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Programmable Decisions for Business Organizations

An Actor-Network Approach to AI-Driven Innovation

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ISBN 978-981-95-0723-8 ISBN 978-981-95-0724-5 (eBook)
https://doi.org/10.1007/978-981-95-0724-5

This Palgrave Macmillan imprint is published by the registered company Springer Nature Singapore Pte Ltd.
The registered company address is: 152 Beach Road, #21-01/04 Gateway East, Singapore 189721, Singapore

Foreword

We are witnessing a transformative era, driven by a surge of innovative artificial intelligence (AI) technologies, methods, and systems that are reshaping our world in profound and often disruptive ways. For businesses, this transformation demands agility and the capability to integrate AI innovations into socio-technical systems that not only maximize organizational productivity and impact but also uphold human values and societal ethics.

As AI research and development continue to deliver unprecedented capabilities—enhancing speed, autonomy, scale, flexibility, decision-making, and personalization—our ability to design systems that effectively harness these features is increasingly challenged. Addressing complex, "wicked" problems with AI-based systems requires more than technical expertise; it demands intellectual control over the design process. This means understanding system behaviors across all levels and contexts of use—not eliminating uncertainty, but developing the engineering and management capabilities to navigate it.

For over five decades, the information systems and management science communities have employed Design Science Research (DSR) and Action Design Research (ADR) to create scientifically rigorous and practically relevant solutions to business challenges. These methodologies foster collaboration between researchers and practitioners, enabling the iterative development and evaluation of innovative artifacts that balance technical functionality with social relevance.

In this context, *Programmable Decisions for Business Organizations: An Actor-Network Approach to AI-Driven Innovation* by Egbert Steyn, Merwe Oberholzer, Matthew Mullarkey, and Pieter Buys offers a compelling and timely contribution. The authors present a robust, industry-relevant design approach for developing AI-based decision-support systems. Through an elaborated ADR process, they guide readers through the diagnosis, design, and implementation of a complex supply chain application that spans finance, marketing, logistics, manufacturing, IT, and strategic development.

What sets this work apart is its focus on the programmability and explainability of AI-driven decision-making across the entire supply chain. Grounded in Actor-Network Theory, the book provides a rigorous framework for capturing the complexity of the problem space and for designing balanced, human-AI decision-making solutions throughout the project lifecycle.

Perhaps most compelling is the book's transparency in detailing the full development process of an innovative AI application. Readers are taken through an iterative, evidence-based journey, with rigorous validation steps that assess how well the evolving system aligns with the goals of human actors, business functions, and the broader social environment. Industry professionals will find practical insights into identifying and developing AI solutions for complex challenges, while academic audiences will appreciate the actionable lessons drawn from a real-world case study using an advanced ADR methodology.

In sum, *Programmable Decisions* is a significant addition to the growing literature on AI innovation. It exemplifies how to achieve intellectual control in the design of scientifically rigorous and industrially relevant AI-driven systems. The authors have delivered a model case study that will inform and inspire practitioners and scholars in the field.

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Abbreviations

4IR	Fourth Industrial Revolution
ADR	Action Design Research
AI	Artificial Intelligence
COGS	Cost of Goods Sold
CPD	Continuous Professional Development
DL	Deep Learning
eADR	Elaborated Action Design Research
EBQ	Economic Batch Quantities
ISO	International Organization of Standardization
ML	Machine Learning
PEoU	Perceived Ease of Use
PU	Perceived Usefulness
SLA	Service Level Agreement
TAM	Technology Acceptance Model
VAM	Value-Based Adoption Model

