce new methods and results. This chapter addresses the marketing perspective of business development considering sustainability aspects.

To execute an AI marketing strategy, one must understand AI's significance, applications, and resources. Improving employee skills and protecting personal data are difficult. Businesses can make transparent AI-driven workflow decisions with explainable AI (EXAI). Balance is stressed by business managers. Sustainable and ethical business practices are needed to implement AI. AI tools can support decision-making with multiple criteria to

select the best alternatives. Innovation and sustainable economic development can reduce environmental and social harm. Sustainable business success requires AI integration and community welfare. Business, government, and stakeholder collaboration is needed to develop AI. The benefits and drawbacks of artificial intelligence must be optimized to maintain technological momentum. Company success depends on integrating AI with society's well-being and advancement. Deployment of AI helps to create new business avenues in a dynamic market scenario. To shape the future of AI, businesses, governments, and other stakeholders must collaborate.

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Chapter 15

Integrating SDGs into Industry 4.0's Sustainable Business Practices: Efficiency and Challenges

Tripti Sahu

15.1 Introduction

The evolution of Industry 4.0 had its origin in Germany in the year 2011. It was a strategic initiative of the German government; later, it transformed and was adapted by various advanced countries as per their own understanding, for example, “Advanced Manufacturing” in the US, “Made in China” in China, “Smart Factory” in Britain, and “Make in India” in India (Hajoary, 2021).

With the advent of technology, the implementation of computer-integrated manufacturing system as well as flexible manufacturing system has become efficient and affordable. Smart manufacturing is the outcome of computer-integrated manufacturing system and flexible manufacturing systems developed in the recent past. Industry 4.0 can be described as the application of flexible manufacturing and business automation, IoT, cloud computing, AI, 3-D printing, robotics, simulations, additive manufacturing, cyber systems, etc., which offer great benefits to businesses (Ejsmont et al., 2020).

Manufacturing as well as service industries, as it constantly involved in bringing modern solutions to contemporary issues, employs state-of-the-art technology like block chain, smart systems, augmented reality, and industrial

internet to boost innovation (Ghobakhloo, 2018; Kamble et al., 2018a). Modern manufacturing has bestowed the world with more promising solutions to pressing industrial challenges (Tofail et al., 2018). Product design complexities, global supply chain issues, and complications of product life cycle are all taken into account. These solutions, apart from being effective in the business environment, are required to be effective for the natural environment and the social environment as well. Thus, it is the need of the time to plan its development around social and environmental agenda. The big step requires changes in institutional values apart from social and cultural amendments. Green development should be made a part of daily working and should be given central role while designing organizational policies (Polasky et al., 2019; Kagermann et al., 2011).

There has always been a debate around the topic that how science and technology could play a part in uplifting the quality of life and at the same time help in restoring the limited natural wealth of the planet (Commoner, 2020; Kumar et al., 2020). In present times, the issue of ecology restoration and social balance has become all the more important. Industry 4.0 is considered as revolutionary in terms of providing absolutely new and unique solutions to the pressing problems related to the sustainable development of the industry (Richnák & Fidlerová, 2022). The challenges related to green energy, judicious use of limited natural resources, social and economic justice for all, and use of modern technology for sustainable development have taken the front seat in industrial development discussions (Adamik, 2020; Basl, 2017).

Infringing the environment has a long-term impact in the form of global warming, scarcity of natural resource, food produce, quality of water and air, and so on (Zhang et al., 2022). These environmental effects lead to social implications like scarcity of food, non-availability of drinking water, or other social issues like inequality among human race, lack of access to education to all, population pressure, etc. (Arora et al., 2025).

The path of managing business in a green way is not easy; it calls for alterations in business models and processes (Devi et al., 2024). Industries need to develop capacities that consume less energy and produce minimal waste. More and more use of renewable sources of energy, developing social infrastructures like urban water and sanitation systems, and using ecofriendly materials for product and process development are other areas where green technologies can contribute (Jaiswal et al., 2022). Modern technology has tremendous opportunities to produce effective solutions to issues world is facing today. Sustainable development goals can serve as a guiding light to make these solutions long lasting. The realization of SDGs

needs a transformation in the way goods and services are being produced today, which is the major obstacle in the way of SDG realization (Caiado et al., 2018).

The very core of sustainable development goals is the balance between society and the environment. The sustainability path requires a handshake between technology and social and environmental good. Appropriate implementation of green technology suitable for the land is something that SDG thrives for (Moallemi et al., 2020). Investment in eco-friendly technology, efficient process designs, sustainable raw materials, and better performance, etc., are the desired outcomes of sustainable development (Kumar et al., 2023). With the philosophy of “no one left behind,” the specified goals demand global participation for collaborative growth. Global performance indexes rank different countries on their performance on various parameters (Lee & Trimi, 2018). Sustainable development goals are one such index that ranks countries on the basis of their social and environmental performance. Sustainable development goals aim to achieve the 17-point agenda by 2030, which includes eradication of poverty, providing quality education to all, improving health care infrastructure, environmental sustainability, social well-being, and prosperity for everyone (Das et al., 2021).

15.2 Literature Review

To evaluate the sustainability performance of any organization, the triple bottom line framework is used, consisting of environmental, social, and economic responsibility (Elkington, 1998; Agrawal, 2024). The environmental aspect can be further subdivided into material usage and the use of alternative sources of energy. Social factors include labor practices, equality for all, practices of human rights, and a decent work and wage for all. The research mostly focuses on the use of material and energy, as this is the major area of concern for Industry 4.0, and it is the area in which the effect can be seen and measured with ease. But these areas need to be further explored. The introduction of technology can further reduce material and energy consumption. Some applications of technology for quality checks could result in less wastage due to failure, leading to cost savings (Stock et al., 2018). With the same logic, the adoption of digital simulations, continuous data consumption, and independent control loops can improve performance through efficient engineering and production processes (Kiel et al., 2017). There are cases of significant savings in important resources like energy, water, and raw material consumption

with the help of digital technology. This trend is likely to increase with time and with the adoption of new, better technologies (Braccini & Margherita, 2018). Thus it is clear that the involvement of technology is going to affect environmental performance. At the same time, it is important to note that every progression comes with a price. In this respect high primary resource consumption could be the cost one has to pay for a fully automated production system. Indeed, the adoption of a fully automated system will increase the demand for devices that drive the automation process. The demand for such devices drives their production, which require heavy primary resources, resulting in environmental degradation (Stock et al., 2018). It has also been observed that with the adoption of new technology by the industry, problems related to manufacturing have increased and are creating sustainability issues. This development demands raw material that are scarce in nature, apart from other natural resources like water and land. Moreover, the disposal of outdated and obsolete devices needs a place for safe disposal. In the absence of such facilities, waste is often disposed of in the open environment, leading to greater ecological damage (Bonilla et al., 2018).

The claims are numerous, be it reduction of carbon dioxide emissions (by 20 percent) or increased profit for the companies (beyond \$11 trillion), and social good by creating an interconnected economy (2.5 billion people) by the stipulated time set by UN for achievement of SDG (Thapa, 2019). Though the fulfillment of the objectives is not going to be an easy journey, the SDG should be integrated with modern organizations since their nascent stage to inculcate sustainability in new technology. Presently, there exists a gap between the research on SDGs and Industry 4.0 requirements.

15.3 Methodology

The study adopted the literature review method for synthesizing existing research on green business efficiency and the associated challenges. The researcher employed a systematic approach to classify, hand-pick, and examined appropriate studies.

For the study, the research used prominent electronic databases, i.e., Scopus, Web of Science, and Google Scholar. Boolean operators were used to ensure the relevance of the selected research. The keywords used included green business, business efficiency, sustainable development goals, corporate social responsibility, sustainability challenges, ecofriendly, and sustainable businesses.

The limitation of language was applied and was restricted to English-language research only. To ensure the relevance and recency of the data, research published between 2018 and 2025 was only considered for the study.

The studies addressing the concepts and issues related to green business practices and industries working in alignment with the relevant SDGs through their CSR practices were considered. Only the studies presented on empirical research and published in peer-reviewed journals were taken. Relevant Industry 4.0 reports and high-quality gray literature were also taken for their relevance.

However, the studies that do not fall under the scope of this research work were excluded, and the conference papers and personal opinions of individuals were avoided to maintain the authenticity of the outcome.

The screening of the collected text was done at three levels. Firstly, the research works were screened by their title and the irrelevant titles were removed at the first level itself. Secondly, the abstracts were screened, and only the studies concentrating on the research topic were kept. Finally, the full texts that had a considerable contribution to the research under consideration were selected for review.

Common themes and patterns were identified through a qualitative synthesis from all the selected studies for review. The companies working towards the achievement of specific SDGs through CSR practices were kept as a case let for reference in the chapter to emphasize the practices adopted by Industry 4.0. The challenges these organizations face were identified and written in a systematic manner.

15.4 Thematic Analysis

15.4.1 Sustainable Supply Chains

Industry 4.0 has changed the way businesses used to operate. The technological disruption has altered operations right from the procurement of raw material to the disposition of the product. With the involvement of suppliers, manufacturers, and consumers, the entire supply chain has become more and more sustainable. To seek long-term sustainable solutions in favor of society and the environment, involvement of all stakeholders has become mandatory. In a study of the Indian economy, Luthra et al. (2020) discovered that “government supportive policies and collaboration and transparency”

have a major role to play in achieving the triple bottom line in the supply chain for any organization. The same holds true for other emerging economies as well. For instance, shipbuilding supply chains have engaged technology for major supply chain prototypes like green, resilient, agile, and lean (Ramirez-Pena et al., 2020). Once it was established that the shipbuilding supply chain is lean and green, it was studied and found that green supply chains are sustainable in nature. There exists a direct correlation between the supply chain and the internet of things. If they are studied under the scanner of triple bottom line sustainability features, they are either found to be economically sustainable, environmentally sustainable, or socially sustainable supply chains. The study also approved that these classifications, in association with other variables, can give better results in organizational decision-making pertaining to sustainability (Shokouhyar et al., 2019). Gruzauskas et al. (2018) says that competitive strategies thrive on cost management for its optimization, which ultimately results in sustainable supply chains. This is an efficient way to reduce the compulsion of choosing either sustainability or cost-effectiveness.

15.4.2 Relevant SDG for Industry 4.0

There has always been a debate around the topic that how science and technology could play a part in uplifting the quality of life and at the same time help in restoring the limited natural wealth of the planet. In present times, the issue of ecology restoration and social balance has become all the more important. Industry 4.0 is considered as revolutionary in terms of providing absolutely new and unique solutions to the pressing problems related to the sustainable development of the industry. The challenges related to green energy, judicious use of limited natural resources, and social and economic justice for all and use of modern technology for sustainable development has taken the front seat in industrial development discussions.

Industry 4.0 is revolutionary for manufacturing as well as service industries as it constantly involved in bringing modern solutions to contemporary issues. It employs state-of-the-art technology like block chain, smart systems, augmented reality, and industrial internet to boost innovation. This has bestowed the world with more promising solutions to pressing industrial challenges. Product design complexities, global supply chain issues, and complications of product life cycle are all taken at bay by modern solutions, giving opportunities to companies to effectively respond to an ever-changing business environment. Improvement in any technology alters the way people

live and it will continue to leave a mark on environment with each step we take towards unplanned development. Infringing on the environment has long term impact in the form of global warming, scarcity of natural resource, food produce, quality of water and air, and so on. These environmental effects leads to social implications like scarcity of food, non-availability of drinking water, or other social issues like inequality among human race, lack of access to education to all, population pressure, etc. Thus, it is the need of the hour for Industry 4.0 to plan its development around social and environmental agenda. The big step requires changes in institutional values apart from social and cultural amendments. Sustainable development should be made a part of daily working and should be given central role while designing organizational policies. Hegab et al. (2023) argue that the value system Industry 4.0 adopts should be conscious of sustainability issues, which is practically possible through modern technology as it offers ample avenues to practice sustainability. Another study conducted in Germany and China to understand the effect of Industry 4.0 concluded that sustainability can be achieved through linking the processes of Industry 4.0 to environmental aspects such as the cautious use of energy and other resources (Burritt & Christ, 2018). The use of modern technology, which provides accurate information about business happenings and pragmatic and real-time management solutions to operate effectively in the VUCA world, is the most prominent offering of Industry 4.0 to overcome the problem of sustainability.

With the advent of technology, the implementation of computer-integrated manufacturing system as well as flexible manufacturing system has become efficient and affordable. Smart manufacturing is the outcome of computer-integrated manufacturing system and flexible manufacturing systems developed in the recent past. The application of flexible manufacturing and business automation, IOT, cloud computing, AI, 3D printing, robotics, simulations, Additive manufacturing, cyber systems, etc., offers great benefits to businesses.

It's established that Industry 4.0 and businesses have a great role to play in achieving sustainable development goals. It makes sense to Industry 4.0 to implement the SDGs if it is related to its core business in some sense such as production of medical equipment or drugs, or peripheral to their business, like reducing emission of harmful gases, etc. in case of pharma companies. In the circular economy, each single sustainable development goal offers an opportunity to give back to the resource providers. As per the KPMG report, the below-mentioned two SDGs directly connect with Industry 4.0 for their fulfillment.

SDG 12: Ensure sustainable consumption and production patterns: demands responsible consumption of resources by Industry 4.0 by adopting sustainable practices and reporting the same.

SDG 17: Strengthen the means of implementation and revitalize the global partnership for sustainable development, which concentrate on multi-stakeholder partnerships in order to achieve the required focus.

Organization for Economic Cooperation and Development (OECD) policy note on Industrial policy for the sustainable development goals suggests further 5 SDGs which are of vital importance to Industry 4.0 in order to contribute their share to building a better world are:

SDG 9: Build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation

Creating shared value through

- Initiating joint efforts from companies and government to develop an industrial zone to foster industrial development and attract better investment.
- Conducting relevant research to replace traditional non-sustainable building materials and find out ways to re-use waste building material.
- Developing financing schemes for low-income groups to promote construction for these income people at an affordable price.
- Tapping high-growth markets with government support to identify ways in which more products, techniques, infrastructure, and supply chains can be made more sustainable. This will also help in exploring new markets.

Corporate Initiative
Cemex In an initiative to collaborate local communities and government to use its cement product Cemex started a program named “Mejora tu Calle.” The program aims at providing small cheap loans to fund street sidewalk pavement. With the help of government and community support most of the programs under the scheme was completed within the record time of 70 weeks, which otherwise use to take 10 years especially in low income societies. This resulted in increased income and property of low paid communities. The program disbursed more than 35000 small loans and constructed more than 400000 square meters of road. The program helped 7000 such families in Mexico and has the scope to cater 50 major cities of the country. The company replicated its model in other places like Latin America as well which also got a very positive response from the community.

SDG 11: Make cities and human settlements inclusive, safe, resilient and sustainable

SDG 8: Promote sustained, inclusive, and sustainable economic growth, full and productive employment, and decent work for all

Creating shared value through

- Sourcing raw materials and parts from local suppliers to boost the economy of the country of operations while simultaneously reducing sourcing costs.
- Maintaining high health and safety standards at manufacturing plants. Inviting employees in the decision-making process and sharing the responsibility in establishing a cordial and safe work environment for all.
- Employing modern technology to ensure perfection in the production system due to human error and to avoid any kind of mishap.
- Hold a rightful policy with suppliers that ensures labor rights are taken care of by the supplying party.
- Extending support to small suppliers by providing proper training, financial assistance, or by establishing supplier hubs for joint procurement.
- Adopting a zero-tolerance policy against the employment of child labor in the entire supply chain
- Keep a provision in internships for the underprivileged section of society. Provide targeted internships for young people from disadvantaged backgrounds in order to promote social mobility while also enhancing company performance through increased workforce diversity.
- Generating opportunities for blue-collar workers to develop new skills will pave the way for them to opt for higher-cadre jobs within or outside the organization.

Corporate Initiative
Hyundai Hyundai believes in inclusive growth across its supply chain, in order to pursue it's this endeavor it support its small-scale suppliers by guiding them to become, efficient, sustainable and competitive. Not only this Hyundai's, offers liquid assets to its small scale suppliers to cover the delivery cost of the goods on the other hand help the suppliers to procure material at competitive prices through joint contracts. Hyundai offers loan facilities to its suppliers to help them in their routine financial requirements for improving product quality, or for other improvement areas. They also provide up to 12 months technical guidance to suppliers (voluntarily by the retired Hyundai employees) to its Tier-I and II suppliers in smaller cities.

SDG 3: Ensure healthy lives and promote well-being for all at all

ages: Particularly the area of operation for the medical service industry 4.0
Creating Shared Value through

- Low-cost technology to innovate production processes production and supply chains in the most cost effective manner. Pharma/pharma equipment manufacturers can develop their low-cost equipment arm to serve the downtrodden portion of the population.
- Providing cordial working conditions for all employees at all levels. Special facilities for needy or handicapped employees should be given. Healthcare/medical policy for employees and their families.
- Keeping a robust disaster mechanism in place to deal with any case of emergency. Providing safe, healthy, and hygienic working conditions. Providing psychological support in times of need.

Corporate Initiative
General Electric
General Electric a pioneer in electric goods manufacturing initiated low cost medical equipment such as ultrasound machines, ECG units, and maternal and infant care equipment to cater to the bottom of the pyramid. GE opened many such manufacturing units to serve the needs emerging market which has surging demand for such low price products.
Another social initiative of GE “Revolution™ ACTs” was introduced in the year 2015, the first Computed Tomography system completely developed in India at a very affordable price which they are supplying all over the world. To provide healthcare facility to the underprivileged world the company started “Developing Health Globally” scheme. Under the scheme the company provides training to the hospital staff for basic medical equipment operation and management so as to reduce dependency on technical staff. The scheme was initiated in 32 district level hospitals in Rwanda The initiative had a visible outcome of 35% reduction in equipment downtime as well as 25% increment in timely issues resolution,

SDG 2: End hunger, achieve food security and improved nutrition, and promote sustainable agriculture: Specifically of interest to agribusiness companies, this SDG thrives towards providing healthy life to all by ensuring proper food supply through sustainable agriculture practices. This SDG is of special importance for India, being an agro-based economy.

Creating Shared Values through:

- Conducting state-of-the-art research in agribusiness equipment development for cost-effective agriculture, developing new crops requiring less water and pesticides, improving industrial processes, etc.
- Modernizing agro processes by making use of AI technology for maintaining temperature, light, water supply, etc.
- Aware, inform, and advise agro producers about supply chain efficiencies, government schemes, warehousing, and other research-based inputs.
- Procure biofuels from agro producers for industrial manufacturing processes to build a win-win ecosystem for sustainable development.

<i>Corporate Initiative</i>
<i>Ambuja Cements</i>
Ambuja Cements initiated farmer's organization in villages of Rajasthan (India). The organization works for supplying bio mass to Abuja Cements manufacturing units. The crop residues which use to be burnt by these farmers is now used for producing biogas which serves as fuel for cement production. The initiative started small with few farmers who use to sell crop residues to the Industry 4.0 took a form of strong farmers' association who command respect amongst the local farmers. The sustainable alternative fuel idea of Ambuja Cements Ltd. Created additional source of income to the farmers apart from conserving the natural nutrient of soil which otherwise would have lost with the process of burning.

To attain SDGs, Industry 4.0 needs to undergo a transformation by altering its production systems. This poses a major challenge for the industry. UN's new SDG principles emphasize industrial development without environmental compromises, ecological harm, or social wrong (Rieckmann, 2017). Driven by technology, the modern Industry 4.0 is all set to develop smart products, processes, and services (Tsaramiris et al., 2022).

15.5 Sustainability Challenges of Industry

Modern Industry 4.0 offers numerous tech advancements; at the same time, it suffers many challenges in the achievement of SDG's three major thrust areas (Sangwan & Bhatia, 2020). Increasing social inequalities on the one hand (Islam, 2024) and widening the gap of equal treatment for industrial

employees on the other hand (Moktan, 2019) need immediate attention. From an environmental angle, discussions are around conserving energy and devising alternative energy methods (Maulidia et al., 2019). Discussions around economic challenges in the path of SDG achievement consists of collapse of industrial sectors, which is a result of the overpowering influence of ICT and digitization (Yaqub & Alsabban, 2023). Despite all these challenges, policymakers and Industry 4.0 stakeholders are very positive about fulfilling the SDG of UN 2030 agenda (Mabkhot et al., 2021). The Global e-Sustainability Initiative, which is an enterprise of information and communication technology companies, declares the initiative's capability to contribute to social and economic welfare.

Digitization of manufacturing products, along with international pressure to adopt the UN's SDGs, is compelling organizations to revisit their supply chains and identify the positive and negative effects of their supply chain on the environment and society. Various misconducts are practiced by organizations in the absence of strict environmental laws in developing economies. In such cases, the positive impact of digitization can be seen on the environment and occupational safety as well. On the other hand, some ill effects of over-digitization can surface in the form of job losses, eliminating the need for middlemen in the system, etc. To understand the positive or negative impact of digitization on environmental and social sustainability, companies need to invest in their research facilities. At the same time, the government needs to pay more attention to social research to find a feasible solution to counter the ill effects of digitization and support the cause of the UN's SDGs. One such initiative is designing fresh sustainable policy programs consisting of various innovative employment solutions in the Universal Basic Income (UBI). Though it seems correct for developed economies, the effect of digitization is worse in developing nations where UBI policies are not practiced. Thus, digitization could be a great servant but a bad master. If digital technologies are integrated with processes in the right blend the results could be amazing.

The pandemic has posed a different set of sustainability challenges in front of Industry 4.0, ranging from organizational work culture to operations and economic performance. Moreover, COVID-19 has put more pressure on corporate to perform on the social side. They are expected to contribute towards the well-being of the community and society.

Moreover, an energy crisis is emerging as a challenge for industry. In digitalization race it is obvious that energy consumption is going to increase manyfold, but is the planet in a position to fulfill all our energy

requirements? There are two different sets of opinions in this regard. Experiences show that the countries which opted for green energy instead of nuclear or fossil fuels are facing energy crises. Their newly opted source of (green) energy is not capable of producing the total household and Industry 4.0 requirements. A live example is Germany, whose renewable energy project was a failure as the German CO₂ emissions were measured to be ten times that of the nuclear power of France. The shortage of energy in Germany was then fulfilled by importing fuel from Poland, Bosnia and Herzegovina, the Czech Republic, and Slovenia in 2020. Example of Germany confirms that inefficient production of green fuel can ultimately lead to buying it at a higher rate from other counties which is neither environmentally sustainable nor financially sustainable. Thus, finding a reliable source of green fuel remains a significant challenge for the industry.

There is an evolving concept of sustainable business finance that is also posing challenge to the industry. Sustainable business finance requires companies to disclose and report their sustainability within the organization. This report should consist of information about the environment, society, and governance (ESG). These reports project the picture of a company on three major parameters, which are extremely important for investors. With the increasing awareness about environmental and social aspects, investors are more and more interested in investing in companies that give due importance to ESGs. For this very reason, many countries have created laws around ESGs. Sustainability reporting has become a must for organizations to survive.

15.6 Results and Discussion

The policymakers need to consider a few things while involving the private sector in the SDG achievement drive. Firstly, policymakers should understand that diversifying in the private sector is not wrong in any sense. Rather, it will provide a room for discussion on diverse opinions and can evolve innovative solutions to strategic problems (Gillard et al., 2018). There are bound to be some spoilers in every organization. It also is a matter of one's point of view as to who is spoilsport. In the case of Sustainable agenda one can always expect someone or a group to be against the sustainable practices, justifying their point by arguing about the compromised profitability of the organization. However, conflicts, if taken in the right spirit, can bring in new avenues by considering different viewpoints. Thus,

it is always good to experiment with new ideas and engage in constructive criticism by considering everyone's opinion. Not only policymaking but also the implementation of such policies is important to bring about positive changes in the required areas. There is no harm in altering policies to make them more environment and socially friendly.

Secondly, over-reliance on impact investing or other such sources for achieving sustainable policy goals can result in outcome loss. Private sector organizations need to design their own fund generation mechanisms. The business models should be designed to generate more profits in the short run while being sustainable. However, one should not forget the inherent challenges related to the implementation of these policies. Separating growth from emission as two different aspects of business could drive inequality and may have an inverse effect on the environment and society. It is better that policymakers conduct a firsthand research before arriving at any conclusions and try to explore ways to attain equitable transformation (Singh et al., 2018). The system should be considered as a whole to understand if the profit-oriented approach is really solving the problem of sustainability or if it's just delaying the process of devastation for some time. If the latter is correct, then there is a serious issue that the private sector needs to tackle.

Thirdly, organizations working in the direction of sustainability like SOHOs cannot stand alone; they need support. If the law of the land is not supportive, or the policy environment is hostile, then bringing considerable change to the prevailing economic and environmental conditions is not possible. The law should support companies in operating for profit with a purpose instead of just increasing shareholders' wealth. These innovative organizations will be the torchbearers of the revolution of a new economic system that is pro sustainability.

15.6.1 Limitations

The study took into consideration peer-reviewed journals in the Scopus, Web of Science, and Google Scholar data base and other high-quality gray literature. Thus, it potentially excluded studies published in other databases. This may result in including studies that present a positive view about the title while unintentionally ignoring its negative aspects.

Further, the study was also restricted to English-language studies review only. There are fair chances of excluding valuable findings published in other languages, possibly from countries emphasizing green practices belonging to non-English-speaking countries.

The study concentrated on the research between 2018 and 2024 only, excluding literature published before this period which could have relevant insights on the problem under consideration.

Moreover, the present study is not specific to any Industry 4.0 sector and thus cannot be generalized for a particular sector without proper contextual analysis. Additionally, the topic of the research is evolving and rapidly changing, influenced by macroeconomic factors such as government policies, technology enhancements, and market conditions. Therefore, the findings of the research may become obsolete within a short span of time.

15.7 Conclusion

In a circular economy, everything is interconnected; this very fact can be embraced by modern industry. By minutely examining the relationship between sustainable development goals and industrial components, a synergy for a win-win situation. Thus the concentration of efforts should be in the direction of analyzing the tools and methods used. Although a good amount of research has already been conducted by researchers on the SDG as well as modern industry, much of it has been carried out in isolation. A comprehensive study considering the opportunities and challenges of both stakeholders can result in a perfect model to achieve the SDGs proposed by the United Nations.

The present study provides a broad investigation into the efficiency of businesses in working towards sustainability and the challenges therein. It was found that many organizations operating in various sectors are making significant efforts to contribute towards the achievement of SDGs and have achieved success to a great extent. However, several challenges in the way of adopting fully sustainable status and green efficiency. Some of the prominent challenges, as reported by organizations, are government regulations, financial constraints, and technological limitations. Some organizations also reported resistance from stakeholders as a challenge.

The study highlights the need for inculcating green practices into business strategies. The results indicate that there is a strong need for government support on the policy front and financial support. To overcome these problems, organizations need to adopt a collaborative approach involving both organizations and policymaker's side involving all stakeholders. A collaborative effort can lead to a conducive environment for adapting green efficiency and curtailing the barriers to achieving relevant SDGs.

The future research agenda should consider identifying unique solutions to the problems posed in the field. Further longitudinal studies can be conducted to trace the trend and establish the impact that green initiatives have created. These studies can provide more robust insights into the impact and will be able to propose feasible solutions to the challenges identified.

The present study has contributed to the body of knowledge by providing a superior understanding of green initiatives; at the same time, it offers valuable insights into the interlinkages of green efficiency and related challenges, which could be highly useful for policymakers and businesses in creating a conducive environment for sustainable development.