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CHAPTER 1

Introduction

Abstract This chapter introduces the book's core themes, which focus on demonstrating the programmability of decisions and enhancing the understanding of the required artificial intelligence (AI) culture to empower agile organizations in dynamic environments. Consequently, the main concepts and their interactions are explained to design an AI decision-support model. On one side, integrated within the broader context of Industry 4.0, AI-based technologies bring profound societal changes as they become increasingly embedded in everyday life. On the other side is decision-making, which requires distinguishing between programmed and non-programmed decisions within AI-based technologies. The chapter establishes the groundwork for developing an AI decision-support model based on Porter's value chain concept. AI cannot operate independently of human involvement, necessitating a balance between social and technical objectives within organizations. This leads to the socio-technical theory, which underscores the mutual influence of humans and machines. The integration of these ideas is crucial for applying AI effectively in decision-making. A framework such as actor-network theory (ANT) is needed to understand how networks of human and non-human actors form and function. The chapter thus outlines the book's objectives and describes the research methodology, including the concept of action design research (ADR), employed to achieve these objectives.

E. Steyn et al., *Programmable Decisions for Business Organizations*,
https://doi.org/10.1007/978-981-95-0724-5_1

Keywords Action design research · Actor-network theory · Artificial intelligence · Decision-support model · Programmability · Socio-technical theory · Value chain

JEL Classification M13 · M16

1.1 Background

In contemporary managerial decision-making, the increasing importance of artificial intelligence (AI) technologies is driven by their ability to process vast datasets, identify complex patterns, and deliver unprecedented speed and actionable insights. As organizations face dynamic environments and heightened competition, AI's predictive capabilities and decision-support tools promise to enable managers to navigate uncertainty and make more informed, data-driven decisions.

Contemporary management research over the past two decades, including Cardinal (2001), Daily (2018), Mak and Pichika (2019), and Mikulic (2021), has explored various instances of managerial decision support in technologically dynamic environments and the efficiency of AI-based contexts. The backdrop of an agile and dynamically innovative environment, along with the necessity of human decision-makers in this context, sets the tone for this book.

1.2 Artificial Intelligence in Context

1.2.1 Introduction

Contemporary organizations operate in a dynamic, rapidly evolving business environment that demands continuous operational adjustments. In the current Industry 4.0 era, technological developments have significantly contributed to organizations' operations, performances, and sustainability. Technological changes, defined as the systematic application of scientific knowledge to practical tasks (Akpoviroro & Owotutu, 2018), have accelerated the pace of change (Ross & Maynard, 2021). Industry 4.0 contextualizes these changes, with AI-based technologies increasingly integrating into daily life and driving radical societal transformations (Ross & Maynard, 2021). Thus, it stands out as a field with immense potential for profoundly impacting society. Therefore, organizations should keep up with appropriate technological advancements to remain relevant in the contemporary business environment.

The broader reality of AI-based technologies can be seen as the study and development of intelligent machines and software capable of reasoning, learning, gathering knowledge, and communication (Pannu, 2015). As such, it essentially encompasses any technique that mimics the human brain, often utilizing concepts such as Machine Learning (ML) or Deep Learning (DL) to build models or identify patterns in data. Mak and Pichika (2019) state that ML entails data analysis methods that automate analytical model building using algorithms that iteratively learn from data. DL is a deeper subset of AI that processes data and creates patterns for decision-making purposes, comprising networks capable of *learning* from unstructured data.

As indicated, the broad definition of AI and its various supportive concepts aim to achieve desired performance-based outcomes in real-world scenarios. The integration of AI into organizational processes, particularly in decision-making, is significant, with rapid advancements in AI-based technologies positioning *algorithmic decision-makers* as critical actors (Shrestha et al., 2019). Once considered a discarded technology due to early research setbacks, AI is currently experiencing a vigorous resurgence, thanks to advancements in computer hardware and software (Pan, 2016; Power et al., 2019). This resurgence has arguably enabled AI applications across numerous fields, including language understanding, learning and modeling abilities, adaptive systems, robotics, and more.

AI-based technologies can add value through automation, decision support, marketing, and innovation, highlighting the importance of investigating their potential role in decision-making. To enable organizations to leverage AI capabilities, Mikalef et al. (2019) identified several internal organizational factors as essential for optimizing potential AI capabilities (see Fig. 1.1).

As illustrated, *data* is the foundational departure point for a practically usable AI system, making it a critical capability when implementing such technologies. Since user acceptance is crucial to avoiding failure, a supportive *AI culture* is also essential for success. Furthermore, organizations need the proper *infrastructure* and *continuous learning* abilities to sustain the AI environment. Finally, *technical and managerial skills* entail

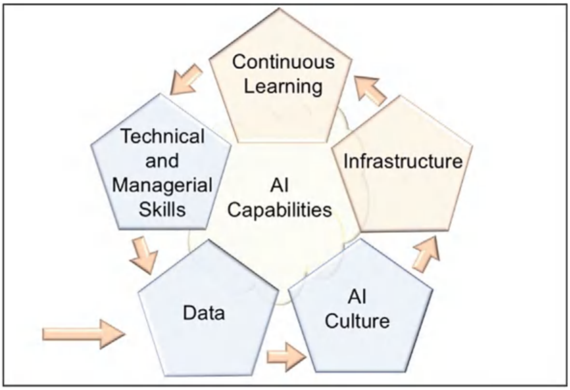

Fig. 1.1 Requisite factors in AI realization (Adapted from Mikalef et al. [2019])

identifying future AI skills, including those of trainers (who teach AI systems), analysts (who bridge the gap between technologists and business leaders), and sustainers (who maintain the systems). This book focuses on three key factors: data (subset of operational structures and performance), AI culture (trait of socio-technical theory), and technical and managerial skills (reflected in decision-making), outlined in the sections below.

1.2.2 Operational Structures and Performance

Effective organizations facilitate collaboration among various functions and departments (Maduenyi et al., 2015), which is essential for addressing low staff morale and ensuring organizational performance (Nene & Pillay, 2019). While operational structures may vary, the supportive activities must be designed to help achieve objectives efficiently in an *agile present* and an *uncertain future* (Chand et al., 2014). These structures aim to identify key performance indicators (KPIs), ensuring an organization's health, effectiveness, and efficiency. Michael Porter's value chain model illustrates a set of business activities that work together to deliver a product or service offering. Figure 1.2 illustrates such a generic value chain.

As shown in Fig. 1.2, each activity will be measured using different KPIs to achieve and maintain a competitive advantage. In this context,

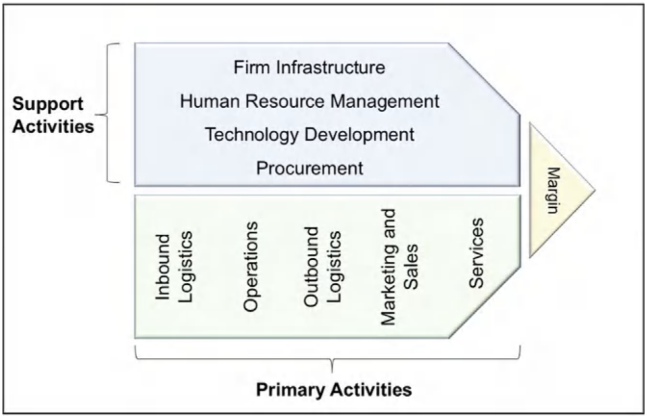

Fig. 1.2 Generic value chain concept (Adapted from Porter [2001])

AI-based technologies can streamline decisions within these activities and effectively manage each, thereby contributing to a competitive advantage. An effective operational structure may foster a positive AI culture, facilitating organizational *data* flow between activities. In turn, AI can assist in decision-making to manage KPIs more effectively within the organization. Applying the value chain concept to a dynamic industry can identify unique activities and their respective KPIs. The value chain concept contextualizes an organization's activities, its KPIs, and the decisions that impact them.

1.2.3 Socio-Technical Theory

Notwithstanding any perceived benefits, AI cannot operate independently of humans within an organization. Creating a *culture* by balancing the organization's social and technical objectives leads to the emergence of socio-technical theory. Originating in Britain's post-war coal mining industry in 1949, socio-technical theory emphasizes the reciprocal relationship between humans and machines (Ropohl, 1999; Trist, 1981), aiming to create an efficient working environment where human workers and technology complement each other.