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Chapter 16

Career Exploration and Sustainable Innovation in Tech SMEs: Advancing Employability Readiness and Business Sustainability

R. Alamelu, K. V. Lakshminarayanan, and Samar Mouti

16.1 Introduction

Indian small- and medium-sized enterprises (SMEs) hold a pivotal role in promoting the circular economy, especially through adaptable strategies and innovative approaches that connect them with practices like waste recycling, resource optimization, and extending product lifecycles. Micro, small, and medium enterprises (MSMEs) constitute 40% of India's GDP and 60% of its employed labor force, serving as a vital pillar for the nation's economic growth. The technology industry comprises over 10,000 SMEs that offer either traditional or digital solutions to technology purchasers. Historically, technology SMEs have primarily provided legacy IT, business process management, and subcontracting services (Devi et al., 2024). The transition to digital services and the dominance of digital-native SMEs have experienced a rapid growth rate exceeding 80% CAGR since FY20. Digital technology SMEs have embraced cloud transformation via partnerships with hyperscalers and system integrators, platform solutions, advanced analytics platforms,

and AI/ML solutions as their primary offerings, whereas pioneering innovative digital SMEs have invested in deep-tech solutions that either vertically integrate functions or horizontally integrate value chains (NASSCOM, 2023). Comparable trends are observed in the talent landscape, with recruitment for digital skills expanding at twice the rate of conventional tech positions. The majority of SME personnel, approximately 70%, are employed in established hubs in India, while around 25% are situated in emerging hubs consisting of Tier II and III cities. Additionally, sales-oriented satellite offices are being established in globally significant locations. As India gears up for a \$5 trillion digital economy, the tech industry's GDP contribution is projected to double to \$500 billion, with the aim for the Tech SME sector to also expand to twice its current magnitude. The anticipated doubling of digital SME revenue is expected to facilitate this objective. The transition to digital is inevitable; otherwise, traditional SMEs must brace for increased challenges (Arora et al., 2025). Their endeavor to expand and innovate, surpass employability networks, and establish sustainable business practices is likely to yield new growth within the next 3–5 years.

Recent initiatives aim to integrate environmental factors into human resource management practices, with organizational support in career architecture, career trajectories, workforce management, performance management systems (PMSs), skill profiling, and talent management being essential for improving employability readiness and promoting sustainable business practices in IT organizations. A clearly delineated Career Architecture and organized Career paths provide employees with a definitive framework for professional advancement, enhancing their adaptability to evolving industry requirements. Workforce management guarantees strategic allocation of talent, harmonizing skill enhancement with organizational requirements to safeguard the future of both employees and the enterprise (Kumar et al., 2023). PMS frameworks promote ongoing learning, adaptability, and performance alignment, directly influencing employability by ensuring employees possess current skills. Skill profiling is essential for identifying competency deficiencies and directing reskilling and upskilling initiatives, thereby enhancing employee competitiveness in a swiftly changing technological environment. Talent management strategies, including leadership development, mentorship, and internal mobility, enhance employee retention and foster a sustainable workforce by minimizing hiring expenses and alleviating talent shortages. Incorporating these practices within IT organizations fosters a robust, future-oriented workforce, harmonizing personal career advancement with enduring business sustainability and innovation. Organizations

that emphasize employability preparedness via systematic career development programs establish a robust talent pipeline, enhancing business continuity and competitive edge in the digital economy (Kumar et al., 2023a).

Moreover, career exploration mediates the relationship among career anchors, social capital, network capital, and career influencers, ultimately influencing career outcomes. Career anchors, characterized by personal values and motivations, affect how employees pursue opportunities that correspond with their long-term goals (Savickas, 1997). Social capital, encompassing mentorship and professional networks, facilitates career exploration by granting access to resources, opportunities, and knowledge (Seibert et al., 2001). Likewise, network capital—utilizing professional relationships for career advancement—enables employees to access varied career trajectories and industry affiliations (Lin, 1999). Career influencers, including mentors, peers, and digital role models, significantly influence career exploration by directing individuals toward informed decision-making and professional growth (Hirschi, 2018). Research indicates that career adaptability mediates the relationship between social capital and career engagement, underscoring the significance of utilizing social resources in career exploration (Sou et al., 2022).

By combining structured career development programs with proactive career exploration, IT organizations cultivate a workforce prepared for the future, thereby ensuring business sustainability and a competitive edge in a dynamic digital economy (Kumar et al., 2023b). Sustainable innovation is increasingly acknowledged as a crucial catalyst for enduring business success and professional advancement within IT organizations. By incorporating sustainable practices and innovative technologies, businesses cultivate an environment that promotes employee development and corporate sustainability. This dedication to sustainability enables organizations to maintain competitiveness by responding to global challenges, including climate change, resource scarcity, and shifting consumer expectations (Schaltegger & Wagner, 2017). Sustainable innovation in career development fosters future-ready skills that employees can utilize to adapt to a changing digital economy. Employees engaged in the development of green technologies or sustainable IT solutions contribute to environmental objectives while simultaneously improving their career prospects through the acquisition of specialized skills that align with future industry requirements. Moreover, sustainable innovation enhances talent retention and engagement by establishing organizations as responsible employers, thereby attracting employees who are fervent about working for companies dedicated to environmental

stewardship (Lozano, 2015). This strategy enhances the company's brand and reputation, leading to increased employee satisfaction and organizational loyalty. By integrating sustainable innovation into the workforce framework, IT organizations address environmental issues while ensuring that their talent pipeline is prepared for long-term employability and adaptability. This, consequently, fosters the organization's sustainable growth and business resilience in a swiftly evolving global environment (Teece, 2018). The research examines career development support systems in Indian Tech SME organizations through sustainable innovation dependence and employee experience analysis to achieve better employability readiness along with sustainable business practice implementation for competitive advantage.

16.1.1 Research Gap and Uniqueness

Research into sustainable innovation and career frameworks in IT organizations needs more development regarding their influence on sustainable business operations and employee preparedness through career exploration mechanisms. Studies about sustainable innovation and sustainable practices exist, but researchers have yet to understand directly how sustainable innovations affect career development and employee development and future employability for IT organizations. Few studies analyzed how sustainable innovation affects employee career exploration as well as the connection of worker education to sustainable corporate practices. The process of career exploration functions as an essential tool to help workers discover new opportunities directed toward sustainability goals, yet research on sustainable employment readiness still lacks proper investigation. Studies about workforce development today minimize the value of joining sustainable innovation with traditional career practices to foster flexible employees who meet evolving industry needs. The studied deficit in research is crucial for IT industries because rapid technological development and environmental changes mandate employees to maintain spinal employment readiness through continuous learning and career adaptability. The study investigates the relationship between sustainable innovation and career development practices as well as career exploration as a mediator through which these elements impact sustainable employment readiness and sustainable business practices in IT organizations.

The study introduces innovative methods to close knowledge gaps by linking sustainable innovation to career development structures and career exploration mediation while exploring their impact on sustainable employee

and corporate practices in IT industries. Research exists for studying individual elements but not enough investigations exist about how sustainable innovation impacts IT careers directly and employee development. This research addresses the gap by offering a comprehensive framework that connects sustainable innovation with the cultivation of a future-ready workforce in IT organizations, thereby enhancing long-term employability and the sustainability of business practices. This innovative method not only improves theoretical comprehension but also offers practical insights for IT organizations aiming to synchronize their workforce strategies with emerging sustainability trends and challenges.

16.1.2 Research Questions, Hypotheses, and Conceptual Model

16.1.2.1 Research Questions

- RQ1:** In what manner do organizational career and skill enhancement ecosystem (OCE and SE) improve the employees' career exploration in Tech SME units?
- RQ2:** In which ways does the employee career exploration (CE) create a sustainable employability readiness (SER) and enhance the small medium units sustainable business practices (SBPs)?
- RQ3:** How does sustainable innovation (SI) promote employees' career exploration (CE), and how it facilitates the sustainable employee readiness (SER) and sustainable business practices (SBPs) of small and medium Tech units?
- RQ4:** In what ways does the practice of organization career and skill enhancement (OCE and SE) support and sustainable innovation (SI) in practice affect the employee career exploration (CE), and how does it impact the workforce readiness and implementing sustainable business practices in SME Tech units?

16.1.2.2 Hypotheses

- H1:** OCE positively and significantly impacts SER and SBP among Tech SMEs
- H1(a): OCE positively and significantly impacts SER
- H1(b): OCE positively and significantly impacts SBP
- H2:** SE positively and significantly impacts SER and SBP among Tech SMEs
- H2(a): SE positively and significantly impacts SER

H2(b): SE positively and significantly impacts SBP

H3: CE mediates the relationship between OCE, SER, and SBP

H3(a): CE positively and significantly mediates SER

H3(b): CE positively and significantly mediates SBP

H4: CE mediates the relationship between SE, SER, and SBP

H4(a): CE positively and significantly mediates SER

H4(b): CE positively and significantly mediates SBP

H5: SI moderates the relationship between OCE, CE, and SER, and SBP

H5(a): SI positively and significantly moderates OCE, CE, and SER

H5(b): SI positively and significantly moderates OCE, CE, and SBP

H6: SI moderates the relationship between SE, CE, and SER, and SBP

H6(a): SI positively and significantly moderates SE, CE, and SER

H6(b): SI positively and significantly moderates SE, CE, and SBP

16.2 Literature Review

16.2.1 Theoretical Contributions

16.2.1.1 Social Cognitive Career Theory (SCCT)

Figure 16.1 shows conceptual model. Employees benefit from social cognitive career theory (SCCT) because it specializes in analyzing self-efficacy and outcome expectations and personal objectives for improved career development comprehension. The work of Lent and Brown between 1994, 2006, and 2020 demonstrates how career development advances employee well-being via relationships between professional growth and work satisfaction along with job performance achievement. SCCT now serves broader groups of marginalized individuals according to Garriott (2020), because he emphasizes cultural and contextual elements that shape career outcomes. The workplace readiness programs and skill enrichment and career exploration

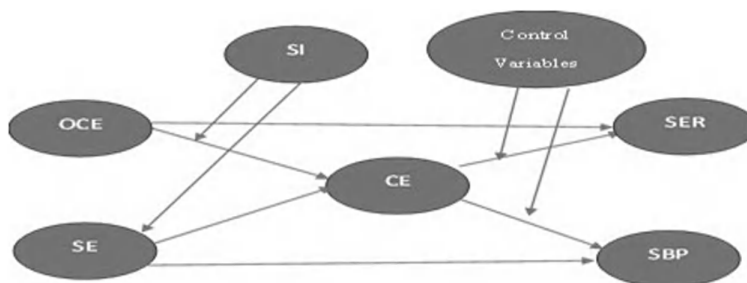


Figure 16.1 Conceptual model

initiatives heavily utilize the implementation of SCCT to help employees better manage changing work environments. Organizations should apply SCCT as their fundamental instrument to enhance employee growth along with organizational adaptability through both self-efficacy creation and goal alignment. The framework enables organizations to obtain sustainable employability and foster innovation. The research utilizes SVF theory to analyze the relationship between circular human resource management and circular employee experiences in small and medium enterprises.

16.2.1.2 Resource-Based View (RBV) in Employee Development

The resource-based view (RBV) identifies essential elements for employee development which include skill development alongside career development training systems and workplace readiness programs to produce adaptable employees within changing corporate structures (Barney, 2021; Kozlenkova et al., 2014). Corporate success requires staff members to implement innovative ideas and sustainable policies. Studies show that an organization's green HR capabilities enable employees to experience circularity which enhances their performance organizationally under three aspects. Future handling of sustainable performance management by corporations will undergo significant influence from these two ideas combined.

16.2.2 Reviews on the Study Dimensions and Operational Definitions

16.2.2.1 Organizational Career Enhancement (OCE)

Studies continue to grow in importance because IT industries need their employees to learn and develop their careers throughout rapid technological transformations. The evidence supports that OCE programs build technical skills and enable mentorship and career path planning to boost employee job satisfaction and organizational commitment according to Lent and Brown (2020). Growth initiatives designed for IT workers produce benefits by both enhancing their competencies and preparing them for upcoming occupational roles. The retention of skilled workers in competitive fields highly depends on OCE programs which pursue employee purpose alongside career development according to Garriott (2020). The usage of digital tools continues to grow in programs that deliver OCE. Researchers now investigate how OCE enables organizations to achieve

sustainable employability together with innovation. Barney (2021) proposes that linking OCE initiatives to business goals generates both adaptable and qualified personnel, helping organizations to succeed in competitive IT markets. Kozlenkova et al. (2014) establish that employee participation from these programs leads organizations to enhance their strategies while increasing employee involvement. A transparent strategy must be developed to advance career development, particularly in industries that experience rapid change.

16.2.2.2 Skill Enrichment (SE)

The ability to improve skills serves as a crucial factor for IT workers' career development because it enhances their adaptability in the dynamic technology environment. The quality with which workers assist their organization in goal acquisition depends heavily on this factor. The alignment between organizational requirements and personnel career objectives in skill development initiatives yields vast enhancements toward employee performance and organizational retention says Garriott (2020). Studies conducted recently show that organizations succeed in business alongside achieving innovation through improved employee skills development. Barney (2021) emphasizes skill improvement as necessary for building teams capable of using new technologies to maintain strategic market positions. According to Kozlenkova et al. (2014) enhanced abilities create benefits for both employees and their organization's total assets. The assessment process for skill development programs identifies inadequate performance analysis as they fail to adapt to employee and organizational requirements. The IT industry requires continuous skill improvement because technology keeps evolving, which prompts organizations to seek constant advances and fresh perspectives. Skill development stands as an essential element which assists IT professionals in incrementing their professional growth. The dynamic nature of an evolving tech industry remains achievable for organizations because their workforce remains competitive and adaptable. The IT field requires employees to continue learning and enhancing their abilities according to research done recently.

16.2.2.3 Career Exploration (CE)

16.2.2.3.1 Mediating Role of Career Exploration

Information technology digital workers who depend on social and network capital to advance their careers now play a substantial role in shaping career exploration for this professional sector. Social capital represents essential resources available to people through their network ties because it enables the exchange of knowledge together with mentor introductions and emotional aid for career choice discovery. Social networks enable workers to discover job listings, necessary skill sets, and market trends that enrich their social capital according to Garriott (2020). Information technology professionals must rely on social capital due to the accelerating changes in their field since the onset of digital trends. It becomes easier for information technology professionals to make the most of targeted career opportunities through their well-connected professional and personal networks. Workers who depend on each other become flexible by adapting to new market requirements as they need to fulfill additional responsibilities.

According to Hirschi et al. (2018) career exploration functions as an essential practice which helps workers match their personal goals with changing work roles which impacts their employability along with their ability to adapt. Matejun et al. (2022) analyze how instrumentally oriented and change-oriented strategies enable workers to become ready for Green Human Resource Management (GHRM) implementation in organizations. The development of personal adaptation skills for organizational transitions stands as a central idea in psychological readiness research about organizational change (Illinois State University Library, n.d.). Wickramasinghe and Premachandra (2021) analyze how career management practices act as mediators between organizational career development and staff growth using research exists to chart employee growth against organizational targets. The research by Naghavi et al. (2021) explores career management practices as mediators between organizational career growth and employee development that supports organization-oriented targets. The researchers from Matejun et al. (2022) discuss how readiness and individual antecedents play vital roles in successful sustainable career transition management.

16.2.2.3.2 Moderating Role of Sustainable Innovation (SI)

As businesses under more pressure to lower their environmental impact and support social well-being, the value of sustainable innovation has

grown recently. To lower their environmental impact, IT companies are progressively using green technologies including renewable energy sources, cloud computing, and energy-efficient hardware, claims Barney (2021). Developing environmentally friendly products is only one aspect of sustainable innovation; another is making sure the methods used to produce and distribute these goods are likewise sustainable. Growing customer demand for environmentally friendly goods and services as well as legal pressures drive this change toward sustainability in IT companies. Investing in sustainable innovation helps IT firms not only contribute to world environmental goals but also establish themselves as leaders in the green technology market, so acquiring a competitive advantage. New studies underline even more the strategic value of sustainable innovation in IT companies. According to Kozlenkova et al. (2014), sustainable innovation is firmly ingrained in the resource-based view (RBV) of companies where the capacity to innovate sustainably is regarded as a valuable resource able to improve competitive advantage. In the context of IT, this entails using current resources—such as intellectual property, staff knowledge, and technological infrastructure—to produce innovations that are both financially and environmentally friendly. This all-encompassing approach to sustainable innovation not only improves environmental performance but also generates value for stakeholders, so strengthening the profile of the company and workforce preparedness.

16.3 Research Methodology

This study employed a survey research methodology and gathered data by disseminating interview schedules to Tech small- and medium-sized units in Tamil Nadu, India. The Tech SMEs in India, including SMEs that focus on BFSI/FinTech, SaaS, Retail and e-commerce, are vital components of the nation's economy. Recent market entries comprise eco-friendly products, as customers, regulatory bodies, and other stakeholders increasingly prioritize sustainability, urging SMEs to adopt more sustainable business practices; it impacts employment creation and sustainable economic development within the SME sector. The sector has an opportunity in environmental sustainability trends, bolstered by governmental policies. The study concentrates on small Tech zones in Tamil Nadu, specifically in two districts recognized for their significant presence of these units.

16.3.1 Sampling Method

The study will employ a multi-stage sampling technique: initially, based on the NASSCOM report (2024), the presence of Tech SME's spread is in five segments, viz., BFSI/FinTech, Health Care, Hi-Tech/SaaS, Retail/e-commerce, and other areas with the spread in two zones— Chennai and Coimbatore subsequently. In each designated zone, the total count of Tech SMEs registered with NASSCOM was determined, and from this pool, 50% selected for data collection. Data was collected via a standardized interview schedule and focus group discussions and online meetings were convened to ensure comprehensive representation of Tech SMEs throughout Tamil Nadu. Moreover, structured interviews engaged stakeholders from the tech units, focusing on the impact of sustainable innovation and business practices on their operations.

Data was gathered from SMEs by distributing 430 questionnaires to SME leaders, resulting in 396 valid responses after excluding invalid submissions, from November 2024 to January 2025. The data was collected through personal visits to independent units as part of the grant from Indian Council of Social Science Research (ICSSR).

16.3.2 Measurement Scales

All the scales used had valid psychometric properties and were culled from relevant prior research. Four dimensions were extracted based on a comprehensive review of related previous studies (Table 16.1). An item on the five-point Likert scale representing “strongly disagree” and “strongly agree” was used. There were no major revisions made to the scale after it was validated by several academics and industry experts.

To account for differences among firms that may affect environmental performance, control variables were utilized, which included firm size, age, and sectoral forms. Following previous research (NASSCOM report, 2023), this finding is consistent. The study employed basic descriptive measures and structural equation modeling with PLS-SEM along with the moderation and mediation model.

Table 16.1 represents the various dimensions and related sources of the study variables.

Table 16.1 Questionnaire Dimensions and Sources

<i>Construct</i>	<i>Dimensions</i>	<i>Sources</i>
Organizational career enhancement	Career architecture, career paths, workforce management, PMS, skill profile, talent demand forecasting, role competency mapping and assessments	Pauceanu et al. (2020)
Sustainable innovation	Energy efficiency and green IT, circular economy, and resource optimization	Yunpeng Sun et al. (2023)
Career exploration	Career anchor, social and network capital, career influencers	Peeters et al. (2019)
Sustainable employability readiness	Continuous learning culture, -selfmotivation and initiative, determination and resilience, effort and exposure	Galina Robertson et al. (2023)
Sustainable business performance	Adoption of eco-friendly, socially responsible, and economically viable IT practices	Soham Roy et al. (2024)

16.4 Results and Inferences

Table 16.2 delineates the distribution of respondents according to their profile base. Respondents are classified into three categories: sectoral coverage, age, and size. The total number of respondents was 396, and their distribution based on responses is presented.

16.4.1 Measurement Model

The reliability and validity analysis results for the identified constructs are summarized in Table 16.3.

Organizational career enhancement (OCE) has four items rating between 0.716 and 0.823. The values of alpha, CR, and AVE for organizational career enhancement construct equal 0.898, 0.885, and 0.797, respectively. Skill enhancement contains four items that demonstrate loadings ranging from 0.703 to 0.816. The alpha and CR ratings along with AVE score for this construct measure 0.754 and 0.731 and 0.623, respectively. Career exploration (CE) presents four items featuring loadings ranging from 0.707 to 0.882. The construct measurement of CE achieved alpha = 0.912, CR = 0.794, and AVE

Table 16.2 Profile of the Tech SME Units

<i>Characteristics</i>	<i>Range</i>	<i>Frequency</i>	<i>Percentage</i>
Age of the unit	Less than 5 years	86	22
	6–10 years	103	26
	11–20 years	114	29
	Above 20 years	93	23
Size of the unit	Less than 50 (employees)	134	34
	51–250 (employees)	262	66
Segmental coverage	BFSI/FinTech	94	24
	Health care	89	22
	Hi-Tech/SaaS	78	20
	Retail/e-commerce	135	34

= 0.632. Four items measuring sustainable innovation exhibit 0.769 to 0.867 loadings. The construct reliability and average variance extraction (AVE) ratings of this measure amount to 0.868 and 0.721 and 0.698, respectively. Next we see that sustainable employability readiness (SER) includes four items which show loadings from 0.861 to 0.884. The measurement model revealed that the alpha value of this construct is 0.810, whereas CR is 0.711 and AVE stands at 0.716. The four items in sustainable business practices exhibit loadings from 0.729 to 0.856. The measurement scale consisting of four items in the sustainable practices construct results in alpha at 0.855 and AVE at 0.686 together with CR at 0.743. The reliability and validity measurements of the constructs are shown in in Table 16.3 through the provided instruments. Table 16.4 presents discriminant validity analysis through both Fronell-Larcker and HTMT criterion evaluation of study constructs. The decomposition of average variance yields square root values that appear on each diagonal element of the table. Each diagonal value in the matrix exceeds the off-diagonal values in its column and row for discrimination validity assessment.

The measurement validity assessment of OCE and SE constructs indicates a square root value which amounts to 0.797 and 0.873. The discriminant validity of this construct is confirmed because the square root of AVE exceeds all values in both the row and column. The relationships between constructs appear in the values that do not lie on the main diagonal. OCE (Construct 1) and CE (Construct 2) correlate 0.722. A correlation of 0.422 exists between OCE (Construct 1) and SI (Construct 3).

Table 16.3 Reliability and Validity Analysis

<i>Construct</i>	<i>Items</i>	<i>Loadings</i>	<i>Alpha</i>	<i>CR</i>	<i>AVE</i>
		>0.704	>0.7	>0.7	>0.5
OCE	OCE_1	0.716	0.878	0.885	0.797
	OCE_2	0.823			
	OCE_3	0.801			
	OCE_4	0.721			
SE	SE_1	0.703	0.754	0.731	0.623
	SE_2	0.792			
	SE_3	0.816			
	SE_4	0.733			
CE	CE_1	0.738	0.912	0.794	0.632
	CE_2	0.811			
	CE_3	0.707			
	CE_4	0.882			
SI	SI_1	0.769	0.868	0.721	0.698
	SI_2	0.792			
	SI_3	0.867			
	SI_4	0.834			
SER	SER_1	0.864	0.810	0.711	0.716
	SER_2	0.875			
	SER_3	0.861			
	SER_4	0.884			
SBP	SBP_1	0.796	0.855	0.743	0.686
	SBP_2	0.729			
	SBP_3	0.794			
	SBP_4	0.856			

16.4.2 Structural Model

Following the validation of the measurement model, the following stage in the PLS-SEM procedure is the evaluation of the structural model.

Determining the path coefficients and their statistical significance, as well as the model's prediction power, are part of evaluating the structural path model. Nevertheless, when conducting mediation analysis, specific recommendations were considered

In the first step, we checked the structural model's R^2 and Q^2 for predictive relevance and accuracy using cross-validated redundancy indices. Figures 16.2 and 16.3 and Table 16.4 show that the relevant exogenous constructs explained 79.4% and 85.1% of the variation in SER and SBP and career exploration, respectively, with R^2 values of 0.851, 0.794, and 0.842, respectively. Sustainable employee readiness, business practices, and career

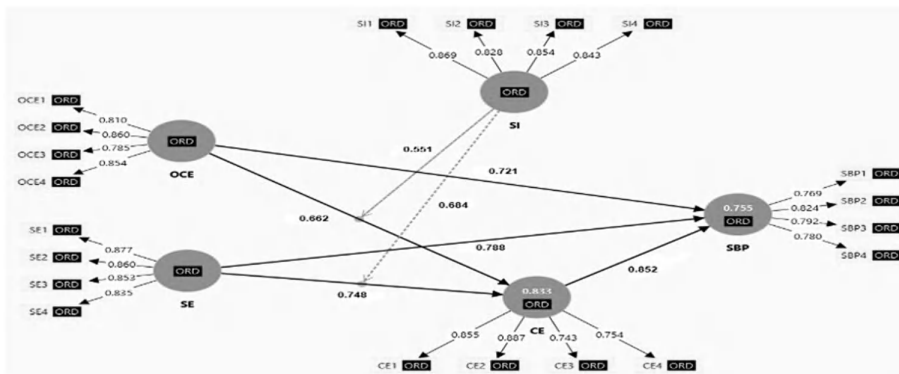


Figure 16.2 Structural model—SER

Table 16.4 Discriminant Validity Analysis—HTMT

Construct	1	2	3	4	5	6
OCE	0.797	0.511	0.578	0.410	0.423	0.277
SE	0.833	0.873	0.378	0.392	0.276	0.543
SI	0.422	0.496	0.565	0.429	0.210	0.277
CE	0.722	0.676	0.432	0.875	0.632	0.317
SER	0.583	0.243	0.189	0.433	0.697	0.432
SBP	0.232	0.201	0.188	0.523	0.574	0.671

exploration have substantial R^2 values. The Q^2 values for each endogenous construct were also generated using a blindfolding technique, as described by Hair et al. (2014). Table 16.5 shows the construct Q^2 values for career exploration (0.323), sustainable employability readiness (0.422), and SBP (0.454). The structural path model's predictive relevance is demonstrated by these Q^2 values, which are greater than zero. Furthermore, the structural model fits well since all VIF values are significantly lower than 0.5.

The evaluation results of the reflective and formative measurement model indicate that all construct measures demonstrate acceptable levels of reliability and validity (Table 16.5). Figure 16.2 illustrates the structural model graphically. Figure 16.3 shows structure model.

The outcomes of the direct effect hypothesis testing on different construct relationships are displayed in Table 16.6. The relationship between sustainable employability readiness and organizational career enhancement is statistically significant ($p < 0.001$) according to hypothesis H1(1), with a standardized beta value of 0.343, a standard error of 0.023, and an exceptionally high t -value of 4.897.