Over the past 60 years, socio-technical theory has evolved from its origins in heavy industry to encompass advanced manufacturing, office-based work, and services (Davis et al., 2014). This expansion into new domains reflects its openness to continual improvement and revision (Appelbaum, 1997). During the Industry 4.0 era, effective knowledge management and decision-making strategies are essential for achieving optimal organizational performance (Abubakar et al., 2019). As such, the decision-making style moderates the relationship between knowledge and organizational performance.

Notwithstanding, system effectiveness can only be protected when implementing technical changes that correspond to changes in the social environment (Davis et al., 2014). Improper management of technology implementation, including AI-based technologies, can negatively affect employee confidence and engagement (Treacy, 2022). Therefore, applying socio-technical theory concepts becomes essential when introducing technologies like AI into organizations.

1.2.4 Decision-Making

Decision-making involves a set of steps and procedures to select the optimal alternative (Lassoued et al., 2020). Consequently, it depends on both *technical and managerial skills*. Understanding decision-making within AI-based technologies requires examining the theoretical building blocks of decision-making. Herbert Simon, renowned for his contributions to bounded rationality and satisficing, has been closely associated with management decision-making since the late 1940s (Pomerol & Adam, 2004). With the advent of computer technology, Simon recognized them as complex information-processing systems akin to organizations, categorizing decisions from programmed to non-programmed (Pomerol & Adam, 2004). This became the basis for the theory of programmable decision-making. Table 1.1 summarizes the differences between programmed and non-programmed decisions.

According to Table 1.1, *programmed* decisions are typically repetitive or routine, whereas *non-programmed* decisions involve more complex scenarios. Understanding the nature of decisions better facilitates their management and integration into AI-enabled systems. In context, AI-based technologies support fast and efficient decision-making, potentially reducing human errors, assisting in repetitive tasks, and fostering innovation (Yarlagadda, 2018), suggesting that AI can be readily applied

Table 1.1 Decision characteristics

Characteristic	*Programmed decisions*	*Non-programmed decision*
Type of problem	Structured/routine	Unstructured/unique
Managerial level	Middle management	Top management
Recurrence of the problem	Repetitive	New and unusual
Judgment	Objective	Subjective
Information	Available	Incomplete
The time frame for the solution	Short	Long term
Solution relies on	Procedures/rules	Creativity

Adapted from Paschek et al. (2018)

to programmed decisions due to its repetitive nature. However, AI's capacity for technical innovation also indicates its potential to address the complexity of non-programmed decisions (Lawrence, 1991). Therefore, there is a strong case for the applicability of AI-based technologies in both programmed and non-programmed decision contexts.

1.2.5 Actor-Network Theory

All the above concepts need to be integrated to enable the pragmatic enablement of AI applications in decision-making. This requires a framework such as actor-network theory (ANT), which has proven invaluable in information systems research, offering both theoretical and methodological approaches (Walsham, 1997). It has been widely used in science and technology since the 1980s (Law, 2009). In this book, *networks* can be seen as uniting *actors* with a common interest, with ANT ultimately enabling an understanding of how these actor networks are formed and function.

While many management theories have typically excluded non-human actors, the ANT framework acknowledges both human and non-human actors, thus enabling the research of non-human actors in context (Heeks, 2013). The exclusion of non-human actors was highlighted while attempting to find common ground between ANT and critical realism; ANT treats humans and non-humans as causal equals, whereas critical realism attributes unique abilities to human actors, necessitating that humans be treated differently from non-humans (Elder-Vass, 2008). For this book, human actors (e.g., decision-makers) and non-human actors