Table 16.5 Coefficient of Determination and Predictive Relevance

Constructs	R^2	Q^2
CE	0.851	0.323
SER	0.794	0.422
SBP	0.842	0.454

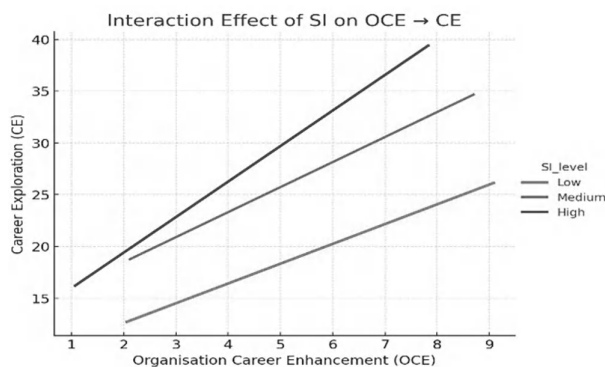


Figure 16.3 Moderating interaction effect—sustainable employability readiness

Table 16.6 Hypothesis Direct Effect Relationships

<i>Hypothesis</i>	<i>Direct Relationships</i>	<i>Std. Beta</i>	<i>Std. Error</i>	<i>t-values</i>	<i>p-values</i>	<i>Result</i>
H1(1)	OCE → SER	0.343	0.023	4.897	***	Supported
H1(2)	OCE → SBP	0.211	0.037	3.543	***	Supported
H2(1)	SE → SER	0.189	0.059	5.897	**	Supported
H2(2)	SE → SBP	0.356	0.044	4.299	***	Supported

***Less than .001.

Table 16.7 Hypothesis Testing Mediation Effect

<i>Hypothesis</i>	<i>Direct Relationships</i>	<i>Std. Beta</i>	<i>Std. Error</i>	<i>t-values</i>	<i>p-values</i>	<i>Result</i>
H3(1)	OCE → CE → SER	0.165	0.021	3.105	**	Supported
H3(2)	OCE → CE → SBP	0.118	0.043	4.121	***	Supported
H4(1)	SE → CE → SER	0.122	0.015	3.876	**	Supported
H4(2)	SE → CE → SBP	0.131	0.041	4.328	***	Supported

**Less than .05.

Hypothesis H1(2) proves valid since it demonstrates a significant positive relationship between OCE and SBP through a t -value of 3.543 ($p < 0.001$). The t -values of 5.897 and 4.299 demonstrate the significance of SE and SER on SBP with a p -value less than 0.01. Research findings from the table demonstrated that a positive connection existed between all the proposed hypotheses. The mediation effects between different construct relationships that were tested by hypothesis appear in Table 16.7. The research evaluates CE as a mediating construct linking OCE to SER through Hypothesis H3 (1). The standard beta equals 0.165 and the standard error measures 0.021 within this mediation process. The significance of mediation occurs at the t -value level of 3.105, which exceeds the 0.01 threshold. H3 (2) examines how CE mediates OCE-SBP. The research yields a significant mediation outcome that satisfies a t -value of 4.121 at the p -value < 0.001 . H4 (1,2) showed that CE acted as a significant mediator linking OCE to SE and SER because the t -values reached 3.876 and 4.328 ($p < 0.01$).

Table 16.8 VAF of the Mediating Construct

<i>Independent Variable</i>	<i>Mediating Variable</i>	<i>Dependent Variable</i>	<i>Indirect Effect</i>	<i>Total Effect</i>	<i>VAF (%)</i>	<i>Result</i>
OCE	CE	SRE	0.045	0.287	23.87	Partial
OCE	CE	SBP	0.053	0.187	35.56	Partial
SE	CE	SRE	0.179	0.429	48.23	Partial
SE	CE	SBP	0.112	0.186	80.31	Partial

Table 16.9 Hypothesis Testing Interaction Effect

<i>Hypothesis</i>	<i>Moderating Relationships</i>	<i>Std. Beta</i>	<i>Std. Error</i>	<i>t-values</i>	<i>p-values</i>	<i>Result</i>
H5(1)	OCE*SI → CE-SER	0.176	0.032	4.665	0.041	Supported
H5(2)	OCE*SI → CE-SBP	0.211	0.021	3.178	0.018	Supported
H6(1)	SE*SI → CE-SER	0.154	0.34	4.219	0.032	Supported
H6(2)	SE*SI → CE-SBP	0.187	0.17	3.012	0.047	Supported
Control variables						
	Age	0.164	0.028	2.876	0.043	Supported
	Firm size	0.133	0.096	1.022	0.024	Supported
	Segmental coverage	0.087	0.133	1.654	0.121	Not supported

To determine how OCE, SE, SER, and SBP are related, we used the variance-adjusted (VAF) method to examine the mediating function of career exploration (Table 16.8).

Complete mediation, partial mediation, and no mediation are the usual terms for VAF values between 20% and 80%, 20% and less than 20%, and 20% and less than 80%, respectively. Mediating effects of 23.87%, 48.23%, and 80.31%, as shown in Table 16.8, are correspondingly high. Findings show that CE mediates the OCE relationship with SER and SBP to a lesser extent than it mediates the SE relationship with SER and SBP. Accordingly, we can conclude that H3(1,2) and H4(1,2) are credible.

Lastly, it was observed that the relationship between organizational career enhancement and skill enhancement and career exploration is considerably impacted by sustainable innovation (as per Table 16.9 values). This indicated that H5 and H6 were accepted. While taking contextual factors into

Table 16.10 Hypothesis Testing Interaction Effect

<i>Hypothesis</i>	<i>Level of the Moderator</i>	<i>Effects</i>	<i>Boot SE</i>	<i>LLCI</i>	<i>ULCI</i>
H5(1)	+1 Std Dev	0.712***	0.051	0.692	0.870
	Mean	0.585***	0.046	0.487	0.657
	−1 Std Dev	0.321***	0.073	0.290	0.387
H5(2)	+1 Std Dev	0.842***	0.034	0.765	0.897
	Mean	0.567	0.054	0.434	0.654
	−1 Std Dev	0.345	0.068	0.319	0.431
H6(1)	+1 Std Dev	0.671***	0.043	0.584	0.711
	Mean	0.452	0.054	0.398	0.538
	−1 Std Dev	0.298	0.038	0.209	0.387
H6(2)	+1 Std Dev	0.743***	0.072	0.631	0.822
	Mean	0.534	0.065	0.491	0.634
	−1 Std Dev	0.376	0.058	0.287	0.472

*Significant paths: *** $p < 0.001$.

consideration, the study also looked at the control roles of firm size, ownership type, and age. Table 16.9 shows that age and company size were all significantly impacted by the chosen Tech SME units' sustainable development initiatives, while segments had a negligible contextual effect.

The strength of the connections between career exploration and sustainable employability readiness along with sustainable business practices gets modified through sustainable innovation (Table 16.10 present values). The bootstrap analysis demonstrates how the conditionally influencing variable operates among the relationships. Sustainable innovation produces a positive effect on career exploration and employability readiness when standard deviation is increased by one (+1 std deviation, $\beta = 0.712$; lower-level confidence interval = 0.692; upper-level confidence interval = 0.890). The values in Table 16.9 demonstrate that sustainable innovation strengthens the relationship between career exploration and sustainable business practices

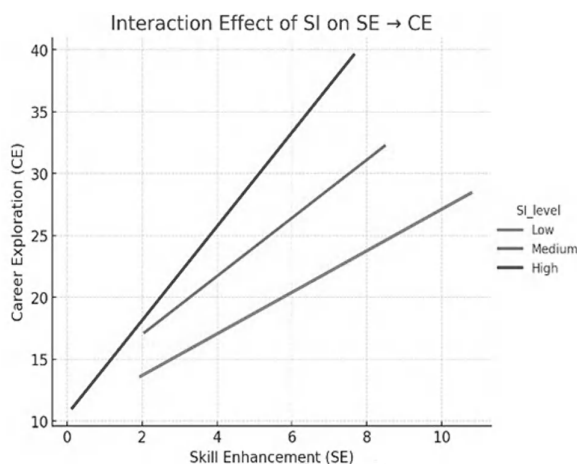


Figure 16.4 Moderating interaction effect—sustainable business practices

performance. Sustainable innovation functions as a conditional factor which heightens career exploration and sustainable business practices (Figure 16.4).

16.5 Discussion

By encouraging lifelong learning, skill improvement, and promotion opportunities, sustainable HR practices are vital to bolstering organizational resilience and long-term employability (Ybema et al., 2023). Companies in highly competitive markets need to adjust their human resource management strategies to have the greatest possible influence on their employees' ability to adapt to new circumstances (Martini et al., 2023). According to Eccles et al., corporate sustainability makes organizations more resilient and gives them a competitive edge in the long run by enhancing stakeholder relations, operational efficiencies, and financial outcomes. Small- and medium-sized enterprises (SMEs) in the marine food processing industry can benefit greatly from implementing Industry 5.0 technologies. These technologies enhance operational efficiency, minimize waste, and create new market opportunities that result in sustainable business expansion. The strategy of adopting innovative solutions together with digital platforms and sustainable integration into core business operations enables small businesses and medium organizations to thrive through uncertain economic circumstances (*World Economic Forum*, July 14, 2023). Organizations concentrating on sustainable HRM practices plus corporate sustainability along with technological

progress can prove to be more resilient during future market uncertainties and competitive conditions. Three successful long-term strategies which technology-driven sustainability provides to small- and medium-sized enterprises (SMEs) include increased efficiency along with competition abilities and environmentally responsible practices (Kannan & Gambetta, 2025). The digitalization process stands as a key sustainability factor since it enables small- and medium-sized enterprises (SMEs) to maximize their resources alongside enhancing their innovation rates and market responsiveness (Korez Vide et al., 2022).

Through green training programs, workers receive essential environmental responsibility and long-term business resilience education that impacts sustainable business practices (Kumar & Singh, 2024). Career strategies at both the organizational and individual levels lead to better long-term employment and career achievements which unlock sustainable careers (Canaj et al., 2021). Active career planning provides individuals with better personal fulfillment that enables them to adjust successfully to evolving job markets per Bazine et al. (2024). The sequence of career exploration into self-reflection and career calling and subjective well-being depends heavily on career adaptability as its central element. People with strong psychological resources tend to achieve career advancement along with job security. Employability functions as a vital element that connects this relationship according to Karatepe and Olugbade (2016). Donald et al. (2024) indicate that career stability over the long run depends on early support systems. Organizational support provides university students with better career exploration opportunities while career adaptability functions as the linking mechanism. Individuals whose careers follow protean paths benefit from positive career sustainability outcomes because they apply self-direction and value-driven decision-making to their career journey (Baruch & Vardi, 2015).

Achieving employment preparedness depends heavily on career exploration which helps students develop three essential elements: self-reflection, purposeful direction, and career flexibility (Zacher, 2014). Research indicates that believing in your future work self demonstrates a positive effect on job readiness. The search for diverse career opportunities enables students to develop employer-sought flexibility and essential skills (Ma et al., 2022). Career exploration demonstrates additional value because it strengthens career commitment while creating subjective joy (Rudolph, Lavigne, & Zacher, 2017). Renwick et al. (2012) established that businesses focusing on environmental and social responsibility achieve better employee retention because quality sustainable practices reduce employee turnover intent.

Sustainable human resource management (HRM) along with career adaptability tactics both help enhance employee welfare and career endurance in the long run (Nakra, Kashyap, & Arora, 2024). The connection between organizational elements and employability receives influence from boundaryless career attitudes prompting organizations to develop proactive career management strategies (Lo Presti et al., 2023). The achievement of long-term employability during the middle and later phases of career progression needs an integrated personal and organizational strategy to maintain workforce engagement and productivity (Alcover, Mazzetti, & Vignoli, 2023). Intensified corporate responsibility toward sustainability directly helps businesses maintain their workforce because sustainable practices lower employee departure intentions (Gomes et al., 2023).

Work outcomes together with sustainable employability determine essential worker productivity levels within flexible workplaces (Gürbüz et al., 2023). Employees who participate in reskilling programs targeting IT work experience better success rates when their career transition readiness matches the training timing according to Obradović et al. (2023). Organizations keeping workforce agility require them to adopt employability-focused human resource management strategies (Stoffers, van der Heijden, & Schrijver, 2018). The mediator role of employability is fundamental in developing innovative work behaviors.

16.5.1 Theoretical Implications

The research provides important theoretical contributions by incorporating organizational and skill development strategies to enhance business and sustainable employability readiness practices. This research enhances the current literature on human resource development and sustainability by framing career exploration as a mediating variable and sustainable innovation as a moderating variable. The conceptual framework connecting Circular HR, employee experience, and circular performance in SMEs within the Indian paper bag manufacturing sector emphasizes the importance of aligning workforce adaptability with sustainable business practices. This study enhances theoretical frameworks regarding the role of career exploration in cultivating employability readiness, thereby promoting sustainable performance. This research empirically validates these relationships, establishing a basis for future investigations into the dynamic interactions among human capital, business sustainability, and environmental performance, thereby enhancing the comprehension of sustainable workforce development.

The subject of environmental performance has notably attracted interest in academic circles. A plethora of studies has been conducted to identify the factors that enhance environmental and sustainable performance in organizations. This study distinguishes itself from prior research, encouraging international scholars and academic professionals to assess its importance. This study offers new opportunities for individuals to examine companies' environmental and sustainable performance concerning green principles. This study presents a conceptual framework that clarifies the connection between Circular HR, employee experience, and the circular performance of SMEs in the Indian paper bag manufacturing sector. This initiative greatly assists researchers worldwide in integrating these concepts into their upcoming research projects. This study broadens its focus by addressing the literature gap and improving firms' commitment to sustainability in a more eco-friendly manner. It encourages individuals to attain a thorough understanding of these concepts and acquire the latest insights into the sustainable performance of companies. This investigation can serve as a valuable resource by enhancing the importance of this subject among individuals, organizations, and communities, thereby raising awareness among key scholars through empirical demonstration of the study's findings in support of environmental issues.

16.5.2 Managerial Implications

For IT companies that aim to improve their employability and business practices in the long run, this study's results have important managerial implications. Information technology managers strengthen workforce flexibility and long-term employability when they create specific initiatives based on recognizing career exploration as a mediator and sustainable innovation as a moderator. Organizations should integrate skill-based practices with organizational improvement methods to respond to technological changes and industrial developments. Organizational outcomes improve as well as employee satisfaction because circular HR strategies establish learning programs and sustainability practices together with development paths for career advancement. The implementation of sustainable innovation practices serves IT corporations as an instrument for developing supportive conditions which promote creativity and environmentally friendly product development and resource maximization. The larger environmental responsibility objective becomes achievable through IT leader implementation of sustainability within talent management systems and company operational frameworks

which simultaneously enhances staff productivity and retention. In the end, this study helps IT managers build a workforce that is resilient and prepared for the future by showing them how to connect human capital development with sustainable business practices.

16.5.3 Study Limitations and Future Directions

This study, while contributing valuable insights, has limitations that suggest directions for future research. The study primarily examines Tech SMEs in Tamil Nadu, potentially restricting the applicability of its findings to other sectors, especially the manufacturing industry, where challenges related to skill enhancement and sustainability vary considerably. Subsequent research should investigate a range of industries, including information technology, to assess the applicability of the proposed framework in different organizational settings. Secondly, the research predominantly depends on a conceptual framework lacking comprehensive empirical validation. Future research should utilize longitudinal and cross-sectional methodologies to evaluate the long-term effects of career exploration and sustainable innovation on employability readiness and business sustainability. This study emphasizes the mediating role of career exploration; however, other psychological and behavioral factors, including employee motivation, digital readiness, and environmental consciousness, warrant investigation as potential mediators or moderators. Future research should consider integrating advanced technologies such as artificial intelligence and big data analytics to investigate the impact of digital transformation on skill development and sustainable employability. Broadening the research scope to a global level would increase the relevance and influence of these findings across various cultural and economic contexts.

16.6 Conclusion

This study emphasizes the critical relationship among organizational improvement, skill acquisition, and sustainable business practices in promoting employability preparedness. The research presents a systematic method for enhancing workforce adaptability and business sustainability by framing career exploration as a mediating variable and sustainable innovation as a moderating factor. The amalgamation of circular HR and employee experience with circular performance underscores the necessity for organizations,

especially in the IT sector, to implement sustainability-oriented talent management strategies. The research underscores that ongoing education, career flexibility, and innovation are essential for sustained competitiveness in a changing digital and environmentally aware context. Despite existing limitations, including an industry-specific focus and the necessity for broader empirical validation, future research may investigate digital transformation, cross-industry applicability, and global perspectives to enhance these findings. This study offers significant insights for organizations and academics, outlining a strategic approach to enhance sustainable employability and business resilience amid rapid technological and environmental transformations.

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Chapter 17

A Bibliographical Analysis of Corporate Social Responsibility and Climate Change through R Studio

Sakshyarjyoti Mishra and Rashmita Sahoo

17.1 Introduction

Corporate social responsibility (CSR) is a principle in management that calls for business enterprises to incorporate environmental and social aspects towards their business operations and involvement with all parties involved. It is a crucial aspect of their role in enhancing the welfare of the community through independent company behavior and company funds (Dahlsrud, 2008). Section 135 of the Indian Company Act 2013 is dedicated explicitly to corporate social responsibility (CSR). As per the act, every company with a net worth of 500 crore or higher (where a crore is equal to 10 million INR; refer to Section 135 (1) for further information) is required to allocate about 2% of its mean net profits over the preceding three years towards fulfilling its Corporate Social Responsibility Policy (as stated in Section 135 (5)). The company is required to form a corporate social responsibility (CSR) committee, which should be composed of at least three directors, to oversee and evaluate the company's CSR initiatives (Gatti et al., 2019; Jain et al., 2021).

Corporate social responsibility is not a new concept in the world of business, and it has evolved from philanthropic activity to a mandatory corporate affair with the promulgation of Company Rules 2014 of the Ministry of Corporate Affairs—GOI (Government of India) (About CSR, n.d.). The evolving nature of corporate social responsibility (CSR) with the CLC scenario after the Paris Climate Action work of the Intergovernmental Panel on Climate Change (IPCC) of the United Nations Framework Convention on Climate Change (UNFCCC) pushes our thinking to think about their association and the way forward for the sustainable practices for the optimum resource utilization of CSR funding in Climatic action (Ortar, 2015).

Talking about CLC, which is a global crisis of urgent concern, needs no introduction as its impacts are felt worldwide through extreme weather events (Mal et al., 2018). Whether in developed or developing countries, everyone can relate to the effects of CLC on their daily lives. Some authors and the United Nations (UN) define it as a long-term shift in temperature and weather patterns (Pielke, 2004). While such changes are natural, human activities, particularly magnifying the change through the rapid usage of fossil fuels, are accelerating these changes (Höök & Tang, 2013).

Climatic actions are never thought of and should be devoid of climate justice, climate equity, and climate financing. The financing parts of the corporate sector delve into two aspects: one—from the side of individual contribution towards this or else mandatory contribution by making the rules and regulations (Arora et al., 2025). This is where we can think of corporate social responsibility. From carbon trading to climate financing, corporate social responsibility (CSR) can play a significant role in the prospects of controlling extreme global events, which is no exception in the international scenario. Whether we are talking about the political, economic, or social aspects of our daily lives, its impacts will be seen, and no one is going to get out the exceptions (Devi et al., 2024).

In recent times, no one can deny the truthfulness of CLC and the impacts it is going to have on human beings. The rise of temperature from the pre-industrial level will be higher than the targeted level of keeping below 1.5–2°C if no sophisticated and crucial steps are taken forward (Pörtner et al., 2022). Many steps have been taken to achieve the target of net-zero emissions in India and the world after the Paris Climate Agreement. The recently held COP 26 (Conference of Party, UNFCCC) in Glasgow discussed the mitigation, adaptation, finance, and human rights in terms of CLC (Lennan & Morgera, 2022).

17.2 Conceptual Overview

CLC has significant ramifications for firms in every industry (Wright & Nyberg, 2017). CLC can lead to several climatic phenomena, including heatwaves, and intense precipitation and intensify the occurrences of many disasters and distress (Coumou & Rahmstorf, 2012). Fluctuations in production in agriculture, which is a primary raw material for various industries, resulting from variations in temperature, rainfall patterns, and the occurrence of any disasters, etc., can cause shortages and price instability. The increase in the level of the sea and intensified weather events have the potential to hinder shipping and transportation routes, resulting in prolonged and heightened expenses (Godde et al., 2021). Nowadays, society is more concerned about CLC, and corporations are being evaluated more rigorously regarding their environmental practices. Undesirable ecological ramifications, such as increased carbon footprints, forest destruction, or contamination, can potentially erode the image in terms of the brand and its hard-earned reputation (Stern & Wolske, 2017). However, companies that adopt environmentally conscious procedures and illustrate a commitment towards reducing environmental damage can improve their credibility and cultivate trust among consumers (Zhang et al., 2022).

After all, considering the impact that changing aspects of climate have on the said sectors, if we look at the variable pattern of corporate spending, we see that it has changed over the years (Kumar et al., 2023a). The impact of divergent ideas regarding CLC on corporations' decision-making regarding their commitment to corporate social responsibility (CSR) based on data from Yale Climate Opinion Maps, which measures "change into climate" beliefs at the country-specific level, analysis reveals that enterprises' environmental and social, and governance (ESG) scores tend to be upper side in countries where a majority of the people believes in CLC happening in the world (Huang & Lin, 2022a). Afterwards, if one takes a closer look at the use of natural catastrophes as external disruptions to gauge perspectives on climatic risk, he/she will continue to find a "+ve" association between CSR and beliefs about climate concerns (Huang & Lin, 2022b). Moreover, we observe a more robust association between corporate social responsibility (CSR) and attitudes regarding climate risk when companies have a higher proportion of local investors (Hossain & Masum, 2022).

The study explores the domains of corporate social responsibility (CSR) and delves deeper into its components to gain insights into its ideas. The document is partitioned into two distinct sections. The first addresses

corporate social responsibility (CSR) inquiries, while the other focuses on the triple bottom line methodology. The study primarily focuses on one of the three components, namely, the planet. There are numerous methods by which firms can adopt environmentally conscious practices. It may ensure that it manufactures things that have no detrimental impact on the environment in a responsible way of handling various environment-friendly acts (Książak & Fischbach, 2018).

Additionally, one can notice CSR involvement in promoting the development of digital education infrastructure, enhancing health support networks in remote areas as necessary, implementing nutritional support programs, etc., bringing the SDGs target closer towards being achievable (ElAlfy et al., 2020). Corporate enterprises are required to collaborate with academic institutions that possess strong knowledge foundations to aid them in effectively managing their CSR projects. This collaboration should begin with doing a thorough assessment of needs and then connecting them with competent implementation agencies for the purpose of impact evaluation (Kappo-Abidemi & Kanayo, 2020). It is necessary to distribute global responsibility fairly and establish a diverse and accountable environment, including multiple stakeholders and centres; thereby, this will foster a sense of accountability and active participation among all parties involved in order to advance the sustainability goal (Rishi, 2022). Green financing and its components (environmental, economic, and social) significantly influence the improvement of various aspects of corporate social responsibility (CSR) (Wang et al., 2022).

This chapter tries to inculcate Carroll's Pyramid of corporate social responsibility (CSR), a widely recognized framework. In this assessment study, the author discusses the extensive adoption of the framework and thereafter provides a concise overview of the four-part definitional framework that served as the basis for constructing the pyramid. He subsequently includes commentary on other attributes of the model that should have been highlighted at its initial publication. Ethics is present throughout the pyramid, with inherent conflicts and trade-offs. It forms an integrated and cohesive whole with a sustainable stakeholder framework. Furthermore, it is of worldwide relevance and may be used in various circumstances (Carroll, 2016).

This study aims to tackle the following enquiries: What is the total number of research articles that have been published on the utilization of corporate social responsibility (CSR) in relation to CLC? What are the temporal patterns of publication and citation for these publications? Which research

papers have garnered the highest level of scholarly attention? Which authors, organizations, publications, and countries have made the most significant contributions to this scientific field? Which journals have the strongest correlation in this field of research? What is the current pattern or tendency in terms of joint efforts among various countries? What are the primary keywords utilized, and what other keywords are associated with them?

17.3 Research Methodology and Data Collection

17.3.1 Research Methodology

We used the Scopus database, known as the most comprehensive database worldwide, in our analysis. The database was selected for its extensive coverage and user-friendly accessibility (Burnham, 2006). We used R Studio to examine the data about our area of interest. R Studio was chosen for its robust data analysis features, enabling efficient processing and interpretation of the extensive information in the repository of Scopus data. This study used the bibliometric R-Tool, a new R package that allows for a thorough bibliometric analysis using specialized quantitative research methodologies in bibliometrics and scientometrics. R is a powerful and versatile statistical software environment that provides an open-source participation opportunity. The software application is designed for data processing, computing, and visual depiction. Bibliometrics can be combined with other relevant software solutions (Büyükkidik, 2022).

A bibliometric analysis, a quantitative method for analyzing academic literature by examining bibliographies to characterize, assess, and track published research, was used to analyze trends in the CSR and climate change (CLC) area. The analytical objective was to study publications, citations, information sources, and other pertinent criteria. Each bibliometric method is used for specific research purposes, with scientific mapping being the most common. The bibliometric analysis procedure comprised data collection and subsequent descriptive and bibliometric analysis at various stages.

17.3.2 Data Collection

The methodology aspect of the study is divided into two main pieces. Researchers gather the essential data for their analysis during the initial phase and develop a well-defined search strategy. The paper involves

conducting bibliometric research using the Scopus Core Collection on 22 July 2024. The search criterion for the database's search term is "CSR and climate change," and the resulting study forms the dataset. There are a total of 623 documents when considering all publication categories. Three hundred seventeen datasets are identified when the survey is restricted to Business, economics, and social science. The project's objective is to assess a grand total of 317 papers that were released from 2005 to 2024. The Scopus data offers extensive information for each article, encompassing authorship, document type, category, keywords, publication year, publishers, connected institutions, countries/regions, and indexes.

All texts classified as "Record Content: Full Record and Cited References" were obtained for the study's second phase by downloading them in Bibtext format. The task was accomplished by choosing the "Export Records to Bibtext File" feature from the pool of 317 articles identified in the survey. Three separate software packages are used to create, display, and examine bibliometric networks using this set of metadata. The apps mentioned are Bibliometrics (version R. 4.2.2), and the other two can be seen through the diagram below. The Co-occurrence Network and Co-authorship Network are analyzed using the R studio program, with a focus on the Emerging Topics, Thematic analysis Map, and Collaborative World Map (Figure 17.1).

17.4 Findings

This study examines the correlation strength, frequency of occurrence, temporal changes, importance, levels of interconnectedness, and the date at which keywords reached their highest citation numbers. Furthermore, it takes into account other characteristics when evaluating countries with the highest rates of academic collaboration and publishing. The article examines authors who have the greatest amount of published works and investigates their connections. The citation rates assess the number of references received by CSR and CLC works, whereas the number of publications determines how productive the journals are (Table 17.1).

17.4.1 Primary Information about the Data

In our search for the term "CSR and climate change" in the Scopus search engine, we identified 615 documents. From 2005 to July 2024, these documents provided significant insights into the CSR domain in the delves of

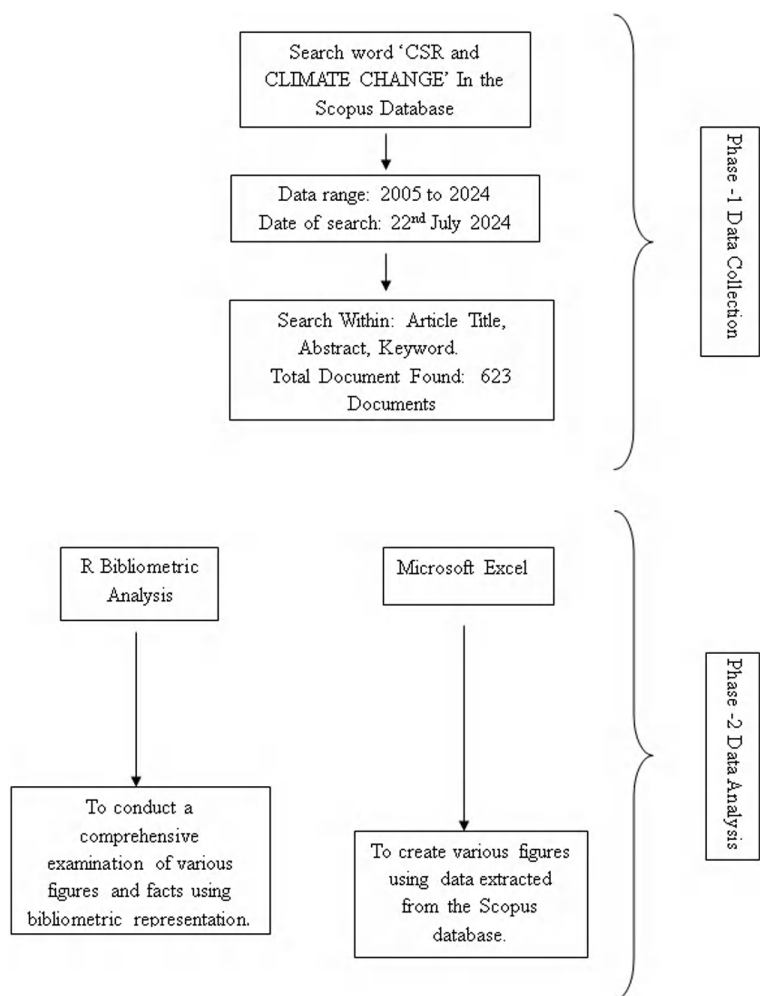


Figure 17.1 Systematic literature review Source: Compiled by author

Climatic Change aspects, and 593 of these documents, which account for approximately 99.02% of the total, have been published in the past two decades. These outcomes highlight the comprehensive investigation and discourse surrounding CSR, highlighting its importance in climate change (CLC). Although the significant contributions in this field are related to environmental science, when we restrict the subject's area of study to SOCI, ECON, and BUSI, we find that around 317 documents are related. This stands out as more than half of the documents retrieved from the database are relevant, which is quite a good number for analysis. The sources in our search results encompass a variety of mediums such as journals, books,

Table 17.1 Prime Info.