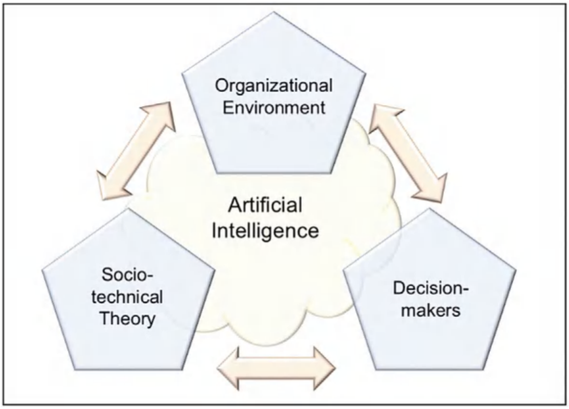

Fig. 1.3 Key actors within an ANT-based AI framework

(e.g., concepts from socio-technical theory and organizational environment) are treated as equals in the context of AI-enabled decision-making. All the actors need to be aligned to optimize the implementation of new technologies.

Figure 1.3 provides an overview of the contextual actors within an ANT network, in line with this book's objectives, to illustrate the interworking of all the required AI capabilities.

As indicated, the concepts of socio-technical theory, the relevant decision-makers, and the organizational environment operate interdependently, and they should be managed as an integrated system within an ANT-based AI framework.

1.3 Defining the Knowledge Gap

With the resurgence of AI-based technologies in various business fields, integrating these technologies into managerial functions within a dynamic decision-making environment becomes essential. Furthermore, socio-technical theory can aid in understanding the reciprocal relationship between humans and machines, thereby facilitating the integration of new technologies. Therefore, the central knowledge gap addressed in this book is understanding (1) the AI decision-making approach and (2) the environment (or culture) to empower the organization to utilize new technologies.

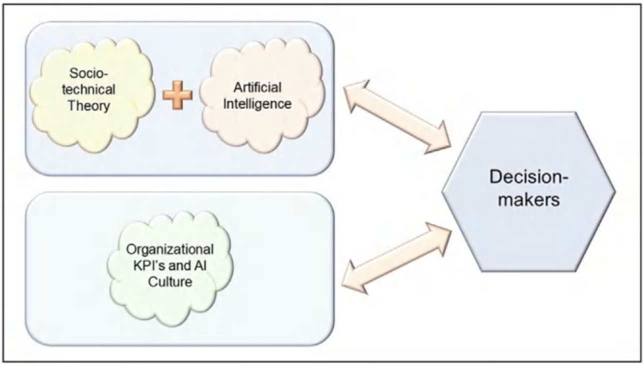

Fig. 1.4 Contextual actors

To empower organizational decision-making, ANT can assist in understanding the relationships between integrated systems and human and non-human actors, as well as the contextual understanding of pertinent technologies. Once this understanding is established, aspects such as the programmability of decisions can provide a framework for determining the level of decision programmability to develop an AI-enabled decision-support model. Integrating the earlier-mentioned actors into the discussed elements, Fig. 1.4 illustrates these elements as relevant actors within the decision-making context.

Figure 1.4 illustrates the connection between socio-technical theory and AI, where AI is integrated into the decision-making processes. AI-enabled decision-making ultimately supports the KPIs of various business functions.

1.4 Problem Definition and Objectives

Earlier research by Lawrence (1991) emphasized the need for further investigation into the impact of AI-based technologies in ensuring organizational competitiveness. Introducing Industry 4.0 technologies can radically change business systems, necessitating new knowledge for practical analysis (Pérez-Lara et al., 2019). This change may be so significant that it requires reconsidering industry operations (Városiné Demeter et al., 2018), which in turn may necessitate an investigation into the underpinnings of current KPIs. This initiative contributes to this effort and explores how an actor-network approach can set the tone for enabling the programmability of management decisions in an AI-driven operational environment.

Since pragmatic research is driven by the need to address real-world issues, this qualitative design science-based initiative aims to gain insights into AI-enabled decision-making within different organizational cultures or environments involving key stakeholders at various levels. This book aims to illustrate the programmability of decisions and enhance the understanding of the required AI culture to empower decision-making in dynamic environments.