<i>Description</i>	<i>Results</i>
Timespan	2005:2024
Sources (Journals, Books, etc.)	212
Documents	317
Document average age	4.58
Average citations per doc	16.57
Authors	786
Single-authored docs	75
Keywords plus (ID)	661
Author's keywords (DE)	999

Source: Scopus database using R Studio.

articles, and more specifically focusing on number 212. According to Table 17.1, a total of 317 papers were published in 212 publications by 786 authors during the years 2005 and July 2024. The mean annual publication count is 4.58, whereas the mean number of citations received per document is 16.57. There are 75 documents with only one author, 661 papers with additional keywords, and 999 documents with author-specific keywords.

The mean number of citations received per document is 16.57. There are 75 documents with only one author, 661 papers with additional keywords, and 999 documents with author-specific keywords.

17.4.2 Annual Scientific Production

From 2005 to 2024, the production of various documents in the “CSR and climate change” field increased continuously. In the last two decades, more papers have been added than those previously added in this field. The year 2023 produced the maximum number of documents in this field, from which the current development and emerging trends can be seen after restricting our study to social science, economics, and business studies. From 2015 onwards, the outcomes in the fields doubled compared to the previous years combined, and one can attribute this to the development of the Paris Climate Agreement and SDGs targeting (Figure 17.2) (Brandi et al., 2017).

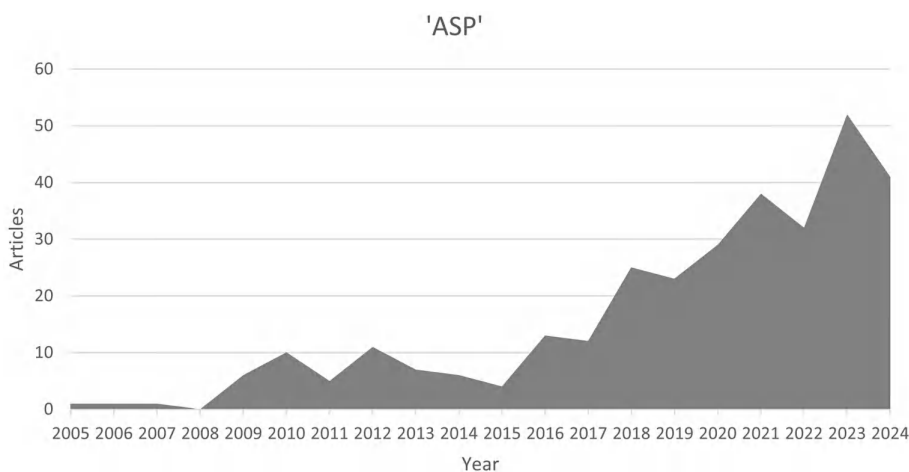


Figure 17.2 Annual production per year for the last two decades Source: Compiled by author

17.4.3 Top Sources and Citation

Academic journals are the primary means of sharing scientific knowledge and are valuable resources in all scientific fields (Wuni et al., 2019). For the analysis of our study we have collected data after `limGovernance, CorporateE-ABS-KEY (csr AND clGovernance ((change) AND PUBYEAR > 2004 AND PUBYEAR < 2025 AND (LIMIT-TO (SUBJAREA, "SOCI") OR LIMIT-TO (SUBJAREA, "BUSI") OR LIMIT-TO (SUBJAREA, "ECON")) AND (LIMIT-TO (LANGUAGE, "English")) AND (EXCLUDE (DOCTYPE, "er") OR EXCLUDE (DOCTYPE, "no"))` one can notice that top 10 most relevant sources (MRS) are *Sustainability* (Switzerland), *CSR, Sustainability, Ethics and Governance*, *Corporate Social Responsibility and Environmental Management*, *Social Responsibility Journal*, *Journal of Cleaner Production*, *Journal of Business Ethics*, *Water* (Switzerland), *Technological Forecasting and Social Change*, *Business Strategy and the Environment*, *Corporate Governance* (BINGLEY) (Figure 17.3).

17.4.4 Country Collaboration Network

According to the country collaboration network in Figure 17.4, one can trace 12 clusters for CSR and climate change (CLC). The country collaboration cluster-1 has significant contributions from the developed world, such as the USA, the UK, Australia, Canada, Germany, Netherlands, France, Sweden, Denmark, South Korea, and others. This cluster dominates thrice

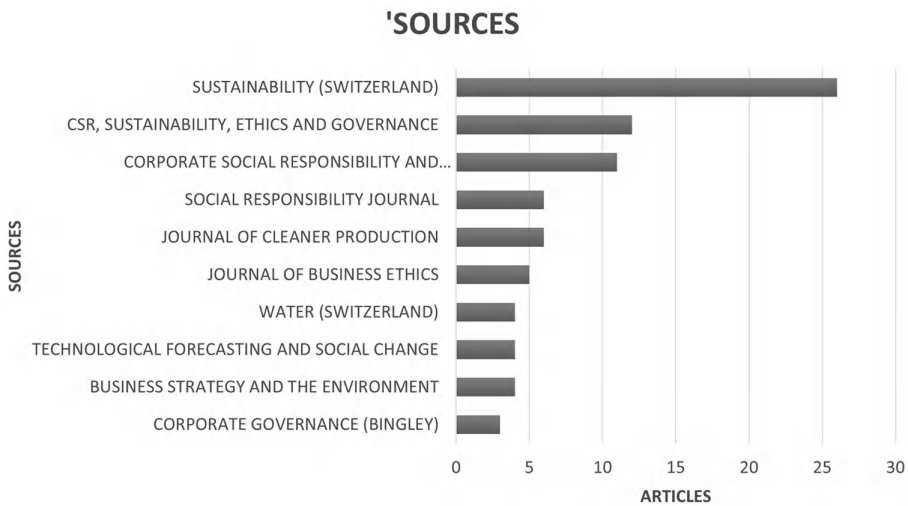


Figure 17.3 Top sources in the field of CSR and CC Source: Compiled by author

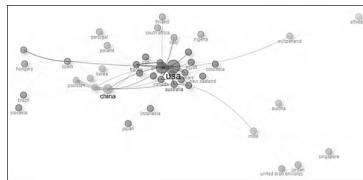


Figure 17.4 Country collaboration network for CSR and CC through R Studio Source: Output from "R Studio"

compared to the second largest cluster, and the linkages between China, Italy, Pakistan, Malaysia, Hungary, Thailand, Romania, and other countries in the second cluster can be said to be in the phase of emerging situations. The third significant node is dominated by European and South American countries like Spain, Portugal, Ecuador, and Brazil. India, along with the United Arab Emirates and Jordan, form the fourth cluster. The emerging countries' network nodes are Austria, Norway, Ghana, Estonia, and Ethiopia, which are in this direction of the research domain. There are clusters with two strings of nodes representing the emergence of CSR and climate change (CLC) fields, including Hong Kong-Switzerland, Finland-South Africa, and Indonesia-Japan.

17.4.5 Thematic view of the CSR and Climate Change (CLC)

Scientific mapping methodologies involve the development of theme maps that visually illustrate the conceptual structure of a certain research field.

A thema map is a visual depiction of the frequency of words, providing insights into the scientific discourse on a particular topic by highlighting important themes and trends (Jain et al., 2022). Density measures the level of integration among nodes, whereas centrality assesses the degree of linkage between different concerns (Jelvehgaran Esfahani et al., 2019).

The thematic review shows us that the seven clusters focus on different quadrants. Most of the studies based on CSR and CLC belong to the motor theme, suggesting that many mature studies have been developed in this field. The highest occurrence of the word is climate change, with an occurrence of 54 in the motor themes. The motor theme includes sustainable development, corporate social responsibility (CSR), and economic and social effects and sustainability. The primary themes cover overlaps with the motor themes and the subject matters related to emission control, carbon emission, and environmental concerns. Niche is represented by a cluster of nodes consisting of decision-making, grace and gravity recovery, and climate experiments. The emerging quadrant shows two clusters included in it, and the areas it covers are extractive industry and forestry in one cluster; carbon sequestration, traffic congestion in another cluster (Figure 17.5).

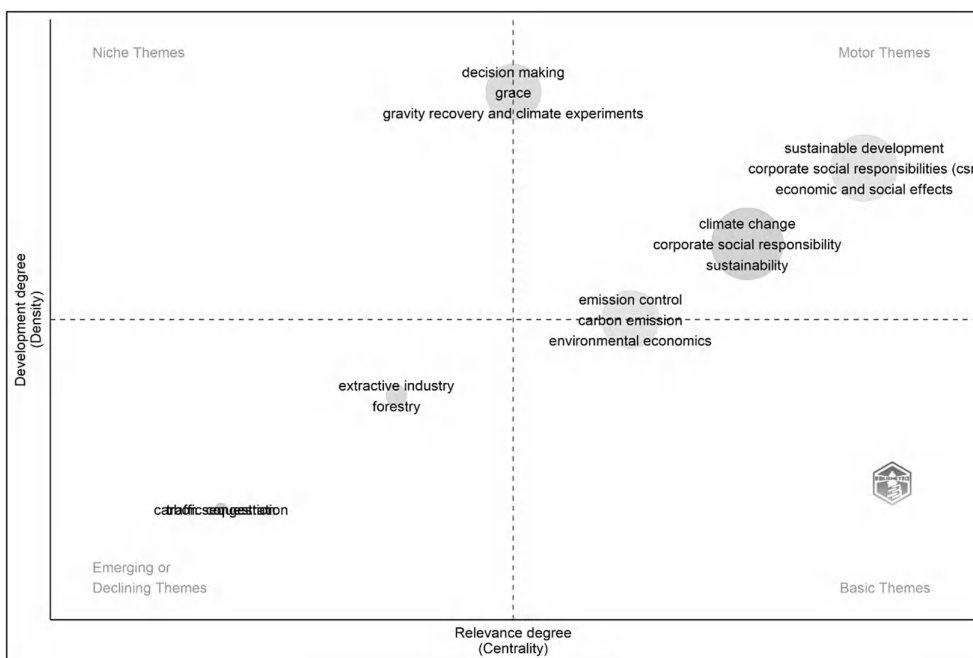


Figure 17.5 Thematic view of CSR and climate change Source: Output from “R Studio”

17.4.6 Most Relevant Words

We searched the word “CSR and climate change” in the Scopus database and, after limiting our study period from 2005 to 2024, found that in our R analysis, the frequency of words used for this inquiry, climate change, corporate social responsibility, sustainability, sustainable development, corporate social responsibilities (CSR), emission control, economic and social effects, environmental management, carbon emission, China. Climate change (CLC) has made us think differently, and so has the industrial organization. The highest use of the word “climate change” is noticeable in the figure. The other most used words in our search can be seen as sustainability and sustainable development, and we can notice here that the leaning of the marked ray symbolizes that. It can be noticed that its development has continued since 2015 and is in line with the Millennium Development Goal. From 2015 onwards, its foot growth can be seen from the given figure, which can be attributed to the inclusion of sustainable development goals (Sachs, 2012) and its seriousness after the Paris Climate Agreement (Brandi et al., 2017). One can quickly notice from the finding that these words erupted after 2015, and since then, these words have developed coherence with the CSR and climate change search. However, we can divide 2014 as the year of distinctions between the previous search and the coherence word with the search word. Since 2014, we have noticed that the critical keywords have proliferated. Over time, this analysis of word frequency provides insights into the evolving trends and priorities in the CSR and CC field, reflecting the changing dynamics (Figure 17.6).

17.4.7 Keyword Plus Co-occurrence Heatmap

In network visualization maps, the density of color represents each label of keywords. The darkness size is based on how often the item is used—more excellent item usage frequency results in a more prominent item label intensity. The internode’s thickness and the connecting line’s density represent the repetition rate at which labels co-occur. Nodes of identical color are more strongly related. Using keyword plus co-occurrence network analysis provides a highly effective means of uncovering scientific trends and emerging challenges by creating compact visual maps. Co-occurrence analysis seeks to delineate or summarize the conceptual structure in a bibliographic collection by employing a co-occurrence network to identify and group the terms obtained from keywords (Aria & Cuccurullo, 2017).

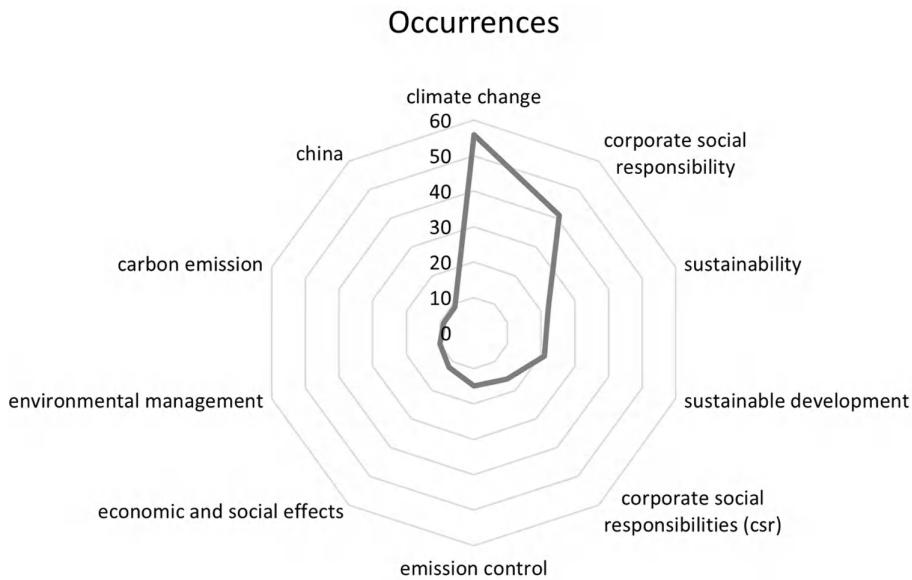


Figure 17.6 Most relevant words occurrences in CSR and CC search Source: Output from “R Studio”

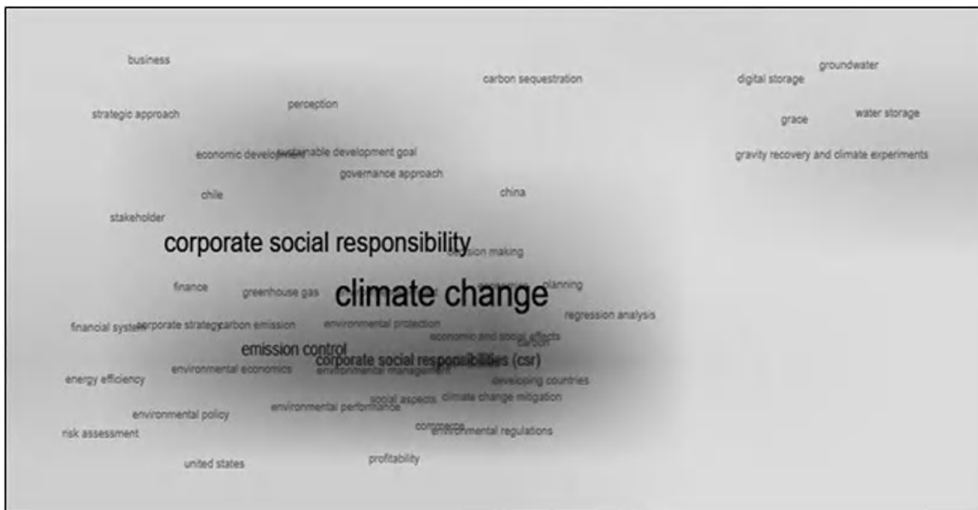


Figure 17.7 Heat map for keywords plus co-occurrence Source: Output from “R Studio”

Figure 17.7 illustrates the simultaneous presence of various keywords and concepts related to the CSR and CC aspects of clustering. The study yielded around nine clusters of word occurrence, along with the most frequently appearing words dominating the first cluster (in the given figure) are climate change, sustainable development, corporate responsibility, economic and

social effects, environmental management, and others. In the second cluster, the words of significance are corporate social responsibility, sustainability, China, and others. Let us look at the new sections in the entry to the keyword plus co-occurrence heat map. We will notice that carbon sequestration, finance, financial system, and risk assessment are separate, and each has unique clusters that notify the growing arena for the research. Grace, gravity recovery and climate experiments, groundwater, digital storage, and water storage formed a unique cluster (5) in the left-hand corner of the map, which has zero betweenness and closeness of 0.25 for each word.

17.4.8 Most Cited Papers (Documents) in CSR and Climate Change (CLC)

The effectiveness of writers, articles, or journals can be assessed by citation analysis, which involves looking at how often they are cited (Büyükkidik, 2022). The objects of examination are documents, writers, and periodicals. Its attributes are beneficial in identifying crucial research in the field. One drawback is that newly published works are expected to have a low cumulative citation rate, with older publications receiving the majority of citations (Zupic & Čater, 2015). 2010 *International Business Review* is the most cited paper in CSR and climate-related change articles in the Scopus database and has a total citation number of around 444 and a total citation for the year of around 29.60, which can be normalized to a total of 7.45. *Journal of Clean Production* is the second most referenced paper in this search query pertaining to CSR and climate change (CLC). It has garnered around 356 citations, averaging 59.33 citations annually. The normalized citations, which measure the paper's impact relative to others in the subject matter, are notably high at roughly 10.93. More sources can be accessed from Table 17.2.

17.4.9 Most Relevant Affiliation and Country's Scientific Production

From Table 17.3, one can notice that the institution most affiliated with CSR and CLC is the University of Reading, which produced the highest number of articles (around 6). It was followed by the Federal University of Bahia (Ufba), which had five articles so as Shanghai University, Universiti Sains Malaysia, University of Central Punjab, and Vilnius University. The Capital University of Economics and Business, Dalhousie University, ESIC University, King Fahd University of Petroleum and Minerals, and the University of California contributed four articles each, respectively.

Table 17.2 Top Cited Papers' Authors and Their Journals

<i>Name of Author</i>	<i>Year</i>	<i>Journal Name</i>	<i>TC</i>	<i>TC per Year</i>	<i>NTC</i>
Ans Kolk, Rob van Tulder	2010	<i>International Business Review</i>	444	29.6	7.45
Francesco Rosati, Lourenço G.D. Faria	2019	<i>Journal of Cleaner Production</i>	356	59.33	10.93
Nan Ye, Tung-Boon Kueh, Lisong Hou, Yongxin Liu, Hang Yu	2020	<i>Journal of Cleaner Production</i>	171	34.2	6.17
Bettina B. F. Wittneben, Chukwumerije Okereke, Subhabrata Bobby Banerjee, and David L. Levy	2012	<i>Organization Studies</i>	142	10.92	4.76
Paul A. Griffin, Yuan Sun	2013	<i>Journal of Accounting and Public Policy</i>	134	11.17	4.58
Juan Piñeiro-Chousa, M. Ángeles López-Cabarcos, Jérôme Caby, Aleksandar Šević	2021	<i>Technological Forecasting and Social Change</i>	113	28.25	9.16
Monika Kolb, Lisa Fröhlich, René Schmidpeter	2017	<i>The International Journal of Management Education</i>	112	14	4.51
Edeltraud Guenther, Thomas Guenther, Frank Schiemann, and Gabriel Weber	2016	<i>Business & Society</i>	108	12	4.73
Rachel Dodds, Jacqueline Kuehnel	2010	<i>International Journal of Contemporary Hospitality Management</i>	101	6.73	1.69
Deborah Doane	2005	<i>Futures</i>	94	4.7	1

Source: Scopus database using R Studio.

TC, total citations; *NTC*, normalized total citations.

Table 17.3 Top Institutes Producing Articles in the CSR and CC

<i>Affiliation</i>	<i>Articles</i>	<i>Country</i>	<i>Freq.</i>
University of Reading	6	USA	85
Federal University of Bahia (UFBA)	5	China	81
Shanghai University	5	UK	69
Universiti Sains Malaysia	5	Australia	32
University of Central Punjab	5	Canada	25
Vilnius University	5	India	25
Capital University of Economics and Business	4	Italy	25
Dalhousie University	4	Spain	22
ESIC University	4	Germany	20
King Fahd University of Petroleum and Minerals	4	Malaysia	20
University of California	4	Pakistan	19

Source: Scopus database using R Studio.

If we look at country-specific production, the USA tops the list with the highest frequency of 85, followed by China with 81 frequencies. The third country, regarding scientific production, is the UK, backed by 69 in terms of frequency after the USA and China. One can notice that India stands out at the top 5 positions in frequency while sharing the same spot with two G7 countries, like Italy and Canada, and a developed economy like Australia. This shows that the interest of developing countries is rising in this field of study, and the frequency of China, India, Malaysia, and Pakistan corroborates the facts.

17.4.10 Most Cited Country

By going through the above data, it is undeniable that the USA has the highest number of sightings. It has an average of approximately 25 citations and an overall of 587 citations. The Netherlands is the second most referenced country, following the USA, with 495 citations and a mean article citation of 82. Although developed countries dominate the list, China is one of the most emerging countries, followed by Malaysia. The contribution of China

Table 17.4 Top Countries' Cited Work

<i>Country</i>	<i>TC1</i>	<i>Average Article Citations</i>
USA	587	24.5
Netherlands	495	82.5
China	485	19.4
Denmark	454	75.7
UK	268	12.8
Germany	266	29.6
Australia	191	21.2
Italy	173	15.7
Canada	162	23.1
Malaysia	158	19.8

TC1: total citations.

Source: Scopus database using R Studio.

in terms of CSR and CLC stands out as the third most cited country in the world, with a total number of that, which means around 485 and an average article citation of around 20. The other countries on the list are Denmark, the UK, Germany, Australia, Italy, Malaysia, and Canada (Table 17.4).

17.5 Future Agenda for Research

We aim to identify and propose potential CLC and CSR research areas. Firstly, we suggested that academics should persist in their efforts to investigate the established topics in research related to CSR funding in terms of climate financing. Additionally, they must prioritize exploring unexplored issues and offer innovative approaches to secure research financing in areas impacted by corporations to inculcate social responsiveness by branding their image, fulfilling the binding objectives and contributing to innovative tools for financing. Furthermore, the study emphasizes the need to conduct research that involves multiple disciplines, i.e., multidisciplinary, and encourages collaboration between different fields of study. The researchers should facilitate the exchange of knowledge between different areas. In order to

achieve the organized, equitable, and long-lasting progress of CLC, it is crucial to establish a link between the fields of sustainable development, environmental management, and least developed countries (LDCs) and developing regions that are affected in terms of social and economic aspects. Furthermore, integrating sustainable goals can foster economic expansion in marginalized and Indigenous sectors of the economy. The study will aid researchers in comprehending the essential elements of CSR concerning resource finance research and augment the significance of their discoveries.

17.6 Conclusion

The articulated and dedicated research in the fields of “BUSI,” “ECON,” and “SOCI” started majorly after the introduction of certain obligations from either societal or government regulation. After searching the data from the Scopus database for 2005 to 2024, the above analysis shows us the light through which many preconceived notions about CSR and CLC can be somewhat dragged to a more apparent side.

The present analysis is limited by inherent limits associated with the bibliometric approach. The results and talks are based on the analyzed sample. Future research efforts could integrate data from many databases to enhance the sample size. Research can also focus on publications exclusively published in journals specializing in corporate social responsibility (CSR) and CLC research. This approach would provide a more up-to-date understanding of the scope of research on climate financing in the least developed and vulnerable islands that are particularly susceptible to CLC risks. Our sample may have omitted other research due to the constraints of our search criteria. This is because different locations have the potential to adopt varied funding methods. Since we specifically searched for “CSR and climate change” in our search query, any research that uses various funding mechanisms may have been left out of our sample. Therefore, future research should involve in-depth investigations focusing on particular locations, with special attention given to the least developed countries (LDCs) and island nations/states. This will facilitate the continued elaboration of the conclusions derived from the current study. Despite its limitations, this study will assist future researchers in integrating novel research topics and approaches. Additionally, it will offer a new and insightful viewpoint on the progress of research regarding various enterprises’ responsibility in financing climate-related initiatives.

Although a lot of efforts in CSR activities in terms of CLC or, we say, global warming are done, we have to ask ourselves—IS IT ENOUGH FOR THAT PART WHICH NEEDED TO BE FUNDED THROUGH CSR? Are we able to achieve the target of Paris Climate Change? If not, then which area should we focus on, funding, equity, justice, or all of them, simultaneously, with competing resources for each of them?

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Chapter 18

A Study on Behavioural Intention and Actual Usage of Artificial Intelligence among the Select Service Sector Employees

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18.1 Introduction

The rapid evolution of technology in recent years has transformed how businesses and individuals interact with innovative tools and systems. Recent advancements in technology have accelerated the expansion of AI, such as speech recognition, text analysis, etc. These advancements have generated interest in systems capable of functioning independently and adapting based on their engagement with surrounding conditions (Kumar et al., 2024). While automation, AI, and ML change job roles, human involvement remains important in organizational and management processes. As a result, many studies have focused on employee attitudes, acceptance, and technology adoption, creating various theories and models to understand and predict trends in technological innovation (Sohn & Kwon, 2020).

AI-based tools like robots, virtual assistants, and advanced algorithms are becoming highly visible in the operations of service industries. These

technologies optimize workflows by acquiring knowledge and making independent decisions, thereby reducing the need for human intervention while enhancing service quality and efficiency. However, integrating AI also changes job responsibilities and work scopes, raising concerns regarding its effects on employees' career trajectories, job satisfaction, and overall work performance. As sectors like banking and information technology increasingly adopt AI-driven solutions, it is essential to address the resultant uncertainties and their possible implications for employee attitudes and behaviours at work (Huang & Dogan Gursoy, 2024).

The top commercial banks like SBI, Yes Bank, HDFC, ICICI, and Axis Bank are leveraging the benefits of AI by partnering with fintech startups to enhance customer experience, reduce operational costs, and increase overall efficiency. Meanwhile, the global technology giants, including Google, IBM, Microsoft, NVIDIA, Amazon, and Infosys, are revolutionizing software development, data analytics, cybersecurity, and IT infrastructure management through AI. Such innovations are meant to create innovative applications that can learn, predict, and function autonomously (John Fanelli, 2024).

According to the McKinsey Global Survey, organizations are embracing AI technologies, particularly generative AI tools, and 40% of respondents are committed to increasing investments in AI. However, less than half of organizations have taken action to mitigate critical risks such as inaccuracies. The global AI market has expanded from \$93.27 billion in 2020 to \$184.04 billion in 2024 and is expecting to grow by 4x times by 2030 (Statista, 2024). India is ranked second in the world for AI talent, with 420,000 professionals, and organizations are increasingly investing in AI applications and appointing dedicated leaders to spearhead AI strategies (ETtech, 2024).

Challenges still prevail even though AI has benefits. In the banking sector, fear of insecurity and fraud discourages customers from accepting AI. The same case occurs in the information technology industry where fear of job loss, low morale, and hacking is associated with the adoption of AI. The challenge is alleviating workforce fears as trust develops in AI systems (Rahi et al., 2019).