The aspects mentioned above quantify the research problem of how a deeper understanding of decision programmability within an AI environment is subject to the interplay of socio-technical theory. Therefore, in this context, the book's primary objective is to develop a framework that illustrates decision programmability, enabling the creation of an AI decision-support model in an AI context to enhance decision-making strategies.

The above objective gives rise to the following sub-objectives:

- Defining the research context and motivating ANT as a conceptual framework to embrace other critical theories and frameworks pertinent to this initiative, including:
  - Porter's value chain as a framework to identify KPIs in context.
  - Decision-support models based on decision trees and fuzzy logic models.
  - Information technology models based on technology acceptance models and value-based adoption models.
  - Socio-technical theory to integrate new technologies by addressing human and technical aspects.
- Develop a diagnosis framework to address the issues identified in the business problem, the AI culture, and the programmability of decisions.
- Develop an initial, practice-inspired, theory-grounded AI decision-support model that functions in technical and social environments.
- Verify and validate the AI decision-support model to present it as a pre-implementation artifact.

1.5 Development of Methodological Justification

Deciding on an appropriate developmental methodology often begins with the researcher's view of a social phenomenon. This book adopts a pragmatic approach, emphasizing the most effective way to address research questions, and favors the use of both quantitative and qualitative data to understand social reality (Wahyuni, 2012). In pragmatism, knowledge is considered acceptable when it is derived from observable phenomena and subjective meanings. Emphasis is placed on practical, applied research that integrates diverse perspectives to effectively interpret data. Therefore, the AI decision-support model developed in this book will reflect the subjective viewpoints of the researcher-practitioner teams involved.

Regarding the applied design approach, the initiative utilized aspects of the elaborated action design research (eADR) approach, as illustrated in Fig. 1.5. This approach comprises *elaborated* iterations, including the diagnosis, design, implementation, and evolution iterations, each entailing five stages: planning (P), artifact creation (A), evaluation (E), reflection (R), and learning interventions (L), as proposed by Mullarkey and Hevner (2019).

This book will primarily focus on the first three iterations of the eADR process, as follows:

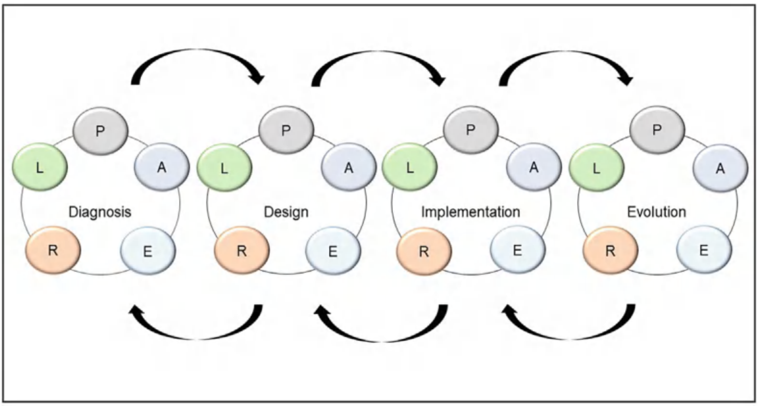

Fig. 1.5 eADR process (Adapted from Mullarkey and Hevner [2019])

- The diagnostic aspect will entail three iterations, i.e.:
  - Validation and refinement of the experienced business problem.
  - Identifying key activity KPIs through group discussions and interviews, ultimately creating a framework for the envisaged AI decision-support model.
  - Investigating the concept of a prevailing AI culture to assess AI acceptance levels.
- The design aspect will entail one iteration, elucidating the development of the initial model based on the findings from the diagnostic iterations.
- Prior to the actual implementation of the model, a first (or *pre-*) implementation iteration will be used to refine and validate it using industry inputs.