The transformational capabilities of AI make it one of the most significant innovations of the 21st century, influencing scientific and technological progress and changing societal trajectories. Even though AI can lead to greater efficiency and better decision-making, its adoption depends on the users' preparedness and trust. Some of the critical factors that contribute to the rate of adoption include perceived benefits, ease of use, and security perceptions. Addressing issues such as security breaches, job loss, and workers'

morale is essential to ensure that growth is sustainable and AI becomes ubiquitous (Demirel & Topcu, 2024).

This chapter examines the factors influencing employees' intention to adopt AI, with precise attention on the role of gender in AI adoption. The findings offer useful information for organizations and leaders to address and develop strategies based on these factors, enabling employees to adapt effectively to the advancements in AI and related technologies, thereby improving the efficiency of the organization.

18.2 Review of Literature

The incorporation of AI and technology within organizations to enhance daily operations is experiencing a significant rise each year, contrasting with the slower adoption seen every decade during the 1990s. The advancement of AI has led to its widespread implementation across nearly all sectors, particularly following the COVID-19 pandemic, which popularized remote work (WFH) and hybrid working models. AI is expected to pose more significant operational and strategic challenges for public organizations compared to any other IT innovation in addition to the technical difficulties it may introduce (Selten & Klievink, 2024).

Different sectors have accepted the involvement of AI in the work process (Arora et al., 2025). People from the public sector doubt the use of AI as they do not want to rely entirely on AI to make decisions. The utilization of AI is regarded as more appropriate for less ideologically driven decisions (Haesevoets et al., 2024). The application of AI in the banking sector has helped banks respond more quickly to customers' needs and helps them comply with the rules, detect fraud, and verify customer details (Meghani, 2020). Implementing AI in the human resource process can enhance the efficiency of the hiring process by bringing automation to the whole recruitment process, lowering expenses, and addressing the difficulties linked to manual candidate evaluation (Tambe et al., 2019).

A McKinsey report stated AI is transforming the banking sector by enhancing customer interactions and streamlining internal processes. In the front office, AI-powered tools like facial recognition enable effortless transactions, while chatbots handle basic service requests, freeing human agents for complex tasks. Humanoid robots in branches offer personalized assistance, improving customer engagement. Virtual loan officers analyse micro-expressions in the back office to provide tailored recommendations, and biometric

technologies ensure secure yet convenient authentication. AI-driven machine learning algorithms detect fraud, cybersecurity threats, and unusual transaction patterns, enabling proactive responses. Additionally, automation of technologies like ML and NLP in banking sector can enhance operation process (Biswas et al., 2020).

Islam et al. (2024) explored AI usage for talent recruiting using the UTAUT model. PeEx, FaCo, and Hedonic Motivation significantly influenced the motive to use AI.

SoIn: SoIn applies to the impact of societal forces, expectations, and challenges that can either encourage or hinder technology acceptance. Interestingly, while SoIn and trust in AI technology do not directly affect adoption intentions, it was found to impact perceived value positively, and trust in AI technology enhanced EfEx (Venkatesh et al., 2003). A recent study also reported that SoIn has a substantial effect on the aim of adopting technology. This implies that positive perceptions and support within the organization are of prime importance for successful technology adoption (Dekkal et al., 2023). SoIn has a positive attitude towards adopting technology, leading to positive BeIn towards using AI (Igbaria et al., 1996). Tomic et al.'s study found that organizational maturity is also a significant predictor of technology adoption intention, and this means that more experienced employees are likely to have more positive attitudes towards adopting technology (Tomić et al., 2023).

H1: *Social Influence significantly influences the Behavioural Intention to use AI*

PeEx: PeEx is described as technology usage that improves job performance by solving a problem or completing a task for which one intends to utilize the technology (Venkatesh et al., 2003). As per Thusi and Maduku (2020), PeEx is a consumer's belief that technology is valuable and beneficial. Sun et al. (2008) agree that efficient communication in the learning system enhances the effectiveness of a specific learning system in learners' perceptions. Cornelissen et al. (2022) found that the perception of PeEx among medical professionals' significantly influences their acceptance of AI-powered care pathways, emphasizing that the perceived improvement in job performance plays a key role in their adoption decision (Jameel et al., 2023).

H2: *Performance Expectancy significantly influences the Behavioural Intention to use AI*

EfEx: EfEx relates to the user-friendly or difficulty of applying a technology. EfEx strongly impacts the motive to use AI and the AcUs, and gender plays as key moderating role in this relationship (Venkatesh et al., 2003). This finding is also backed by Ahmad et al. (2020), where it is reported that EfEx highly motivates the motive to accept technology. Teo (2011) observed that teachers' intentions to use technology were positively associated with EfEx, which indicates that easy user experience (UX) encourages the adoption of technology. Thus, based on previous studies, it can be predicted that EfEx has a positive effect on BeIn.

H3: *Effort Expectancy significantly influences the Behavioural Intention to use AI*

FaCo: Variables that are considered as technical that can support the use of technology or systems and the extent to which a person puts trust in the infrastructure in the organization is defined as FaCo. Venkatesh et al. assert that FaCo, including access to resources and infrastructure, enhances users' intentions to adopt technology. When users believe that the essential resources and support are available, they are more likely to believe in their capability to utilize the technology successfully. Therefore, FaCo overcome many perceived barriers and enhance greater technology acceptance (Venkatesh et al., 2003). Ebadi and Raygan (2023) found that robust FaCo significantly enhances technology acceptance among Iran's public and private school teachers. Brown et al. (2008) identified that FaCo, as a direct determinant, significantly influenced user behaviour in technology adoption scenarios. Zhou (2012) reported that FaCo substantially impacted initial trust in using technology, thus indicating the need for proper infrastructure and support. Thus, according to the literature, it could be hypothesized that FaCo significantly affect user behaviour.

H4: *Facilitating Conditions significantly influences the Behavioural Intention to use AI*

BeIn and AcUs:

BeIn indicates the readiness of an individual to acceptance and utilize a specific technology (Noel Nino Valle et al., 2024). Gupta et al. (2022) revealed that technological aspects such as relative advantages and environmental aspects such as regulatory support were significant drivers for BeIn. BeIn is not majorly impacted by FaCo, but BeIn do have an immediate effect on actual use, especially as users gain experience.

H5: *Behavioural Intention significantly influences the Actual Usage of AI*

The connection between SoIn and the motive to accept artificial intelligence is moderated by gender. Research shows that women are more sensitive to social cues, which communal norms can explain. In contrast, men are less reliant on social factors and more likely to adopt technology autonomously (Kim Ngan et al., 2024). Gender influences the connection between PeEx and the motive to accept artificial intelligence. This can be explained by the conventional gender roles, which portray men as more efficacious and knowledgeable in technology. Organizations must address these biases (Venkatesh et al., 2003). The moderating role of gender suggests that efforts related to expectancies have some moderation on relationships in terms of AI adoption through younger women's greater perceived difficulty concerning navigating technology (Devi et al., 2025). There seems to exist some perception stemming from traditional expectations based on convention gender roles through which women prefer emphasis on easier navigation and utility usage of these systems.

H6: *Gender regulates the relationship between Social Influence and Behavioural Intention to use AI.*

H7: *Gender regulates the effect of Performance Expectancy on Behavioural Intention to use AI.*

H8: *Gender regulates the relationship between Effort Expectancy and Behavioural Intention to use AI.*

H9: *Gender regulates the relationship between Facilitating Condition and Behavioural Intention to use AI.*

18.3 Data and Methodology

18.3.1 Sample

The study adopted a quantitative and descriptive research design. Primary data was collected specifically for this research using a self-reported questionnaire. The survey questionnaire included both open and close ended questions. The questionnaire was adopted from the research study of Venkatesh (2013). Data was collected using the questionnaire distributed via Google Forms, which was shared with participants through email and messaging platforms. The study's sample size was 120 participants from IT and banking sectors across India, representing varying levels of work experience. Participants were selected through a convenience sampling method,

targeting individuals known to the researchers who were employed in the IT and banking sectors. Additionally, the snowball sampling technique was utilized to recruit more participants through referrals from the initial respondents.

18.3.2 Latent Variables

The six variables were adapted from the model of UTAUT by Venkatesh et al. (2003), namely SoIn, PeEx, EfEx, FaCo, BeIn, and AcUs. The moderating variable considered was “gender.” Each construct was measured using the UTAUT questionnaire and modified for AI. Each construct was calculated using four objects (questions), each on a 5-point Likert scale from strongly agree to strongly disagree. AcUs was measured using a 5-point scale, 5—Daily to 1—Never. Two items from AcUs were dropped post exploratory factor analysis (EFA) as it was not found reliable. The items were “Most of my time were spend on AI for work” and “I frequently use AI application for my work.” Demographic details of the respondents like age, gender, marital status, location, job sector/profession, and experience were also collected.

18.3.3 Theoretical Background

The structural equation modelling (SEM) path diagram represent the UTAUT model. Venkatesh and colleagues utilized the theory of planned behaviour and the technology acceptance model (TAM) to develop the UTAUT model. This model elucidates that BeIn influences the actual utilization of artificial intelligence. The model comprises four central components: SoIn, PeEx, EfEx, and FaCo, which collectively serve to forecast users’ acceptance of new technologies (Venkatesh et al., 2003). The UTAUT model is an extensively adopted framework to understand the factors that affect how technology is adopted and used.

18.4 Data Analysis

The collected data was evaluated utilizing SmartPLS. Cronbach’s alpha (α) was utilized to evaluate the dependability of the items, while composite reliability was employed to assess the reliability of the questions and data. To check validity, the Fornell-Larcker criterion was applied by ensuring that every construct measures the intended variable with no overlap of

constructs. Then, exploratory factor analysis was done to find out the underlying constructs, followed by confirmatory factor analysis to validate the constructs obtained and remove all the unnecessary factors. The R^2 and adjusted R^2 values were used to determine the fit of the model with the sample data. Additionally, sample mean, standard deviation, P -values, and T -values were computed to evaluate the hypotheses' path effects and analyse the relationships between variables.

18.4.1 Reliability and Validity

Table 18.1 depicts the constructs, its respective measurement items, and their factor loadings derived from EFA followed by CFA. Cronbach's alpha (α) and composite reliability (CR) of each of the constructs are presented in Table 18.1. The constructs of the study demonstrated strong internal consistency, with α ranging from 0.79 to 0.875, and CR values exceeding the suggested threshold of 0.70, indicating strong internal consistency. Convergent validity was established with factor loadings between 0.742 and 0.952, all outdid the threshold of 0.70, and average variance extracted (AVE) values beyond 0.50, ensuring that the constructs captured a significant proportion of variance. Thus, the measurement model was confirmed reliable and valid for further analysis.

Table 18.2 demonstrates that Fornell Larcker Criterion was utilized to establish discriminant validity. Discriminant validity examined by the Fornell-Larcker Criterion demonstrated the square root of AVE for each construct surpassed its correlation, higher than correlations with other constructs resulting each construct was unique. The reliability (Cronbach's $\alpha > 0.70$), high factor loadings, and strong discriminant validity validate that the model was fit for analysing the factors influencing AI adoption.

Figure 18.1 presents the SEM path diagram, illustrating the observed variables, latent constructs (represented by circles), and the relationships between them (depicted by lines). The moderating variable, gender, is shown to influence the connections between SoIn, PeEx, EfEx, FaCo, and BeIn through dotted lines. The respective P -values for these moderating relationships are also indicated in the diagram along the lines.

18.5 Results

Table 18.3 represents the coefficient values, P -values, and t -values of the hypotheses. Hypotheses with P -values less than 0.05 are significant, and

Table 18.1 Measurement Items and Their Reliability

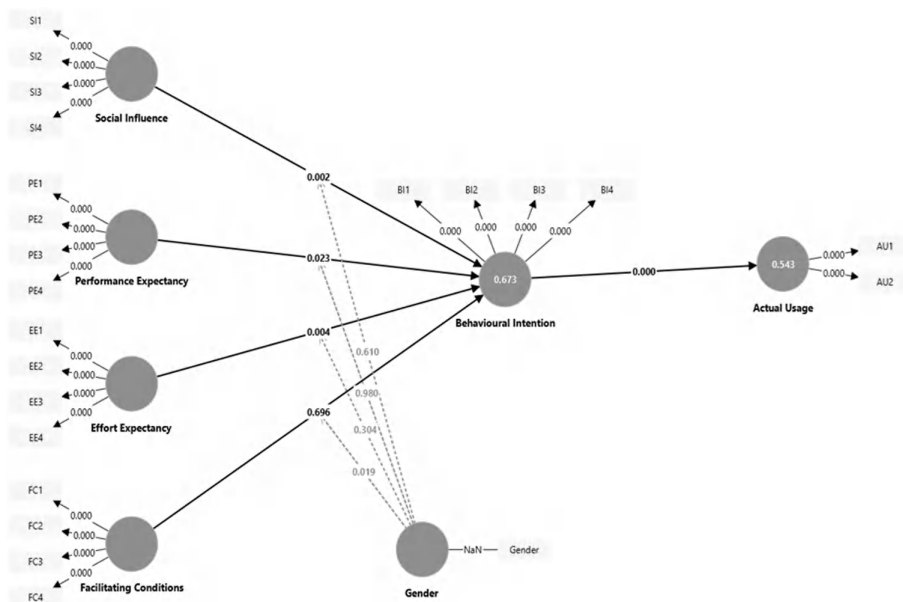
<i>Constructs and Their Respective Items</i>	<i>Factor Loadings</i>	
Soln (Soln, α : 0.872, CR: 0.882)		
Soln1	0.864	
Soln2	0.851	
Soln3	0.881	
Soln4	0.797	
PeEx (PeEx, α : 0.854, CR: 0.856)		
PeEx1	0.894	
PeEx2	0.873	
PeEx3	0.765	
PeEx4	0.802	
EfEx (EfEx, α : 0.864, CR: 0.871)		
EfEx1	0.882	
EfEx2	0.809	
EfEx3	0.841	
EfEx4	0.837	
FaCo (FaCo, α : 0.79, CR: 0.793)		
FaCo1	0.777	
FaCo2	0.800	
FaCo3	0.812	
BeIn (BeIn, α : 0.875, CR: 0.88)		
BeIn1	0.834	
BeIn2	0.886	
BeIn3	0.872	
BeIn4	0.816	
AcUs (AcUs, α : 0.506, CR: 0.819)		
AcUs1	0.952	
AcUs2	0.611	

α signifies the value of Cronbach's alpha and CR signifies composite reliability.

Table 18.2 Discriminant Validity Analysis

	<i>AcUs</i>	<i>BeIn</i>	<i>EfEx</i>	<i>FaCo</i>	<i>PeEx</i>	<i>Soln</i>
AcUs	0.8					
BeIn	0.737	0.852				
EfEx	0.518	0.658	0.843			
FaCo	0.515	0.61	0.673	0.783		
PeEx	0.522	0.708	0.554	0.511	0.835	
Soln	0.669	0.698	0.517	0.541	0.731	0.849

Source: Primary data.

**Figure 18.1 SEM path diagram**

hypotheses with P -values greater than 0.05 are not significant. H1, H2, H3, and H9 are significant as their $P < 0.05$.

The current study offers a comprehensive examination of the components that affect BeIn and AcUs of AI and the moderating influence of gender on these factors. The study shows that SoIn significantly affects the BeIn to adopt AI in the workplace. The path coefficient (β) for SoIn is 0.405 with a P -value of 0.002, indicating that social dynamics and external societal

Table 18.3 Summary of Hypothesis Testing

<i>Hypothesis</i>	<i>Coefficient</i>	<i>t-value</i>	<i>P-value</i>
<i>H1: Soln</i> → <i>BeIn</i>	0.405	3.169	0.002
<i>H2: PeEx</i> → <i>BeIn</i>	0.263	2.266	0.023
<i>H3: EfEx</i> → <i>BeIn</i>	0.318	2.905	0.004
<i>H4: FaCo</i> → <i>BeIn</i>	−0.048	0.39	0.696
<i>H5: BeIn</i> → <i>AcUs</i>	0.737	17.481	0
<i>H6: Gender</i> × <i>Soln</i> → <i>BeIn</i>	−0.091	0.511	0.61
<i>H7: Gender</i> × <i>PeEx</i> → <i>BeIn</i>	−0.005	0.025	0.98
<i>H8: Gender</i> × <i>EfEx</i> → <i>BeIn</i>	−0.199	1.028	0.304
<i>H9: Gender</i> × <i>FaCo</i> → <i>BeIn</i>	0.424	2.352	0.019

pressures that individuals encounter at their workplace influence their intention to utilize AI. *PeEx* substantially affects the *BeIn* to use AI, as well. The β of *PeEx* was measured to be 0.263 with a *P*-value of 0.023. People who expect AI to help boost their job performance tend to exhibit greater intention to adopt it. *EfEx* significantly affects the *BeIn* to use AI in addition to *Soln* and *PeEx*. The β of *EfEx* is 0.318, and the *P*-value is 0.004. This states that *EfEx* significantly influences *BeIn* to use AI. However, *FaCo* doesn't significantly impact the *BeIn* to integrate and use AI. The β value is −0.048 and the *P*-value is 0.69, indicating that *FaCo* does not significantly influence people's intent to adopt AI. The motive to utilize AI has a significant impact on its *AcUs*, demonstrated by a β value of 0.737 ($P = 0.00$), which demonstrates that the higher the intention to adopt AI, the higher the prospects of *AcUs*. Gender regulates the link between *FaCo* and *BeIn*. The interaction between gender and *FaCo* is statistically significant with a *P*-value of 0.019.

Gender doesn't moderate the influence of *PeEx* on *BeIn*, as indicated by a *P*-value of 0.98. The result recommends that both male and female individuals are similarly affected by their perceptions of AI's ability to enhance job performance, indicating that gender doesn't influence the result of *PeEx* on the motive to utilize AI. Similarly, the influence of *EfEx* on *BeIn* is not influenced by gender. With a *P*-value of 0.304, this suggests that all genders have comparably perceived usability and gender has no significant effect on the influence on *EfEx* with regard to *BeIn*. Gender plays a moderating role while influencing *FaCo* on *BeIn* with a favouring *P*-value of 0.019.

18.6 Discussion

The study explores the factors influencing BeIn and AcUs of artificial intelligence, offering insights into how organizations can effectively integrate AI into their operations.

SoIn established as a primary driver of BeIn, highlighting the value of recommendations from peers, organizations, and society. When people feel that their colleagues, friends, or the larger community endorse AI, it encourages them to adopt it as well. This approval creates a chain reaction where the positive perception spreads and motivates others. Moreover, leaders and managers promoting the adoption of AI as part of workplace culture amplify this effect, marking the strategic importance of cultivating a supportive environment where AI use is normalized and celebrated. Social cues, including societal acceptance and organizational encouragement, are central in shaping individuals' decisions to embrace AI. This result corresponds with the research undertaken by Kulviwat et al. (2008), which found that individual attitudes and the social norms prevalent within a reference group can influence technology adoption.

Another critical factor influencing BeIn is PeEx, which refers to the belief that AI can improve one's job performance. Employees are naturally drawn to technologies that offer clear and measurable benefits like enhanced productivity and better decision-making. This makes PeEx an essential motivator for AI adoption, as people value tools that address their professional needs and help them advance in their careers. The interaction between PeEx and BeIn is not influenced by gender, meaning both men and women similarly perceive AI's performance-enhancing capabilities (Batucan et al., 2022). Capability of AI to improve efficiency, accuracy, and productivity is attractive to everyone, regardless of gender. Moreover, as organizations increasingly promote a culture of equality, both genders have equal access to technology and opportunities, leading to similar attitudes towards AI.

EfEx, or how easy people believe it is to use AI, also significantly impacts BeIn. When AI systems are intuitive, user-friendly, and straightforward to navigate, people feel more confident and are more likely to adopt them. This is because simplicity reduces hesitation and anxiety associated with it, especially in organizations with employees who have varying levels of technological expertise. The ease of use becomes a central factor in encouraging AI usage. People tend to use more of technology specially AI tools to attain their work end goal, which is revealed in a study that EfEx impacts the motive to utilize AI-generated images in business contexts, with the effect

being more pronounced in individuals with lower creativity levels (Maican et al., 2023).

Furthermore, gender doesn't regulate the connection among EfEx and BeIn as both men and women value usability similarly. The primary concerns of organizations are often the efficiency and functionality of tools, irrespective of gender. Thus, both men and women can access it the same way. This shared perspective reinforces the need for organizations to design accessible and easy-to-use AI systems that cater to all users, across genders.

FaCo, which include the availability of resources, infrastructure, and organizational support, surprisingly do not significantly influence BeIn. This is because FaCo may be crucial for sustaining AI usage in the long term. It may not play a major role in the initial decision to adopt AI. However, FaCo becomes essential later for the long-term use of AI. Venkatesh et al. (2003) found that individuals prioritize intrinsic motivators in the short term, such as clarity of use and perceived performance benefits, when deciding whether to adopt a technology. FaCo do not directly impact BeIn or usage (Venkatesh et al., 2003).

According to the present study, women tend to rely more on FaCo than men, as women seek external resources, such as training, guidance, or support, to feel more confident when using new technologies. This extra support helps reduce uncertainty and boosts their confidence in adoption. Venkatesh et al. (2003) also highlighted that females tend to experience higher levels of anxiety regarding technology usage, which lowers their self-efficacy and, in turn, increases their perception of the effort needed to use IT. However, men may not require the external push to begin using a new technology, but they may need it later to learn its nuances through training and guidance. This highlights the importance of gender-sensitive approaches, such as targeted training and mentorship programs, to create an equitable adoption environment.

BeIn strongly influences AcUs, indicating that individuals with a positive motive to utilize AI are highly likely to incorporate the technology into their daily tasks. This connection exists because BeIn reflects a person's attitude, interest, and commitment to adopting AI. Positive attitudes lead to active engagement. Therefore, organizations must focus on fostering positive intentions towards AI. Highlighting AI's benefits, addressing potential concerns, and providing functional support can bridge the gap between intention and AcUs among workers. The findings align with the previous study conducted by Venkatesh et al. (2003), which stated that SoIn, PeEx, and EfEx are significant drivers of BeIn to adopt any technology. However, contrasting

research, such as Islam et al. (2024), indicates that FaCo plays a more prominent role in contexts where resource availability is a critical concern. These differences emphasize the need to consider situational and demographic factors when developing AI adoption strategies.

18.6.1 Managerial Implications

The result of this research emphasizes key managerial strategies for encouraging AI utilization within organizations. Leaders and managers could aim to strengthen employees' willingness to embrace AI by leveraging factors such as SoIn, perceived performance benefits, and effort expectations.

Creating an environment where AI usage is encouraged by peers, the organization, and leaders can significantly drive positive attitudes among employees. Compensation can be linked with using AI to get the work done, thus motivating employees to switch to AI-driven decision-making. Organizations can introduce Peer Mentorship Programs, which can be done by pairing less tech-savvy employees with AI-literate colleagues for one-on-one mentorship. This personalized guidance can make learning less intimidating and foster stronger team bonds. In addition to peers, managers play a pivotal role in integrating AI into workflows, addressing employee concerns, and modelling AI usage to inspire confidence and motivation. Organizations can reduce employees' resistance to AI by aligning it with job descriptions and responsibilities. Addressing the diverse needs of the workforce can further promote innovation. This approach ensures fair and sustainable AI adoption, benefiting all employees effectively.

Designing AI systems that are intuitive and accessible is crucial for encouraging user adoption. The necessity for skills like prompt engineering to interact effectively with AI can lead to anxiety and resistance among employees, especially if they perceive the required upskilling as beyond their current capabilities. Conversely, when new technologies are straightforward and demand minimal training, employees are more inclined to accept and integrate them into their workflows. This perspective aligns with findings of Mahmood et al. (2021), which demonstrated that involving users in the AI training process can enhance their perceptions of the AI's capabilities and increase their comfort with adopting AI-based technologies. Organizations can improve the adoption of in-house AI systems by actively involving the employees in the development process. Gathering employees' perspectives and feedback helps them become more familiar and

comfortable with the AI tools, increasing the likelihood of successful integration with minimal resistance.

It is essential to communicate AI's benefits and how it has helped employees in the past, with improved productivity, creativity, decision-making, and job promotion. A few effective strategies may include employees sharing success stories and testimonials about how AI helped them improve their performance and advance in their careers. Companies can exhibit how AI and related skills would help employees stand out during promotions, appraisals, or cross-functional opportunities. Integrating AI into the Human Resources Information System (HRIS) and the regular feedback loop ensures that employees incorporate it into their daily tasks, e.g., applying for leaves, monitoring their feedback, or raising tickets, thus gradually becoming accustomed to it. Overall, when employees feel confident in the capabilities of AI and consider it an integral part of their workflow, they are more inclined to incorporate it in their daily practices.

Furthermore, organizations must adopt gender-sensitive strategies to ensure equitable access and integration. Organizations can offer inclusive AI training programs that are accessible to all employees, regardless of their gender, background, or role. Ensuring that the AI tools implemented are free from gender bias by conducting regular audits and updates is vital. Other initiatives like mentorship programs and collaborative support networks are essential to address demographic-specific barriers and promote inclusivity.

18.7 Conclusion

This study concludes that societal factors, PeEx, and EfEx significantly impact employees' readiness to embrace and integrate AI in the IT and banking sectors. However, FaCo did not exhibit a direct effect on AI implementation. Similarly, gender was found to have no notable impact on AI utilization, as both male and female employees demonstrated comparable perceptions and usage patterns. Nonetheless, the interplay between gender and FaCo was recognized as a factor affecting the readiness to adopt and integrate AI. FaCo affect each gender differently, shaping their responses to AI adoption. The research findings can be applied in organizations by leaders and managers as organizational strategies to motivate employees to leverage AI, thus improving the organization's efficiency.

18.8 Scope for Future Research Work and Limitations

The study did not address intergenerational or professional variations in AI adoption, which may significantly influence attitudes and behaviours towards AI. Future research could tap into increasing the sample size and examine the differences across professions and intergenerational groups (e.g., Baby Boomers, Millennials, and Generation Z) to understand how technological familiarity, cultural context, and age shape AI adoption. Incorporating personality traits as moderating variables could further enrich insights, enabling policymakers, educators, and businesses to develop targeted strategies for promoting AI adoption across diverse segments.

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Chapter 19

Geo-Based Causal Analysis and Risk Evaluation of BOPIS Fee Elimination in Retail Store Rollouts

Bhavnish Walia, Banani Mohapatra, and Kushal Walia

19.1 Introduction

Buy-online-pickup-in-store (BOPIS) is an important retail channel strategy. It connects digital and physical shopping experiences (Bell et al., 2014). BOPIS offers benefits for both customers and retailers. For customers, they can save on delivery costs and gain timely access to their purchases. For retailers, it can tap into cross-selling opportunities and improve operational productivity. It enhances the shopping experience by combining the convenience of e-commerce with the tactile benefits of physical retail (Kumar et al., 2019). BOPIS sales are expected to reach \$154.3 billion by 2025 (Damen, 2023).

An important factor influencing BOPIS adoption is the structure of its associated fees. Offering free pickup enhances customer satisfaction, reducing friction for low-value orders and encouraging repeat purchases (Chatterjee, 2012). However, free pickup strategy presents trade-offs, such as the loss of a potential revenue stream, strain on operational resources, and the risk of inefficiencies due to frequent low-value orders (Jing & Lewis, 2011). To account for these challenges, retailers must evaluate the practical and financial impacts of fee elimination.

Measuring the effects of eliminating pickup fees requires robust causal inference methodologies due to the complex interplay of factors such as customer behavior and regional variability (Xu et al., 2019). This study uses a geo-based approach. It utilizes clustering techniques like DBSCAN and K-means to segment stores into comparable groups based on geographic, operational, and demographic attributes. The Difference-in-Differences (DiD) method is then used to isolate the causal impact of fee elimination. DiD controls for confounding variables and ensures reliable measurement of changes in sales, customer behavior, and operational dynamics (Card & Krueger, 1994).

This chapter offers a robust framework for evaluating the implications of BOPIS fee elimination in diverse retail environments (Kumar et al., 2023a).

19.2 Literature Review

BOPIS retail strategy has created interest for both academic scholars and industry professionals. This section brings attention to research on clustering techniques and causal inference and how this chapter contributes to the existing body of research.

19.2.1 *Studies on BOPIS and Pickup Fee Elimination*

BOPIS not only benefits buyers but also sellers; however, limited works exist on the impact of pickup fees. Chatterjee (2012) notes that fee elimination improves customer adoption but may strain operational resources. Xu et al. (2019) extended this work by studying online-to-offline retailing and the importance of fee structures in creating customer preferences and seller profitability. Despite these insights, there is limited research on the localized impact of fee elimination in physical retail stores that have different customer demographics and operational resources.

19.2.2 *Clustering Techniques in Retail*

Techniques in clustering have widely been used in retail experimentation and research. They help with segmenting customers and stores, optimizing marketing strategies, and improving operational efficiency. K-means and hierarchical clustering are two such techniques that are popular due to their simplicity and effectiveness in identifying patterns (Lloyd, 1982; Hartigan & Wong, 1979). To

create targeted marketing strategies, Bilgic et al. (2015) used hierarchical clustering to segment supermarket chains based on store attributes like size, trade area demographics, and competitor proximity. Spiller and Lohse (2015) also used clustering to classify e-commerce stores based on interface quality and service offerings, underscoring its relevance in retail contexts.

However, K-means and hierarchical clustering often rely on predefined assumptions about data structure, limiting their applicability to complex, real-world datasets. DBSCAN, a density-based method (Ester et al., 1996), has gained popularity as it can detect arbitrary shaped clusters and handle outliers. This makes them suitable for spatial segmentation in retail networks. Whereas DBSCAN is effective for geospatial clustering, K-means excels in refining clusters based on multidimensional attributes like sales, inventory, and customer demographics. The combination of these methodologies' accounts for limitations in traditional clustering techniques and allows for more robust segmentation in physical retail environments that have divergent customer demographics, sales, and inventory (Kumar et al., 2023b).

19.2.3 Causal Inference in Retail

Studying the impact of interventions, such as pickup fee elimination, requires robust causal inference methods. The gold standard for causal inference is randomized controlled trials (Fisher, 1935), but their implementation in retail is constrained by operational and geographical challenges. Difference-in-Differences (DiD) is an alternative method that has gained significance in evaluating interventions in observational settings. Card and Krueger (1994) demonstrated the efficacy of DiD in isolating treatment effects by comparing pre- and post-intervention trends between treated and control groups.

Synthetic control (Abadie et al., 2010) and regression discontinuity design (Hahn et al., 2001) are other elaborate causal methods. However, their dependence on specific assumptions or data structures constrains their flexibility in retail contexts with heterogeneous store environments. Since DiD's can control time-invariant confounders, it becomes a practical choice for evaluating the impact of fee elimination across geographically and operationally diverse stores. It does have a straightforward implementation.

19.2.4 Distinct Contributions of This Chapter

This study stands out by integrating advanced clustering techniques with causal inference methods to address the complicated issue of evaluating

BOPIS fee elimination in offline retail environments. The novel contributions of this research span methodological innovations, practical applications, and provide the sellers with insights that they can act on.

19.2.4.1 Integration of Clustering and Causal Inference

While clustering methods such as K-means and DBSCAN have been applied in retail, their joint use in the context of causal analysis remains under-explored. This study uses a two-step clustering process that begins with DBSCAN for spatial clustering to group geographically proximate stores, mitigating network effects and ensuring that test and control groups are spatially distinct. This is followed by K-means to refine these clusters based on multidimensional operational attributes such as sales volume, customer demographics, and inventory levels. This two-step method ensures that clusters are not only geographically cohesive but also operationally similar, providing a strong foundation for causal inference using the Difference-in-Differences (DiD) methodology.

19.2.4.2 Causal Analysis in Offline Retail

Previous research majorly focuses on online retail or generalized pricing interventions, whereas this study targets offline retail environments, where operational complexities, regional variability, and customer demographics play a significant role. By applying the DiD method at the geo/store level, the research isolates the causal impact of fee elimination while accounting for confounding factors such as seasonal trends, competitor actions, and local economic conditions (Arora et al., 2025). The inclusion of assumption validation, such as verifying parallel trends, improves the reliability of the causal estimates.

19.2.4.3 Solution to Avoid Network Effects

A major challenge in retail experimentation is the presence of network effects implying that changes in one store can influence nearby stores or related entities. This chapter overcomes this challenge by selecting test and control stores that are geographically distant but operationally similar. The joint use of DBSCAN and K-means clustering reduces spillover effects, thereby preserving the validity of the experimental design and causal attribution. This method also highlights a scalable framework for managing network effects in multi-location retail studies.

19.2.4.4 Evaluation of Risk in the Methodologies

This chapter evaluates the limitations associated with the chosen methodologies. There is a risk of biases in clustering (e.g., parameter sensitivity in DBSCAN), and there is dependence on the assumption of parallel trends in DiD. They have been both accounted for and that helps to strengthen the credibility of the findings. It also provides direction for future research to improve these methodologies in retail contexts.

19.2.4.5 Scalability

The methodological framework developed in this study is highly practical for real-world applications. Retailers can leverage this framework to conduct localized experiments, optimize fee structures, and roll out policy changes across diverse markets. Scalability, flexibility to different retail contexts, geographies, and interventions beyond pickup fee elimination comes through a blend of clustering and causal inference methodologies.

19.3 Methodology

The purpose of eliminating pickup fees for retail stores is to evaluate its impact on key business and customer metrics, such as average sales, order volumes, and customer behavior. The seller aims to determine whether this fee elimination can lead to pickup adoption and drive incremental revenue. The sellers at the same time want to reduce the operational and delivery revenue cannibalization risks. The chapter also examines how indicators such as geographic location, customer demographics, and operational capacity influence outcomes, enabling optimization across segments.

The methodology begins with data collection of operational, geographic, and demographic store attributes. Data analysis addresses missing values, outliers, and feature scaling for compatibility with clustering algorithms. A two-step clustering approach is used to segment the stores. DBSCAN groups geographically proximate stores to minimize network effects. K-means refines clusters based on operational metrics, demographics, and sales attributes. A statistical power analysis determines the required sample size for reliable test and control groups.

The chapter tracks key metrics over three critical phases: a two-week pre-intervention period, a ramp-up phase, and a two-week post intervention

period. Key performance metrics such as average sales and order distributions (pickup vs. delivery) are analyzed to assess the broader impact of fee elimination on customer behavior and operational dynamics. This framework provides insights into the strategy's effectiveness while accounting for the risks of a retail environment (Figure 19.1).

19.3.1 Data Collection

This study was conducted for a seller carrying general merchandise. This retailer operates both in physical stores and online, with locations spanning multiple geographies. Data from 160 stores were considered for this study, which included different data types such as operational data, geographic distribution, and customer demographics.

19.3.1.1 Operational Data

Store operational data were sourced from systems such as Point-of-Sale (POS) for sales, orders, and profit margins, inventory management systems for stock levels, and workforce systems for employee counts.

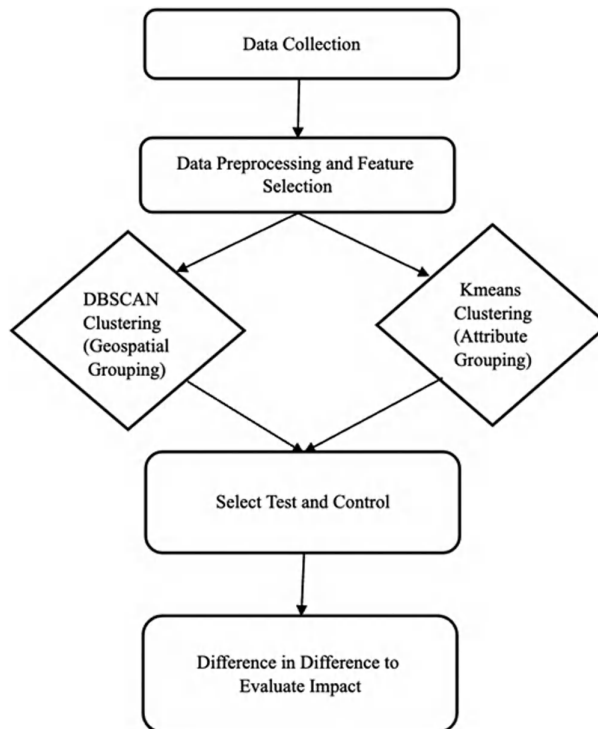


Figure 19.1 Methodology for evaluating the impact of pickup fee elimination in retail stores

19.3.1.2 Geographic Data

Geographic information was obtained through store location records, and longitude, latitude, and regional categorizations were sourced from that.

19.3.1.3 Demographic Data

Third-party databases and retailer loyalty programs provided consumer demographic data, which gives insights into population density and median household income.

All the data collected are proprietary and cannot be shared publicly due to confidentiality and business sensitivity concerns. Sharing such data could expose competitive vulnerabilities or operational strategies and may violate customer privacy regulations. Only aggregated results and summaries are presented in academic outputs to be compliant and maintain confidentiality.

19.3.2 Data Preprocessing and Feature Correlation

19.3.2.1 Data Preprocessing

One of the critical data pre-processing methodologies is missing value imputation. This was conducted for all variables. Variables that had 80% of their values missing were considered superfluous and were dropped from the study. For outlier detection, interquartile range (IQR) and box plots were performed for all variables. To handle these outliers, capping and flooring were performed. This involved capping values at the 99th percentile and flooring them at the 1st percentile, replacing extreme values with mean or median. Inputs were also checked for logical consistency; for example, `median_household_income` cannot have negative values.

19.3.2.2 Feature Correlation

Pearson correlation coefficients ($|r|$), one of the most common correlation metrics, were involved to generate feature correlations. A correlation matrix was developed to visualize the relationships between these variables. Variable pairs with high positive or negative correlations ($|r| > 0.8$) indicate similar and overlapping information. For such highly correlated pairs, only the most representative variable was retained. Operational metrics were analyzed for interdependencies, and attributes with moderate correlations (0.5

$|r| < 0.8$) were further assessed. Attributes with low correlations ($|r| < 0.5$) were reviewed for their independent explanatory value, ensuring diversity. Data dictionary shown in Table 19.1. Demographic variables were also included after analyzing their correlation with operational and sales metrics, adding a unique dimension to the dataset.

Table 19.1 Data Dictionary

<i>Variable Name</i>	<i>Explanation</i>
store_id	A unique identifier assigned to each store in the dataset.
Latitude × longitude	Geographic coordinates represent the location of the store.
average_daily_sales	The average sales generated by the store per day. It is calculated by dividing the total sales revenue for the month by the number of operational days in the month.
average_profit_margin	The average percentage or dollar value of profit earned from sales by the store per day. It is calculated as the total profit for the month divided by the total sales revenue for the month.
average_orders_per_day	The average number of customer orders processed by the store daily. It is calculated as the total number of orders fulfilled by the store during the month divided by the number of days in the month.
store_size_sqft	The size of the store is in square feet.
employee_count	The total number of employees working in the store.
inventory_level	The quantity of inventory available at the store indicating stock availability.
population_density	The number of people living per unit area (e.g., per square mile or square kilometer) in the store's vicinity.
median_household_income	The median income of households in the store's surrounding area. It provides insights into the economic profile of the customer base, often influencing purchasing behavior and product mix.

19.3.3 DBSCAN Clustering (Geospatial Grouping)

Density-based spatial clustering of applications with noise (DBSCAN), introduced by Ester et al. (1996), is a clustering algorithm that creates homogeneous clusters by grouping closely located points while labeling sparse regions as outliers or noise. Its ability to handle nonlinear data distributions makes it particularly relevant for real-world scenarios, especially in spatial clustering. In this chapter, DBSCAN is used to cluster stores based on geographic attributes (e.g., latitude and longitude). It leverages its capability to identify natural groupings without requiring a predefined number of clusters.

19.3.3.1 DBSCAN Algorithm Intuition

DBSCAN clusters points based on density and identifies outliers as noise. It uses two parameters: *eps*, the radius defining a neighborhood, and *min_samples*, the minimum number of points required to form a dense region. The algorithm begins by marking all points as unvisited. For each point, it calculates the number of neighbors within the *eps* radius. If the number of neighbors meets or exceeds *min_samples*, the point is classified as a core point and forms a new cluster. The cluster is expanded by iteratively including all reachable neighbors that also satisfy the density criteria. Points that do not belong to any cluster are marked as noise. The core intuition of DBSCAN is that clusters are dense regions separated by areas of lower density. This allows DBSCAN to detect clusters of arbitrary shapes and sizes without the need for a predefined number of clusters. The algorithm evaluates clustering quality using metrics like the silhouette score. Silhouette score measures how well points fit within their assigned clusters compared to others. By tuning the *eps* parameter, meaningful and well-separated groupings can be identified. This makes DBSCAN highly effective in handling irregular distributions and noise.

19.3.3.2 Cluster Quality Evaluation

DBSCAN performance is evaluated using the silhouette score. The silhouette value is a measure of how similar an object is to its own cluster (cohesion) compared to other clusters (separation).

The silhouette score for a single point i is computed as:

where

$a(i)$ = average distance between point i and all other points in its cluster

$b(i)$ = minimum (average) distance between point i and all points in each other cluster)

The silhouette ranges from -1 to $+1$, where a high value indicates that the object is well matched to its own cluster and poorly matched to neighboring clusters. A score near 0 suggests overlapping clusters, while negative values indicate faulty clustering (Rousseeuw, 1987).

19.3.3.3 Adjust Cluster Parameters

The ϵ parameter is iteratively tuned to optimize clustering. By evaluating different ϵ values alongside their corresponding silhouette scores, the optimal ϵ is determined. This allows a balance between meaningful clusters and minimal noise, making DBSCAN effective for segmenting stores based on metrics like location, sales, and inventory levels. The ability to adjust these parameters dynamically improves the flexibility and accuracy of DBSCAN in clustering complex datasets.

19.3.4 K-Means Clustering

K-means clustering was first used by James MacQueen in 1967. It is an unsupervised learning algorithm that begins by selecting random points as initial centroids and then assigns data points to clusters based on their proximity to these centroids. The centroids are subsequently updated to minimize variance within clusters. Unlike DBSCAN, K-means requires the number of clusters (k) to be predefined, making it useful specifically for datasets with linear separations (Hartigan & Wong, 1979). In this study, K-means was used alongside DBSCAN to refine clustering results based on store attributes such as sales, inventory, and customer demographics after spatial clustering was completed.

Though DBSCAN excels at identifying spatial clusters and handling noise, it is less effective for datasets with overlapping densities or requiring

compact, well-separated groupings. K-means complements DBSCAN by partitioning store attributes (e.g., sales, inventory, employee count) into distinct clusters. It leverages its effectiveness with spherical clusters. By using K-means after DBSCAN, the resulting clusters are both geographically meaningful and operationally relevant.

19.3.4.1 Algorithm Intuition

The algorithm follows these steps:

Step 1: Initialize k centroids randomly or using predefined methods (e.g., K-means++ for optimized starting points) (Arthur & Vassilvitskii, 2007).

Step 2: Assign each data point to the nearest centroid, creating k clusters.

Step 3: Update each centroid by calculating the mean of all points assigned to its cluster.

Step 4: Iterate steps 2 and 3 until a defined number of centroids (k) is obtained or the iteration limit is reached.

19.3.4.2 Evaluate Cluster Quality

The quality of K-means clustering is evaluated using metrics such as inertia (sum of squared distances) and the silhouette score.

Inertia measures the total squared distance between data points and their assigned cluster centroids. Lower inertia values indicate stronger, more compact clusters. However, inertia does not account for the separation between clusters, making it less useful for generating the optimal number of clusters.

$$\text{Inertia} = \sum_i \sum_x ||x - \mu||^2$$

where

- x is a data point
- μ is the centroid (mean) of cluster i
- $||x - \mu||$ is the Euclidean distance between x and μ
- First $\sum$ sums over all clusters i
- Second $\sum$ sums over all data points x in cluster i

19.3.4.3 Adjust Cluster Parameters

To determine the optimal number of clusters (k) in the K-means analysis, we employed a combination of established techniques. The elbow method

was used to plot inertia (sum of squared distances) against different k values, identifying the “elbow point” where the reduction in inertia began to plateau, suggesting the optimal k (Thorndike, 1953). In addition to the elbow method, silhouette analysis was performed to evaluate silhouette scores across different k values, with the highest score representing the most appropriate cluster count by balancing intra-cluster cohesion and inter-cluster separation (Rousseeuw, 1987). To confirm the results, we visualized the outputs of K-means clustering to understand how homogeneous the clusters were in terms of their internal composition and how well-separated they were from each other.

19.3.5 Select Test and Control

Figure 19.2 shows the process for determining test and control stores for a Difference-in-Differences (DiD) analysis. It starts with a statistical power analysis to calculate the number of stores required, how long to run the

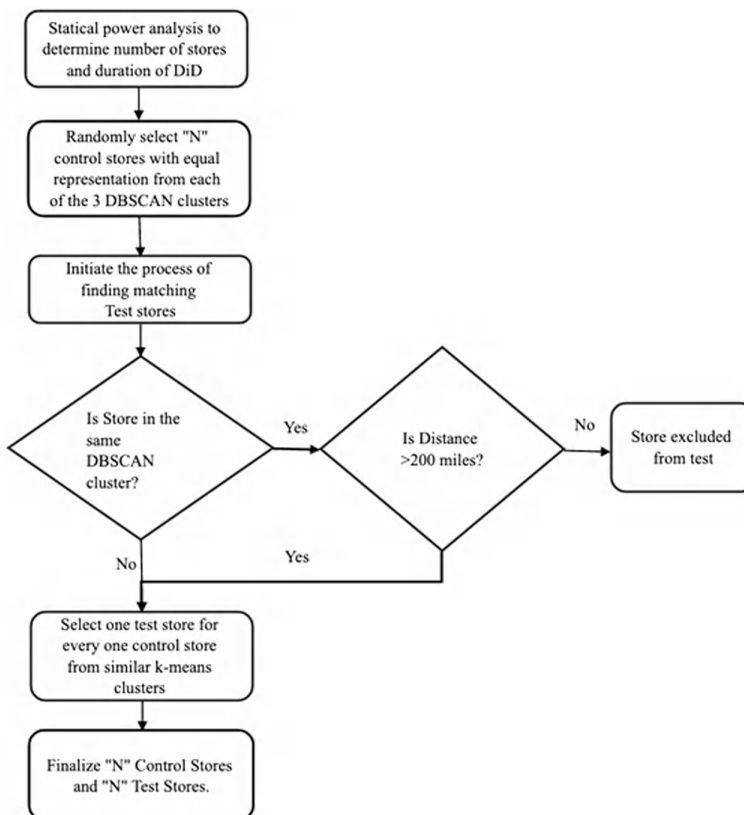


Figure 19.2 Decision flow for selecting the test and control stores

intervention and the time period to use for comparison. Once the necessary sample size of stores is determined, control stores are randomly selected with equal representation from each spatial region, identified through DBSCAN clustering. Thereafter comes the second step of finding matching “test stores.” A preliminary check is used to confirm that test stores are in the same DBSCAN cluster as control stores and are located at least 200 miles apart. The 200-mile threshold was determined through a sensitivity analysis. The analysis showed that this distance of 200 miles significantly reduces cross-movement of users between stores, helping minimize network effects. Despite this threshold, the analysis confirmed that there were ample number of stores available to choose for test and control groups. Only if these criteria are not met, test stores are selected from similar K-means clusters. Lastly, the selection process undergoes a bias evaluation to ensure fairness and representativeness in the test-control pairings. This approach combines clustering techniques, sensitivity analysis, and statistical rigor to minimize bias and maintain analytical validity.

19.3.6 Difference-in-Differences to Evaluate Impact

Once the test and control stores were selected, we proceeded to measure the impact of eliminating the pickup fee on a key sales metric. Traditional A/B testing could not be applied in this case due to network effects, where changes in one store could influence nearby stores. That makes it difficult to isolate the individual store’s impact. To ensure validity, we implemented Difference-in-Differences (DiD) by selecting comparable test and control stores. Additionally, we accounted for network effects, recognizing that changes in one store—such as eliminating the pickup fee—could influence nearby stores. For example, customers from control stores might shift to test stores to take advantage of the fee elimination. This may artificially inflate test performance while reducing control outcomes. To mitigate such spillover effects, we selected test and control stores that were geographically distant, such as 200 miles apart, yet operationally similar.

19.3.6.1 Algorithm Intuition

The core intuition of DiD lies in isolating the intervention’s effect by comparing the changes in outcomes for treated and control groups, at the same time accounting for shared underlying trends. This relies on the parallel trends assumption, which states that both groups would have exhibited

similar trends in the absence of treatment. By subtracting the pre-treatment differences from the post-treatment differences, DiD effectively removes confounding influences. The method is implemented using a regression model with the following formula:

$$Y_{it} = \alpha + \beta^1 \text{Post}_t + \beta^2 \text{Treatment}_i + \beta^3 (\text{Post}_t \times \text{Treatment}_i) + \varepsilon_{it}$$

where

Y_{it} is the outcome for unit i at time t ,

Post_t indicates the post-intervention period,

Treatment_i indicates whether the unit belongs to the treated group,

$\text{Post}_t \times \text{Treatment}_i$ captures the interaction effect (treatment effect).

19.3.6.2 Algorithm Intuition

For validity of DiD results, several critical assumptions must hold:

Parallel Trends Assumption: The treatment and control groups must follow the same trajectory over time in the absence of treatment. This can be verified through pre-treatment trend comparisons using visual inspection or statistical tests.

No Simultaneous Interventions: There should be no other interventions or external shocks affecting the groups differently during the study period.

Stable Composition of Groups: The composition of treated and control groups must remain constant over time.

19.3.6.3 DID Output Evaluation

The key metric in DiD analysis is the interaction coefficient β^3 . This interaction coefficient captures the causal impact of the intervention. Statistical significance and confidence intervals are assessed for the reliability of the results.

19.4 Results

19.4.1 Missing Value Analysis

The study of key inputs revealed missing values in the `store_size_sqft` and `employee_count` columns, requiring remediation for accurate modeling.

These were accounted for by imputing values based on average population density to confirm data completeness.

19.4.2 Outlier Detection Analysis Results

The analysis identified outliers in the revenue metrics of average_daily_sales, average_profit_margin, and average_orders_per_day, which accounted for approximately 1% of the data. To account for this, values below the 1st percentile were floored and data values above the 99th percentile were capped. Variables such as store_size_sqft, employee_count, and inventory_level had their distributions well-defined, with values within expected ranges. However, median_household_income revealed a few negative values; this discrepancy was rectified by converting them to positive values.

19.4.3 Attribute Analysis and Findings

This section presents an analysis of the key inputs used in the study. We have looked at their distributions and what that implies. Each attribute was evaluated for patterns, identified for variability, and confirmed for suitability for clustering and causal analysis.

- average_daily_sales: The sales distribution shows most stores cluster around a daily sales range of \$200,000–\$400,000. There is a long tail extending toward higher sales (up to \$700,000).
- average_profit_margin: The profit margin distribution is uniform with most stores having profit margins averaging between 7.5% and 15%. The peak is around 12%.
- average_orders_per_day: The orders distribution represented by a histogram shows stores processing between 1000 and 2500 orders per day. This distribution has less variance compared to other distributions.
- store_size_sqft: Most stores are medium-sized, clustering around 1500–2000 sqft. There is a gradual decline for larger sizes beyond 3000 sqft.
- Employee_count: The employee count distribution peaks around 40–50 employees. This indicates the typical workforce size for most stores. A smaller number of stores have employee counts exceeding 70 or fewer than 20.
- inventory_level: Inventory levels are between 6000 and 10,000 units.

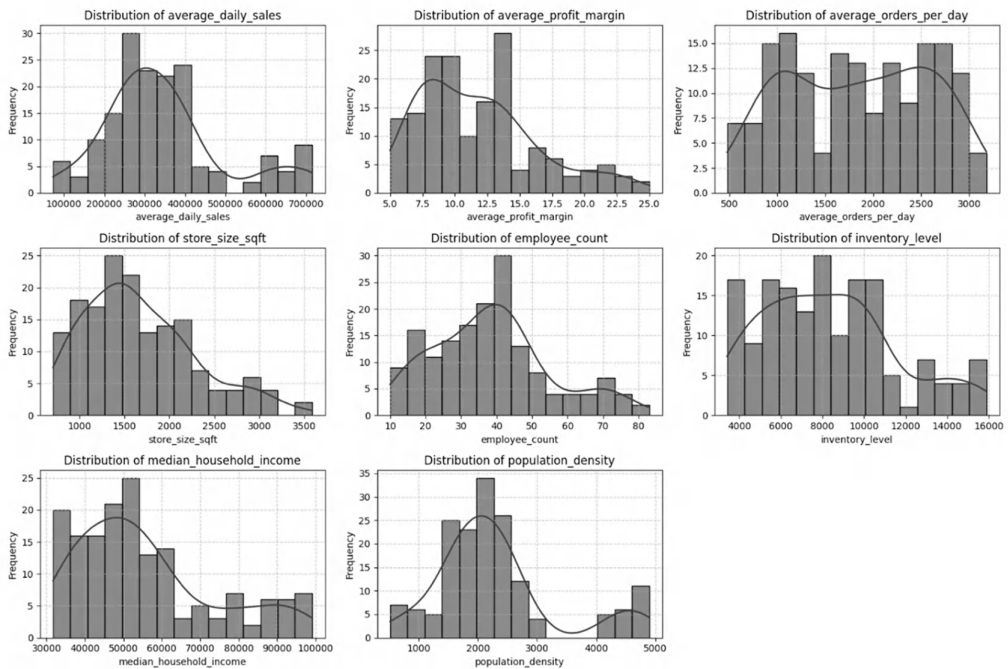


Figure 19.3 Distribution of attributes

- **median_household_income:** The median household income is centered around \$70,000 and follows a long-tail distribution.
 - **population_density:** Most stores are located in moderately populated areas (peak around 2000). A fewer number of stores serve sparsely populated (<1000) and highly urbanized regions (4500–5000). Therefore, there is a need for customized strategies for stores in outlier locations.
- Figure 19.3 shows distribution of attributes.

19.4.4 Analysis of the Feature Correlation Matrix

The feature correlation matrix depicts the relationships between different variables in the dataset. By analyzing these correlations, we can derive insights into the interdependence among the features (Figure 19.4).

19.4.5 Analysis of the Feature Correlation Matrix

The feature correlation matrix provides the relationships between different variables within the dataset.

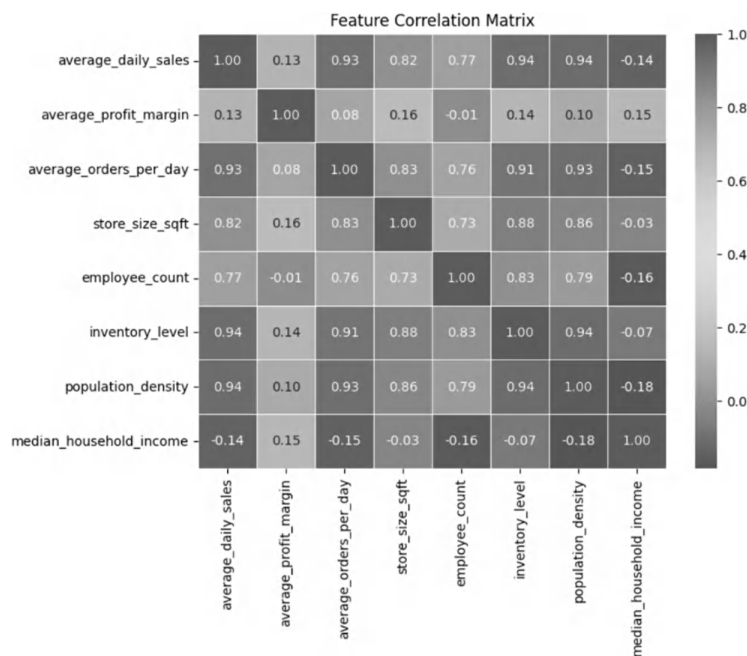


Figure 19.4 Feature correlation matrix

19.4.5.1 Strong Correlations

Several strong positive correlations are observed in the correlation matrix. Average_daily_sales shows a high correlation with inventory_level ($r = 0.94$), population_density ($r = 0.94$), and average_orders_per_day ($r = 0.93$). This indicates that stores with higher inventory levels or higher population densities have increased daily sales and order volumes. Similarly, inventory_level is strongly correlated with population_density ($r = 0.94$) and average_orders_per_day ($r = 0.91$), suggesting that inventory planning is intricately linked with customer demand.

19.4.5.2 Medium Correlations

Medium positive correlations are observed between store_size_sqft and inventory_level ($r = 0.88$) as well as average_daily_sales ($r = 0.82$). This means that larger stores carry more inventory and generate higher sales. Additionally, employee_count shows moderate correlations with average_daily_sales ($r = 0.77$), inventory_level ($r = 0.83$), and average_orders_per_day ($r = 0.76$), implying that workforce size is linked with operational activity and customer demand.

19.4.5.3 Weak Correlations

Weak correlations are seen between `average_profit_margin` and most variables, with the strongest being `store_size_sqft` ($r = 0.16$). This implies that profit margin is relatively independent of operational indicators like store size or sales volume, potentially driven more by pricing strategies or cost efficiencies. `Median_household_income` has weak negative correlations with `average_daily_sales` ($r = -0.14$), `average_orders_per_day` ($r = -0.15$), and `population_density` ($r = -0.18$), suggesting that higher household income areas may not directly translate to higher sales or orders, which may reflect diverse customer preferences or competition dynamics.

19.4.5.4 Summary

For clustering, it is important to retain variables that provide diverse and independent signals while eliminating redundancy caused by highly correlated attributes. For instance, `average_sales` and `average_orders` are highly correlated, so only `average_sales` was retained to represent the revenue aspect effectively. Within operational attributes like `store_size_sqft`, `employee_count`, and `inventory_level`, which show medium to high correlations, `inventory_level` was chosen as it also strongly overlaps with sales. `Average_profit_margin` was also retained as a variable of analysis since its correlation with other variables is minimal, offering a unique angle. From the demographic attributes, `median_household_income` was retained despite its lower correlation with sales, as it adds diversity to the data. This selection ensures the clustering algorithm focuses on meaningful variations while avoiding redundancy.

19.4.6 Results from DBSCAN Clustering

19.4.6.1 Clusters

DBSCAN identified three clusters (Cluster 0 (blue), Cluster 1 (orange), and Cluster 2 (green)). Each cluster represents a group of spatially dense points within the defined neighborhood radius (`eps`). The ellipses surrounding the points show the approximate spherical ranges (or boundaries) of each cluster, underscoring the density-based structure of DBSCAN.

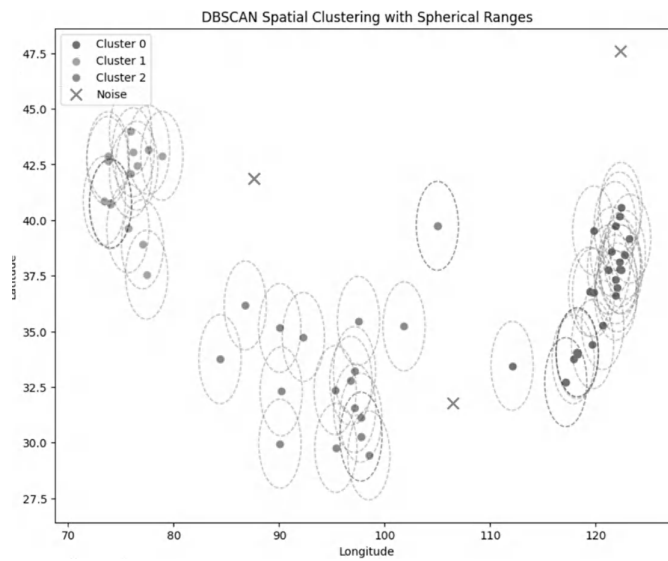


Figure 19.5 DBSCAN clustering

Core Points: These points are located in the densest regions of their respective clusters and serve as the “core” for clustering. They form the basis for expanding the cluster by including neighboring points.

Border Points: These points lie near the borders of clusters and are also in the neighborhood radius of core points.

Noise Points: Noise points are shown in red crosses. They do not belong to any cluster due to their lack of proximity to core points.

The graph below shows three sets of separate clusters identified by DBSCAN. The spherical ranges highlight the clusters’ approximate boundaries and illustrate how DBSCAN clusters can overlap or remain distinct based on density thresholds (eps and min_samples). The red noise points highlight DBSCAN’s ability to filter out outliers that do not fit within any cluster (Figure 19.5).

19.4.6.2 Evaluate Cluster Quality

The silhouette score for the clustering is 0.65, which indicates moderately well-separated clusters. Scores close to 1 suggest distinct clusters. Lower scores indicate overlapping clusters. This value of 0.65 suggests the clustering is logical.

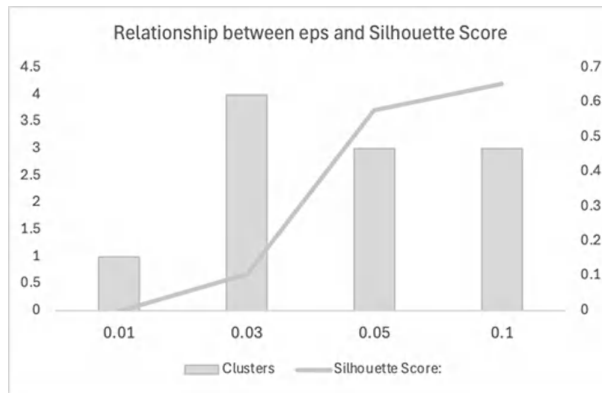


Figure 19.6 Graph of eps and silhouette score

19.4.6.3 Finetune Cluster Parameters

The DBSCAN tuning results show how the eps parameter impacts the number of clusters and silhouette scores, which measure cluster quality. At $\text{eps} = 0.01$, only one cluster was identified, making it extremely difficult to compute the silhouette score. After increasing eps to 0.03, it generated four clusters but with a low silhouette score of 0.105, indicating poor cluster separation. After further increasing eps to 0.05, the number of clusters reduced to three, and the silhouette score improved to 0.578. The most optimal result was achieved at $\text{eps} = 0.1$, with three clusters and a silhouette score of 0.654, indicating well-defined clusters with good separation and compactness (Figure 19.6).

19.4.7 K-Means Clustering Results

19.4.7.1 Clusters

The K-means identified six clusters based on sales, inventory levels, profit margin, and income. Cluster 3 is the largest followed by Cluster 5. Clusters 2 and 4 are moderately sized. Clusters 0 and 1 represent smaller segments.

The below clusters explain the characteristics of each group:

Cluster 0: Stores in this cluster exhibit low daily sales, low profit margins, small inventory levels, and the lowest median household income. This would indicate the underperformance of stores in less affluent regions.

Cluster 1: This cluster exhibits moderate sales, low profit margins, high inventory levels, and high median household income. This indicates stores in affluent regions with moderate profitability.

Cluster 2: This cluster represents stores with the lowest daily sales, moderate profit margins, and small inventory levels. This cluster may include underperforming or small-format stores in regions with medium income.

Cluster 3: This cluster has high-performing stores with high daily sales, significant profit margins, and large inventory levels. The median household income is relatively low.

Cluster 4: Stores with the highest daily sales, moderate profit margins, and the largest inventory levels. These stores are in affluent regions. They likely represent top-performing urban or suburban locations.

Cluster 5: These stores exhibit moderate daily sales but stand out with the highest profit margins and high-income levels. These are highly profitable stores due to optimized operations or premium pricing strategies (Figure 19.7).

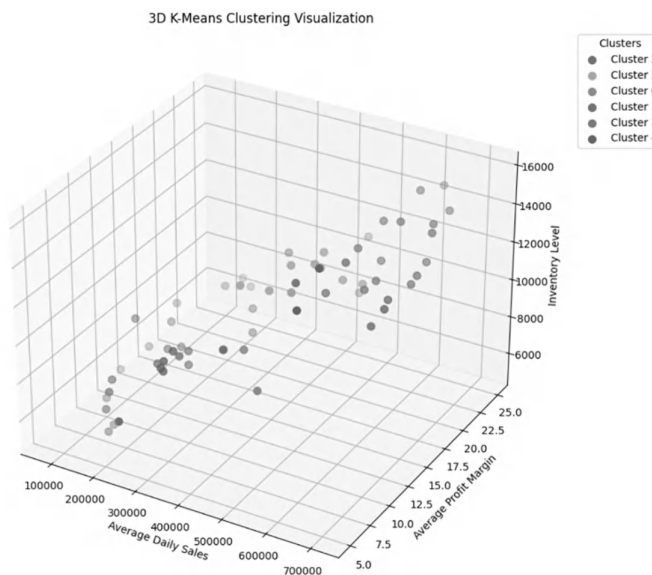


Figure 19.7 K-means cluster visualization

19.4.7.2 Evaluating Cluster Quality

The clustering results show an inertia value of 64.35, indicating cohesive clusters with data points closely grouped around their centroids. Although inertia alone is insufficient to evaluate the solution due to its tendency to decrease with more clusters, a silhouette score of 0.33 reflects moderately well-separated clusters. This suggests the clustering is somewhat effective but leaves room for improvement. The cluster distribution showcases variability, with some clusters representing broader groupings (e.g., Clusters 2 and 5), while smaller clusters, such as Cluster 6, may indicate niche segments or outlier groups.

19.4.7.3 Finetune Cluster Parameters

Elbow method (left chart): The plot shows the inertia decreasing as the number of clusters increases. Inertia is defined as the sum of squared distances from points to their cluster centers. An “elbow” is observed around four to six clusters. This highlights the trade-off of minimizing inertia while also preventing overfitting with too many clusters.

Silhouette score (right chart): The silhouette score measures the quality of clustering by evaluating the cohesion within clusters and separation between clusters. A high silhouette score is observed at six clusters (Figure 19.8).

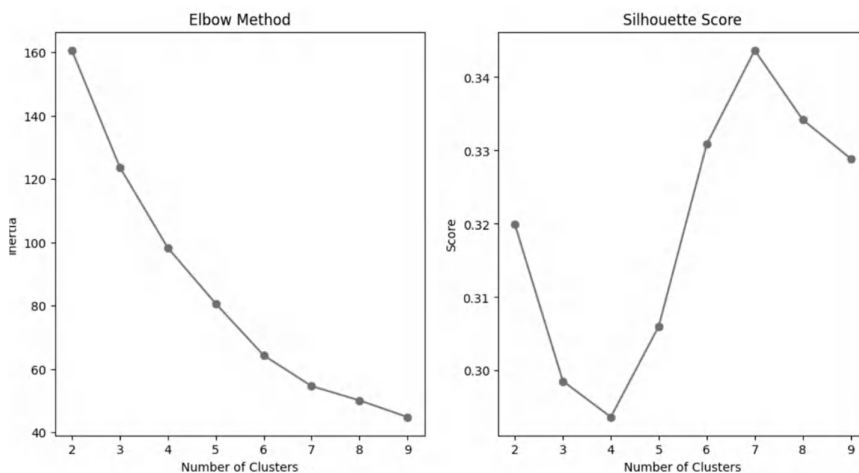


Figure 19.8 Graph of the elbow method and silhouette score

19.4.8 Difference-in-Differences (DiD) Results

19.4.8.1 Details of Experiment Launch

The experiment was designed to launch with the minimum number of stores. This would reduce negative impacts and ensure a manageable environment for data analysis. The timing of the launch was scheduled for Thursday. This enabled the team to monitor and address any operational and technical difficulties before the weekend traffic. The intervention was integrated into the online checkout process for test stores, where the pickup fee was automatically waived for all users placing a pickup order. This approach ensured minimal disruption to users.

19.4.8.2 Statistical Power Analysis

Statistical power analysis was conducted to confirm the experiment was adequately designed to detect a meaningful effect size while reducing the risk of Type II errors. Based on the analysis, an effect size of 4% was determined. This meant having at least 60 stores in each control and test group. Sales data was collected for a 2-week period prior to the launch to establish a baseline. This was followed by a 2-week ramp-up phase to account for novelty or primacy effects as users adapt to the intervention. Lastly, a post-period of 2 weeks was included to allow the system to stabilize.

19.4.8.3 DID Assumptions

The parallel trends assumption of DiD states that, in the absence of the intervention, the control and test groups will follow similar trends over time. When studying the data, the average sales for both test and control groups exhibit relatively stable trends during the pre-intervention period, with no deviations.

19.4.8.4 Average Sales Impact with Intervention

The figure illustrates the average sales per store for both control and test groups. It is segmented into a pre-intervention phase, ramp-up phase, and post-intervention phase. During the pre-intervention phase, the sales trends for both groups remained stable, with a small 1.03% difference. This small variation is expected as DBSCAN and K-means clustering can optimize

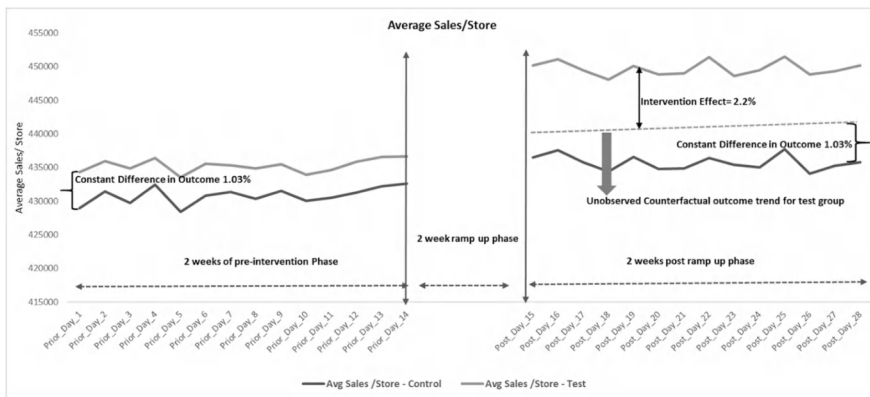


Figure 19.9 Average sales impact pre and post with intervention

matching based on specified attributes, though some marginal error persists. This alignment satisfies the parallel trends assumption, which is essential for Difference-in-Differences (DiD) analysis. Following the intervention, the test group experienced a 3.3% increase in average sales compared to its pre-intervention period. The control group saw a 1.1% increase over the same period. The net impact of the intervention was calculated as a 2.2% lift in average sales for the test group. This significant increase highlights the effectiveness of the intervention (Figure 19.9).

19.4.8.5 DiD Output Evaluation

In the below equation, “Post” column indicates the intervention period, and the “Treatment” column differentiates between control and test groups. A constant term (α) is introduced in the regression model to represent the baseline average sales for the control group during the pre-intervention period. An interaction term (“Post_Treatment”) represents the causal effect of the intervention. An OLS regression model is fitted using these variables, and the output provides insights into the statistical significance and magnitude of the intervention’s effect.

$$Y_{it} = \alpha + \beta^1 \text{Post}_t + \beta^2 \text{Treatment}_i + \beta^3 (\text{Post}_t \times \text{Treatment}_i) + \varepsilon_{it}$$

- Y_{it} : Represents the outcome variable, in this case the average sales for store i at time t . This dependent variable is analyzed to measure the intervention’s effect.
- α (Constant: \$430,800): The intercept indicates the baseline average sales for the control group during the pre-intervention period. It

provides a reference point for comparing changes between the test and control groups.

- Post_i (Coefficient: \$294): A binary variable that takes the value of 0 during the pre-intervention period and 1 during the post-intervention period. This binary variable captures the effect of time-related changes. However, with a p -value of 0.526, this effect is not statistically significant, suggesting that time alone did not significantly impact sales.
- Treatment_i (Coefficient: \$4453): A binary variable distinguishing the groups, where 0 represents the control group and 1 represents the test group. This coefficient highlights the baseline difference between the test and control groups before the intervention. The positive and highly significant value ($p < 0.001$) confirms that the test group initially had higher average sales compared to the control group.
- $(\text{Post}_i \times \text{Treatment}_i)$ (Coefficient: \$9403): The interaction term represents the DiD effect. It captures the incremental change in average sales for

OLS Regression Results						
Dep. Variable:		Avg_Sales		R-squared:	0.960	
Model:		OLS		Adj. R-squared:	0.957	
Method:		Least Squares		F-statistic:	411.1	
Date:		Sun, 19 Jan 2025		Prob (F-statistic):	3.47e-36	
Time:		13:32:33		Log-Likelihood:	-475.31	
No. Observations:		56		AIC:	958.6	
Df Residuals:		52		BIC:	966.7	
Df Model:		3				
Covariance Type:		nonrobust				
		coef	std err	t	P> t	[0.025 0.975]
const		4.308e+05	325.778	1322.491	0.000	4.3e+05 4.31e+05
Post		294.0000	460.719	0.638	0.526	-630.501 1218.501
Group		4453.5714	460.719	9.667	0.000	3529.070 5378.073
Post_Group		9403.5000	651.556	14.432	0.000	8096.058 1.07e+04
Omnibus:	0.949	Durbin-Watson:		1.933		
Prob(Omnibus):	0.622	Jarque-Bera (JB):		0.715		
Skew:	-0.276	Prob(JB):		0.700		
Kurtosis:	2.954	Cond. No.		6.85		

Figure 19.10 OLS regression results

the test group due to the intervention, beyond any time-related or baseline differences. This term indicates a 2.2% lift in average sales per store in the treatment group, which is equal to an increase of about \$9403 in average sales per store.

- ε_{it} : The error term accounts for unobserved factors or noise that may influence average sales but are not captured within the model (Figure 19.10).

19.4.8.6 Average Sales Impact by Geospatial Clusters due to Intervention

In Cluster 0, the control group has stable sales in the pre-intervention phase, averaging approximately \$272,000. Post-intervention, the test group sees a significant relative lift of 8–9%, rising from \$284,000 to stabilize around \$302,000. While the control group shows a marginal increase, its performance remains below that of the test group. This consistent growth in the test group emphasizes the intervention's positive impact in this cluster.

In Cluster 1, during the pre-intervention, the average sales for the control group (\$408,000) were consistently lower than those for the test group (\$420,000). Following the intervention, the test group illustrated a significant lift of approximately 7%, with sales averaging around \$450,000. Although the control group also experienced a slight uptick in sales, the test group's performance clearly outshines it, demonstrating the intervention's effectiveness in this cluster.

In Cluster 2, pre-intervention sales are \$610,000 for the control and test groups. Post-intervention, the test group experiences a slight decline of 1.5–2%, while the control group remains stable at pre-intervention levels. This indicates that the zero pick-up fee had a limited or negative effect in this region. This could be due to external indicators or differing customer preferences that did not align with the fee elimination strategy. It is important to



Figure 19.11 Impact on average sales with intervention by geospatial clusters

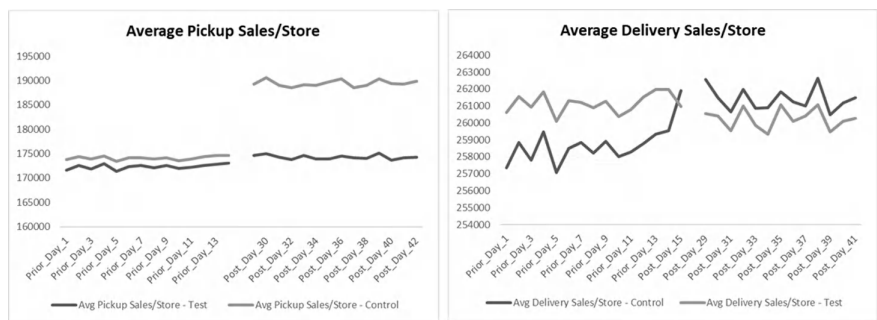


Figure 19.12 Average sales per store between pickup and delivery

examine results at the cluster level to avoid heterogeneous effects, which can occur when aggregated data obscures individual cluster trends (Figure 19.11).

19.4.8.7 Shift between Pickup and Delivery

The objective of this intervention was to enhance sales growth by encouraging customers to opt for pickup orders, which may change sales dynamics. Average sales per store showed a 3.3% increase in test stores, compared to a 1.1% improvement in control stores, resulting in a net positive change through DiD of 2.2%. Pickup sales saw a major uplift of 8.8% in test stores, significantly outpacing the 1.1% rise in control stores, yielding a net change of 7.7%. This shows the intervention’s success in driving a share shift toward pickup orders and encouraging new orders. However, delivery sales in test stores experienced a -0.3% lift compared to a 1.1% increase in control stores, yielding a decline of 1.5%. Despite this drawback, the overall positive impact on sales shows the intervention’s effectiveness in promoting higher-margin pickup orders, underscoring its business value (Figure 19.12 and Table 19.2).

19.5 Risk Assessment

A comprehensive risk management framework was established to ensure the robustness of the experiment. The risks were categorized into customer, business, and operational categories, with a custom mitigation action plan to account each.

Table 19.2 Average Sales per Store between Control and Test

Average Sales/Store	Control Stores	Text Stores	Average Pickup Sales/Store	Control Stores	Text Stores	Average Delivery Sales/Store	Control Stores	Text Stores
Pre-period	430,838	435,292	Pre-period	172,335	174,117	Pre-period	258,503	261,175
Post-period	435,746	449,727	Post-period	174,298	189,431	Post-period	261,448	260,297
Lift	1.1%	3.3%	Lift	1.1%	8.8%	Lift	1.1%	-0.3%
	Change	2.2%		Change	7.7%		Change	-1.5%

19.5.1 Customer Risk

Eliminating pickup fees may inadvertently alter customer behavior, causing dissatisfaction if expectations are not met. For instance, while the intervention encourages a shift toward pickup orders, customers accustomed to delivery may perceive reduced service value. Additionally, customer trust is important to maintain, and it is possible that test stores fail to meet increased pickup demand due to operational bottlenecks, in which case customer trust may reduce in the sellers. Therefore, to minimize these risks, customer feedback is solicited during the ramp-up period, and operational capacities are made more dynamic at test stores to handle fluctuations in order volume.

19.5.2 Business Risk

The major business risk is a profit decline due to the potential cannibalization of delivery orders, which typically have higher margins compared to pickup orders. Therefore, if the intervention fails to generate sufficient incremental revenue from pickup sales, sellers will likely suffer a hit to their bottom lines. The intervention was strategically rolled out in a controlled subset of stores to mitigate this risk. Rolling out in a subset of stores helps in monitoring sales dynamics before scaling. A post-intervention study also quantified the effects on both pickup and delivery sales to help direct future decisions.

19.5.3 Data Integrity Risk

Data accuracy and completeness are essential for clustering, measurement, and data analysis. Missing data, incorrect imputation, or inaccuracies in sales records could impact the validity of the research findings. Data validation and preprocessing steps were implemented to mitigate data integrity risk.

19.5.4 Analytical Risk

Clustering stores based on geographic and operational attributes introduces the risk of suboptimal groups, which could distort the test-control store selection process. While DBSCAN clustering is effective for identifying dense regions, it is sensitive to the choice of parameters (e.g., epsilon and min_samples). This could result in either over-clustering or the exclusion of meaningful data points. K-means clustering also cause risks due to its

dependence on predefined cluster numbers and sensitivity to initial centroid placement. This can cause poorly defined clusters or biased groupings. In Difference-in-Differences (DiD) methodology, a slight deviation in the parallel trends assumption can compromise causal inference. Therefore, validation of this assumption is critical. These risks were minimized through iterative tuning of DBSCAN parameters and careful selection of K-means initialization strategies, in conjunction with sensitivity analyses to validate cluster robustness. Further, pre-intervention analysis confirmed parallel sales trends between test and control groups.

19.5.5 Statistical Power Risk

There is a risk of insufficient statistical power to detect meaningful differences with a small number of stores in the test and control groups. Therefore, statistical power analysis was conducted prior to optimizing the number of stores and test duration.

19.6 Conclusion

The objective of the chapter was to study the impact of eliminating pickup fees in a buy-online-pickup-in-store (BOPIS) retail environment. It focused on customer behavior, sales, and operational dynamics, with the objective of determining whether the intervention could improve customer adoption of pickup services and increase overall sales. A two-step clustering process—DBSCAN and K-means clustering—was used to segment stores based on geographic, operational, and demographic factors. This novel approach ensured balanced test and control groups while also minimizing store-related network effects. Difference-in-Differences (DiD) methodology was implemented to assess the causal impact of the pickup fee elimination. DiD accounts for confounding variables and validates assumptions through pre-intervention trend analysis. The intervention resulted in a statistically significant net lift of 2.2% in average sales, though it fell short of the expected effect size of 4%. DBSCAN Cluster 0 and 1 experienced a significant increase in pickup adoption and sales in line with expectations. Cluster 2 showed negative effects due to external indicators or differing customer preferences. Delivery sales declined slightly in test stores, suggesting some degree of cannibalization. These findings highlight the localized impact of reducing the pickup fee to zero. The results suggest that a one-size-fits-all

method is unsuitable for such interventions. Sellers should adopt customized store strategies based on specific location and market conditions. The chapter presents a unique use case of combining advanced clustering methods with causal inference techniques in an offline retail setting. It also addresses operational, demographic, and geographic nuances while establishing a scalable framework for evaluating pricing interventions in omnichannel retail environments. This approach also offers broad applicability across industries and diverse use cases. Applications could include optimizing delivery fee structures for food delivery services, assessing pricing models for subscription-based platforms, or evaluating the impact of dynamic ticket pricing in the travel and entertainment sectors.

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Index

- 17-point agenda, 327
 - Accountability frameworks, 184
- Active Green Banking Cell, 123
- Adobe Sensei, 312
- Advancements in AI, technologies, 395–397
 - AI adoption strategies, 406–408
 - managerial implications, 408–409
 - data analysis, 400–402
 - reliability and validity, 402–404
 - future research, 410
 - hypothesis testing, 402, 404–405
 - incorporation of, 397–400
 - limitations, 410
 - methodology, 400–401
 - societal factors, 409
- Agility, 24, 51, 290, 366
- Agricultural innovation, 82, 85
- Agricultural Insurance Scheme, 81
- Agricultural Knowledge and Innovation System (AKIS), 83
- AI-assisted analytics, 282
- AI-based financial forecasting (AFF), 266, 268, 269
- AI-driven disruption
 - adopting and implementing, 53
 - challenges, 52
 - deep learning, 48
 - future research, 53–54
 - growth, 53
 - market effectiveness metrics, 49–50
 - methodology, 47
 - ML, 47–48
 - recourse optimization, 50–51
 - top management support, 48–49
 - transformative power, 51–52
- AI-driven risk assessment (ARA), 159, 251, 266, 268, 269
- Airbnb, 130, 144
- AI segments customers, 49–51
- Albert, 313
- American Clean Energy Initiative, 280
- Analysis of Moment Structures (AMOS), 258, 259, 261
- ANOVA, 168–170, 240, 242
- AnyVision, 11
- Artificial intelligence (AI), 2, 14–16, 20–24, 26, 28–31, 35, 38–40, 45–46, 60–62, 65, 70, 72, 74, 154–155, 228–229
 - advantages of, 233–234
 - AI-driven risk assessment, 251
 - algorithms, 9, 177, 189
 - analytics, 158, 178
 - application, 3
 - automated sustainability reports, 157
 - blockchain integration, 186
 - in business intelligence systems, *see* Business intelligence systems
 - capabilities of ChatGPT, 318–320
 - in circular economy system, 171–172
 - corporate governance reporting, *see* Corporate governance reporting
 - data analysis, 258–266
 - mediation analysis, 268–269
 - regression weights, 266–267
 - decision-making, 252

- decision-making in circular supply chains, 159–160
- definition, 1, 3–4
- disadvantages of, 234–235
- discussions, 269–273
- emerging trends, 294–296
- energy demand forecasting, 159
- environmental, social, and governance (ESG), *see* Environmental, social, and governance (ESG)
- in environmental impact assessments, 159
- features of, 232–233
- financial forecasting, 254–255
- and financial sustainability, 249–251
 - AI-driven risk assessment, 251
 - credit scoring, 253
 - decision-making, 252
 - financial forecasting, 254–255
 - financial transparency, 255
 - fraud detection and compliance, 253–254
 - green investments, 252–253
 - mediator, 255
- financial transparency, 255
- fraud detection and compliance, 253–254
- Green, 37, 40
- green investments, 252–253
- integration of, 154–155
- intersection of, 249–251
- and inventory management, 275–277
 - benefits of, 289–291
 - emerging solutions, 280–283
 - traditional challenges, 278–280
- key challenges of
 - algorithmic bias, 292
 - data availability, 292
 - ethical concerns, 292
 - legacy logistics, 292–293
 - quality issues, 292
 - regulatory challenges, 293
- in logistics, 159
- machine learning in carbon footprint reduction, 156
- in manufacturing, 160
- marketing tool, 311–313
- methodologies, 287–288
 - analysis, 288
 - data collection, 288
 - implementation process, 288
 - key challenges, 289
 - objectives, 229
 - in product management, 157
 - in product recycling systems, 157
 - recommendations, 296–298
 - in renewable energy, 156
 - research methodology
 - respondents sample, 256–257
 - sampling methods, 256
 - sampling techniques, 256
 - scaling, 257–258
 - in resource management, 158
 - review of literature, 230–232
 - risk assessment, 159
 - scope of study, 229–230
 - in SDG, 156
 - sensor networks, 157–158
 - Specific Regulations, 187
 - in sustainability analytics review, 156
 - sustainable business development, 302–304
 - application of, 308–311
 - challenges of, 314–317
 - new AI trends in, 317–318
 - significance of, 304–308
 - techniques of explainable, 313–314
 - sustainable business intelligence, *see* Sustainable business intelligence
 - sustainable consumer behaviour, 157
 - in sustainable logistics, 275–277
 - advanced technologies, 283–286
 - benefits of, 289–291
 - emerging solutions, 280–283
 - real-world applications of, 286–287
 - traditional challenges, 278–280
 - in sustainable retail management, 160
 - sustainable urban planning, 157
 - usages of, 235–236
 - use of, 177, 178
 - in water conservation, 158
- Asian economy, 114
- Asia-Pacific bank, 112–113
- Audit trails, 181

- Automated decision-making (ADM), 266, 268, 269, 272
- Autonomous systems, 66
- Autonomous vehicles (AVs), 295–296, 309
- Average variance extracted (AVE), 402

- Bangladeshi commercial bank regulatory guidelines, 113
- Banking business model, 114–115
- Bartlett's test, 163–164
- B Corps platform, 134
- Bias amplification, 183
- Bias detection tools, 184
- Big data analytics (BDA), 37, 63, 67–68, 72–74, 288, 368
- Blockchain technology, 21, 22, 24, 29–31, 37, 39, 66–67, 71–74, 76, 137–138, 144
- BRIC countries, 108
- Brundtland Report, 6, 10
- Business intelligence (BI), 2, 13, 14
 - application, 3
 - definition, 1, 3–4
 - systems, 155
 - aim, 161
 - artificial intelligence (AI) in, 156–160
 - BI tools, 160–162
 - EFA
 - Bartlett's test, 163–164
 - Cronbach's Alpha, 166
 - factor development, 166
 - KMO value, 163–164
 - total variance, 165
 - findings
 - AI Adoption and Sustainability, 162
 - challenges, 162
 - impact on decision-making, 162
 - proposed framework, 162
 - sector-specific insights, 162
 - methodology, 161–162
 - MRA
 - Adjusted R2, 168
 - ANOVA, 168–170
 - R square (R^2), 168
 - R value, 167
 - Std. Error of the Estimate, 168
 - objectives, 160–161
 - use of AI in, 170–173
 - tools, 160–162
- Business models, 45, 49, 107
- Buy-online-pickup-in-store (BOPIS), 414–415
 - applications, 443
 - methodology, 418–419
 - data collection, 419–420
 - data preprocessing, 420–421
 - DBSCAN clustering, 422–423
 - Difference-in-Differences, 426–427
 - feature correlation, 420–421
 - K-means clustering, 423–425
 - select test and control, 425–426
 - result analysis
 - attribute analysis and findings, 428–429
 - DBSCAN clustering, 431–433
 - Difference-in-Differences, 435–440
 - feature correlation matrix, 429–431
 - K-means clustering, 433–435
 - missing value, 427
 - outlier detection, 427–428
- retail strategy, 415
 - causal inference, 416
 - clustering techniques, 415–416
 - distinct contributions, 417–418
 - pickup fee elimination, 415
- risk management
 - analytical risk, 442
 - business risk, 440, 442
 - customer risk, 440
 - data integrity risk, 442
 - statistical power risk, 442
- Carbon economy, 111–112
- Carbon footprint reduction, 31, 156
- Carbon footprints, 67–69, 107, 113, 282, 290, 376
- Carbon taxation, 211–212
 - and business behavior, 212–213
 - challenges and opportunities, 206
 - climate change, 205–206
 - equity considerations, 213
 - global and indian context, 206–208
 - global trends in, 212
 - hybrid approaches, 213

- revenue recycling, 213
- review of literature, 209–211
- role of, 215–216
 - climate goals, 218
 - economic incentives, 216
 - global and indian perspectives, 217
 - implemation, 217–218
 - mechanism of, 216
- Career exploration (CE), 345, 349, 353
- Chatbots, 48, 50, 52, 182, 250, 307, 313
- Chatfuel, 313
- ChatGPT, 313
- Chi-square test, 90, 121–122, 240, 241
- Circular business models, 25, 26
- Circular economy, 37, 130
 - collaborative platforms, 133–134
 - direct economy to, 149–150
 - e-business models, 28
 - efforts, 66, 72
 - EU's Circular Economy Action Plan, 145
 - H&M's Garment Collection Program, 147–148
 - initiatives, 30–31
 - Material Exchange Platforms (MEP), 132–133, 149
 - models, 14, 15
 - motivating forces, 145–146
 - Patagonia's Worn Wear Program, 146–147
 - Patagonia way, 131–132
 - principles, 25, 26
 - product-as-a-service (PaaS), 135–136
 - Repair Café movement, 148
 - resource sharing, 131
 - sustainability, 142
 - data privacy, 144
 - data security, 144
 - logistics, 143–144
 - regulation, 145
 - standardization, 145
 - transportation, 143–144
 - system, 171–172
 - technology in, 137
 - challenges and opportunities in, 138–139
 - reduced resource consumption, 139–140
- Circular supply chains, 159–160
- Climate change, 107, 108
- Climate resilient projects, 107
- Cloud systems, 67, 68, 72
- CO₂ emissions, 61, 64, 71, 74, 106–109, 112, 114, 120
- Co-evolutionary process, 34
- Cognizant utilization, 133
- Collaborative platforms
 - challenges, circular economy, 142
 - data privacy, 144
 - data security, 144
 - logistics, 143–144
 - regulation, 145
 - standardization, 145
 - transportation, 143–144
 - community building, 133–135
 - Fabric Trade Stage, 149
 - H&M's Garment Collection Program, 147–148
 - MEP, 132–133
 - motivating forces, 145–146
 - PaaS model, 135–136
 - Patagonia's Worn Wear program, 146–147
 - product lifecycle management, 131–132
 - Repair Café Movement, 148
 - repair stages, 136–137
 - resource sharing, 131
 - sharing economy, 135
 - technology in, 137
 - challenges, 138–139
 - economic benefits, 140–141
 - environmental impact, 141
 - opportunities, 138–139
 - reduced resource consumption, 139–140
 - waste minimization, 140
 - waste exchange, 137
- Community building, 133–135
- Competitive edge, 38–39
- Composite reliability (CR), 262, 402
- Computer-integrated manufacturing system, 325, 331
- Consumer advocacy, 188
- Cooperativa platform, 134
- Core banking solutions (CBS), 250, 251
- Corporate governance reporting
 - advanced predictive analytics, 186

- AI in ESG report, 188–191; *see also*
 - Environmental, social, and governance (ESG)
- challenges and best practices
 - AI development and deployment, 183
 - clear accountability, 184–185
 - mitigating potential risks and biases, 183–184
 - oversight mechanisms, 184–185
 - transparency and disclosure of
 - AI-related information, 185–186
- emerging trends and technologies, 186
- implications, 203
- regulatory landscape, 187
- stakeholders, 187–188
- sustainability reports, 180–181
 - metrics and indicators, 181–182
 - stakeholder communication, 182
 - stakeholder engagement, 182
- Corporate social responsibility (CSR), 108, 114, 172, 374–375
- data collection, 378–379
- findings, 379
 - affiliation and scientific production, 387, 389
 - annual scientific production, 381–382
 - bibliometric approach, 391–392
 - citation analysis, 387, 388
 - climate change, 383–384
 - co-occurrence analysis, 385–387
 - country collaboration network, 382–383
 - data information, 379–381
 - future agenda for, 390–391
 - most cited country, 389–390
 - most relevant words, 385
 - thematic view, 383–384
 - top sources and citation, 382
- research methodology, 378
- significant ramifications, 376–378
- Cortex by AdParlor, 313
- COVID-19, 108, 122, 336, 397
- Cronbach's alpha (α), 89, 166, 401
- Cross-functional complexity, 184
- Customary straight model, 134–135
- Customer relationship management (CRM), 28
- Cutting-edge technology, 23, 39, 76
- Data algorithms, 52
- Data analytics, 28, 40, 146, 158
- Data breach, 144
- Data integration, 180
- Data privacy, 30, 34, 35, 39, 144
- Data security, 144
- Data vulnerabilities, 183
- Decentralized systems, 144
- Decision-making processes, 2, 9, 12, 14, 15, 22, 34, 60, 65–67, 75, 76
- Decision trees, 280
- Deep learning (DL), 48, 62, 65, 280
- Density-based spatial clustering of applications with noise (DBSCAN), 422
- Descriptive statistics, 240
- Difference-in-Differences (DiD) method, 415
- Digital/mobile/online/e-banking, 113, 116, 120–123
- Digital natives, 231
- Digital technology, 144
- Digital tools, 22, 24, 27, 28
- Digital transformation, 24, 29
- Digital transition, 31
- Digital twins, 186–187
- Digital twin technology, 21, 22, 24, 37, 40
- Digitization, 336
- Disruptive technology, 45–47, 54
- DIY (Do It Yourself) repair culture, 136, 147
- Drift, 313
- Dual-channel green supply chain (DGSC), 71
- Dutch Bangla Bank Limited, 123
- Dynamic benchmarking, 181
- Eco-friendly products, 112
- E-commerce, 71
- Economic benefits, 140–141
- Edge computing, 186
- Employee participation, 188
- Energy consumption, 110
- Energy demand forecasting, 159
- Energy management systems (EMS), 68, 155
- Environmental (E) aspects, 6

- Environmental, social, and governance (ESG), 5, 6, 9–10, 12, 14, 15, 20–22, 28, 35, 37, 39, 158, 173, 177, 179–184, 186–191, 199, 252, 271, 337, 376
 - advancements in, 198–199
 - AI impact on, 195–196
 - AI in ESG report, 191–192
 - algorithmic bias, 201–202
 - continuous improvement, 198
 - cross-functional collaboration, 197–198
 - data accessibility, 200
 - data availability, 200
 - enhancing ESG report, 192–193
 - ethical and regulatory challenges, 192–193
 - ethical and regulatory considerations, 196–197
 - evolution of AI, 201
 - future concern, 194–195
 - generalizability, 200–201
 - implications, 203
 - operational challenges in
 - AI integration, 197
 - stakeholder, 198, 202
 - technical challenges in
 - AI integration, 197
- Environmental compliance, 69
- Environmental degradation, 106, 109, 113
- Environmental impact assessments, 159
- Environmental sustainability, 7–8
- Ethical AI frameworks, 183
- Ethical AI systems, 14, 15
- Ethical dilemmas, 183
- Ethical supply chain management, 31–32
- Ethics committees, 183
- European banks, 114, 115
- European Green Deal, 280
- European Union, 6
- Explainable AI (XAI), 185
- Explainable artificial intelligence (EXAI), 302, 303, 313
- Exploratory factory analysis (EFA), 401
 - Bartlett's test, 163–164
 - Cronbach's Alpha, 166
 - factor development, 166
 - KMO value, 163–164
 - total variance, 165
- Extended producer responsibility (EPR), 145
- Fabricating firm, 140
- Farmer producer organizations (FPOs), 81
- Fat Llama, 135, 139, 143
- Financial transparency and governance (FTG), 266, 268, 270
- Flexible manufacturing systems, 325
- Floow2, 135, 139
- Fossil fuels, 68, 206
- Fourth Industrial Revolution, 63
- Fraud detection and compliance (FDC), 269
- Freecycle, 134
- General Data Protection Regulation (GDPR), 196, 316
 - principles, 179
- Generation Z (Gen Z)
 - artificial intelligence, *see* Artificial intelligence (AI)
 - features of, 236–237
 - need for study, 238–239
 - research methodology, 239–247
 - statement of problem, 238
 - statistical facts about, 237
- Global banking sector, 106–107, 111, 122
- Global e-Sustainability Initiative, 336
- Globalization, 112
- Global Sustainability Agenda, 6
- Goods and Services Tax (GST), 206
- Google Analytics, 313
- Governance (G) aspects, 7
- Governance sustainability, 9
- Gramin Bank, 112, 123
- Green banking
 - application of, 122
 - Asian economy, 114
 - Asia-pacific bank, 112–113
 - awareness and effectiveness of, 113
 - Bangladeshi commercial bank regulatory guidelines, 113
 - banking business model, 114–115
 - banks related to carbon emission, 106–107
 - corporate social responsibility (CSR), 108, 114
 - customer's satisfaction, 113

- European banks, 114, 115
- globalization, 112
- Gramin banks, 123
- green banking practices, 113
- green services, 108, 109
- HDFC green practices, 114
- initiatives of, 107–108
- investment in renewable energy, 109
- Japanese financial sector, 114
- Pakistan banks, 113–114
- Paris Agreement Capital Transition Assessme, 114
- regulations of, 109
- U.S. banks, 114
- UGB
 - annual reports, 115–116
 - chi-square test, 121–122
 - cost efficiency, 111–112
 - demographic profile, 116–117
 - eco-friendly products, 112
 - financial products, 110
 - green banking policy in Uttarakhand, 118–121
 - green buildings, 111
 - green efficient practices, 111
 - less energy consumption, 110
 - LPG/electric vehicles, 111
 - paperless banking, 110
 - plantation by banks, 112
 - renewable energy, 110
- Green buildings, 111
- Green efficient practices, 111
- Green energy, 68–71
- Green financial policy, 108
- Greenhouse gas (GHG) emissions, 72, 74, 205
- Green Human Resource Management (GHRM), 353
- Green image, 63
- Green investment policies, 108
- Green investment strategies (GIS), 269
- Green logistics, 70
- Green potential, 114
- Green product, 107, 108, 113, 114, 116
- Green projects, 109
- Green supply chain management
 - AI, 65–66
 - barriers, 74–76
 - big data analytics (BDA), 67–68
 - blockchain technology, 66–67
 - components of, 69
 - dual-channel green supply chain (DGSC), 71
 - future developments, 76–77
 - implications, 71–72
 - agriculture, 73–74
 - energy, 74
 - food, 73–74
 - healthcare, 73
 - manufacturing, 72
 - retail, 73
 - integrating green energy, 68–69
 - IoT, 66
 - literature review, 62–64
 - methodology, 64–65
 - ML, 65–66
 - role of green energy, 70–71
- Greenwashing, 63, 189
- H&M's Garment Collection Program, 147–148
- HDFC green practices, 114
- HubSpot, 312
- Human cognition, 53
- Human resource management (HRM), 38, 39
- Human Resources Information System (HRIS), 409
- Hybrid working models, 397
- IBM Watson Marketing, 312
- iFixit, 136, 140, 145
- India, 108, 110, 112
- Indian banks, 107, 108, 115
- Indonesia, 116
- Industry 4.0, 325–327
 - challenges, 339–340
 - discussion, 337–339
 - methodology, 328–329
 - outcomes, 337–339
 - sustainability challenges, 335–337
 - technology, 33–37
 - thematic analysis
 - relevant SDG for, 330–335

- sustainable supply chains, 329–330
- triple bottom line framework, 327–328
- Information analytics, 138
- Innovative technology, 48, 49
- Integrating multimodal AI, 63
- Intelligent technology sensors, 157–158
- Interactive dashboards, 182
- Intergovernmental Panel on Climate Change (IPCC), 375
- International Sustainability Standards Board (ISSB), 187
- Internet-connected traffic movement
 - sensors, 111
- Internet of Things (IoT), 5, 12, 14, 15, 20–24, 29, 35–37, 39, 66–68, 70, 72, 73, 76, 137, 144, 146, 180, 186, 194, 317
 - traffic movement sensors, 11
- Interquartile range (IQR), 420
- IT-enabled banking services, 106, 110, 115, 119, 122
- IT organizations, 347
- Japanese financial sector, 114
- Kaiser-Meyer-Olkin (KMO), 163–164
- K-means cluster, 423
- Knowledge and innovation management (KIM), 83
- Latin American banking, 114
- Least developed countries (LDCs), 391
- Local zoning/licensing, 138
- Logistics, 143–144, 159
- LPG/electric vehicles, 111
- Machine learning (ML), 21, 24, 28–29, 38, 46–48, 60, 62, 65, 70, 76, 156, 172–173, 303
 - algorithms, 15
- Material Exchange Platforms (MEP), 132–133, 149
- Mauritius, 113
- McKinsey Global Survey, 396
- Mega-farms, 99
- Micro, small, and medium enterprises (MSMEs), 81, 345
- Microsoft, 206, 207
- Mission-oriented innovation systems, 87
- Mission Shakti program, 81
- Modern manufacturing, 326
- Mud Jeans, 143
- Mud Pants, 136, 141
- Multiple regression analysis (MRA)
 - Adjusted R², 168
 - ANOVA, 168–170
 - R square (R²), 168
 - R value, 167
 - Std. Error of the Estimate, 168
- National Action Plan on Climate Change (NAPCC), 206, 207, 215, 219
- National Agriculture Market, 81
- National Centre for Atmospheric Research, 11
- National Mission for Enhanced Energy Efficiency (NMEEE), 207–208
- National Mission for Sustainable Agriculture, 81
- Natural language processing (NLP), 48, 177–178, 182, 189, 192, 195, 196, 201
- Neural network architecture, 48
- Non-Solar RECs, *see* Renewable Energy Certificate (REC)
- Oman banks, 113
- Opaque algorithms, 185
- Organization's value chain, 54
- Organization career enhancement (OCE), 349, 351–352
- Organization for Economic Cooperation and Development (OECD), 332
- Pakistan banks, 113–114
- Paperless banking, 110
- Paris Agreement Capital Transition Assessment, 114
- Patagonia, 131–132
- Pearson correlation coefficients ($|r|$), 420
- Peer-to-peer rental administrations, 141
- Perform, Achieve, and Trade (PAT), 215
- Performance management systems (PMSs), 346
- Personalized reporting, 182
- PET plastic, 137

- Philips, 136, 140
- Phrasee, 313
- Policymakers, 109, 113, 122, 199
- Porter Hypothesis, 209, 212
- Power purchase agreements (PPAs), 68
- Predictive analytics, 4, 5, 14, 30, 31, 53, 60, 61, 65, 70, 72
- Process optimization, 65
- Product-as-a-service (PaaS) model, 135–136, 138, 141, 143, 145
- Qualitative interviews, 47
- Quantitative data analysis, 47
- RBI, 107
- RBI regulatory framework, 115–116
- Real-time monitoring, 180
- Real-time sensors, 12
- Recruitment process, 50, 51
- Reduced resource consumption, 139–140
- Regression analysis, 240, 243, 280
- Regular audits, 184
- Regulating frameworks, 34, 35
- Regulatory gaps, 184
- Reinforcement learning, 46
- Remote work (WFH), 397
- Renewable energy, 61, 68, 70, 74, 110
- Renewable Energy Certificate (REC), 208, 215
- Renewable Purchase Obligation (RPO), 208
- Repair Café, 134, 136
 - movement, 148
- Repair platforms, 135–136
- Repair stages, 136, 140–142, 145
- Resource-based view (RBV), 351
- Resource management techniques, 158, 170–173
- Reverse logistics, 70
- Risk assessment, 159
- Rubicon, 137, 140
- Salesforce Einstein, 312
- SBI, 113
- SDG 2015, 6
- Semi-supervised learning, 46
- Sentiment analysis, 182
- Shallow-structured learning, 47, 48
- Sharing economy platforms, 135, 143
- Silhouette value, 422
- Siloed data systems, 32
- Skill enrichment (SE), 349, 352
- Small- and medium-sized enterprises (SMEs), 345–348
 - Agriculture in, 80–82
 - chi-square test, 90–92
 - correlation analysis, 93, 95
 - distribution of government support, 90
 - ensure sustainability, 99–100
 - frequency distribution, performance and innovation, 90, 91
 - government policies, 83–87
 - Indian agricultural inputs industry, 87
 - methodology, 89
 - research context, 87–88
 - research gaps, 88–89
 - innovation as predictor, 94, 96
 - innovation system, 82–83, 98–99
 - limitation and future scope, 99
 - mean difference, performance and innovation, 93, 94
 - performance, 83–87, 98–99
 - performance and innovation score, 93, 94
 - performance as predictor, 96–98
 - total number of, 93
- conceptual model, 350
- discussion, 364–366
 - future directions, 368
 - limitations, 368
 - managerial implications, 367–368
 - theoretical implications, 366–367
- hypotheses, 349–350
- research gap, 348–349
- research methodology, 354–356
- research questions, 349
- results and inferences, 356
 - measurement model, 356–358
 - structural model, 358–364
- study dimensions
 - career exploration, 353–354
 - OCE programs, 351–352
 - skill enrichment, 352
- systematic method, 368–369
- theoretical contributions

- RBV in employee development, 351
- SCCT, 350–351
- uniqueness, 348–349
- Smart agriculture, 80
- Smart grids, 74
- Smart grid technology, 8
- Smart manufacturing, 325
- Smart measurement equipment signals, 8
- Social (S) aspects, 7
- Social cognitive career theory (SCCT), 350–351
- Social responsibility, 8–10, 14, 16
- Social sustainability, 8–9
- Solar RECs, *see* Renewable Energy Certificate (REC)
- Spooky, 315
- Stakeholder engagement, 182, 185
- Stakeholder resistance, 34
- Statistical Package for the Social Sciences (SPSS), 258
- Structural equation modelling (SEM), 258, 261, 401
- Supply chain management (SCM), 8, 59, 60, 62, 64, 67
- Supply chain optimization models, 8
- Surgical robots, 53
- Sustainable business intelligence, 1, 5
 - artificial intelligence and
 - application of, 14–16
 - challenges of, 12–13
 - ESG strategies, 9–10
 - future direction, 13–14
 - sustainable development business model, 6–9
 - Telefónica, 11–12
 - Xcel Energy, 10–11
- Sustainable business practices, 158
 - carbon taxation, *see* Carbon taxation
 - challenge in, 214
 - comprehensive blueprint, 218
 - circular economy, 219
 - clear policy frameworks, 218–219
 - collaboration *vs.* government, 220
 - green financing, 220
 - green innovation, 219
 - findings, 221
 - government policies, 215
 - in India, 213–214
 - suggestions, 222–224
 - technologies role in, 215
- Sustainable consumer behaviour, 157
- Sustainable credit scoring (SCS), 269, 271
- Sustainable development, 6, 10
- Sustainable Development Business Model, 6, 12, 16
 - environmental sustainability, 5, 6, 9–10, 12, 14, 15
 - governance sustainability, 9, 10, 16
 - social sustainability, 8–10, 14, 16
- Sustainable development goals (SDGs), 20–22, 24, 29, 30, 39, 68, 71, 326–327
- Sustainable employability readiness (SER), 349
- Sustainable innovation (SI), 349, 353–354
- Sustainable intelligence business practices
 - business practices
 - carbon footprint reduction, 31
 - circular economy initiatives, 30–31
 - ethical supply chain management, 31–32
 - challenges in, 39
 - co-evolutionary processes, 34–35
 - ethical considerations, 34
 - financial barriers, 32–33
 - organizational barriers, 32–33
 - regulatory challenges, 34–35
 - stakeholder resistance, 34
 - technological barriers, 32–33
 - drivers for adopting, 26–27
 - future trends, 40
 - competitive edge, 38–39
 - emerging technologies, 37–38
 - impact on business transformation, 38
 - studies, 40
 - innovation, role of, 27
 - key milestones, 24, 26
 - overview of, 22–23
 - technology, role of
 - AI applications, 28–29
 - blockchain application, 29–30
 - internet of things, 29
 - ML applications, 28–29
 - traditional business practices *vs.* sustainable practices, 23–25

- Sustainable manufacturing, 160
- Sustainable retail management, 160
- Sustainable supply chains, 329–330
- Sustainable urban planning, 157

- Talent management, 32, 33
- Task Force on Climate-related Financial Disclosures (TCFD), 190, 193
- Technology acceptance model (TAM), 401
- Telefónica3, 11–12
- Top management support, 48–49
- Transparent security policies, 144
- Transportation, 143–144
- T*-test, 240
- Turo, 144
- Two-way communication, 182

- U.S. banks, 110, 114
- Unilever, 206, 207
- United Nations 2030 Agenda, 71
- United Nations Framework Convention on Climate Change (UNFCCC), 375
- United Nations Sustainable development goals, 6, 7, 12
- United Nations World Commission for Environment and Development, 6
- Universal Basic Income (UBI), 336
- Unsupervised learning, 46
- UTAUT model, 401
- Uttarakhand Gramin Bank, green banking initiatives, 107
 - annual reports, 115–116
 - chi-square test, 121–122
 - cost efficiency, 111–112
 - demographic profile, 116–117
 - eco-friendly products, 112
 - financial products, 110
 - green banking policy in Uttarakhand
 - awareness level, 118–119
 - in carbon emission reduction, 119–120
 - IT-enabled banking services, 119
 - not secure and effective, 120–121
 - paperless work and e-banking services, 121
 - green buildings, 111
 - green efficient practices, 111
 - less energy consumption, 110
 - LPG/electric vehicles, 111
 - paperless banking, 110
 - plantation by banks, 112
 - renewable energy, 110
- Valencia Smart City project, 12
- Variables, 166
 - Bartlett's Test, 163
 - dependent *vs.* independent, 168, 169
 - R square (R^2), 168
 - R value, 167
 - X1 (AI in sustainability), 170
 - X2 (AI-driven optimization), 170
 - X3 (resource allocation), 170
 - X4 (supply chain efficiency), 170
- Variance, 164, 165, 168

- Waste exchange platforms, 137
- Waste minimization, 140
- Workforce management, 346
- World Economic Forum, 10
- Worn Wear program, 131–132
- WWF, 134

- Xcel Energy Inc, 10–11