Embedded in the design sciences, the approach allows continuous interaction between academic researchers and knowledgeable industry experts. Semi-structured interviews and group discussions with open-ended questions will serve as qualitative measuring instruments. This ensures that the problem domain is thoroughly understood and that the envisaged AI decision-support model is adequately validated.

1.6 Ethical Considerations

Ethics can be defined as the moral principles that govern or influence conduct (Myers & Venable, 2014), and as such, they are fundamental to academic and business research. Ethical considerations are paramount, particularly when research involves human or animal subjects. Ensuring participants' dignity and ethical treatment throughout the data collection process is essential. This project followed all relevant ethical research guidelines and obtained the necessary institutional approvals.

The industry participants selected for this project were chosen based on their relevant experience. Participation was entirely voluntary, with informed consent obtained in writing. No personal or company-specific information was collected, and participants retained the right to withdraw from the project at any time. The data collected focused solely on business-related aspects aligned with the book's objectives, drawing on the participants' industry experience, expertise, and opinions. This information was utilized conceptually to inform the design and development of a comprehensive model.

1.7 Book Layout

This book comprises the following chapters:

- This chapter introduces the topic, including background information, critical theories, and the underlying literature review. It also presents the book's problem definition and objectives.
- Chapter 2 explains the development approach and methodological assumptions. The chapter also elucidates eADR as the research and design approach.
- Chapter 3 focuses on the different actors within the ANT context. As the literature shows, this theoretical framework can explain AI's interaction with other actors within a technology-based decision-making environment.
- Chapter 4 conducts the first eADR diagnostics iteration to establish the most used and essential KPIs within different organizational functions and the corresponding decisions influencing these KPIs.
- Chapter 5 conducts the second eADR diagnostics iteration, focusing on socio-technical theory. It aims to establish the necessary AI culture within the industry, enabling the adoption of AI technology.
- Chapter 6 conducts the third eADR diagnostics iteration, focusing on the degree to which decisions can be programmed, applying the theory of decision programmability.
- Chapter 7 aims to develop an initial solution based on the earlier diagnostics iterations. Considering the AI culture, it illustrates the most pertinent decisions in an organization and their programmability within an AI system. The chapter conducts the design iteration to develop the AI decision-support model artifact.
- Chapter 8 subsequently aims to validate the design in the *pre*-implementation iteration, gathering further insights from participants to verify and validate the model, creating a verified artifact. A final AI decision-support model is presented, incorporating practical input from industry experts.

- Chapter 9 concludes by illustrating how the model can empower dynamic organizations, considering the implementation of AI-based technologies within the decision-making sphere.

1.8 Summary

Rapid technological advancements have created a need to understand and effectively implement fast-evolving technological developments. As evidenced by a resurgence in AI-based technologies, it is extensively researched and implemented across various organizational domains, including decision-making. This chapter briefly highlights the foundational pillars of the book's approach thus far by contextualizing AI within the framework of organizational performance, social-technical theory, decision-making, and ANT. The chapter also defines the key objectives and highlights the methodological rigor. Socio-technical theory offers a comprehensive approach that balances technical and social environments to align organizational objectives. The next chapter will elaborate on the integrative development methodology within the context of the book's objectives.

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CHAPTER 2

Methodological Justification

Abstract This book followed a systematic research methodological process to achieve its objectives: developing an artificial intelligence (AI) decision-support model, demonstrating the programmability of decisions, and enhancing understanding of the required AI culture to empower decision-making. This chapter reveals how Wilson's honeycomb was applied to ensure a logical and systematic process for reaching these objectives. In the first component, the philosophical choice includes pragmatism as epistemology and subjectivism as ontology, embraced by a value-bound axiological approach. The second component is the research approach, which found inductive reasoning to be more appropriate than deductive reasoning. The third is the research strategy, which found qualitative research more relevant than quantitative research. The research design is the fourth component, where the choice of employing action design research (ADR) is justified to guide the empirical research. This section also introduces elaborated ADR (eADR), an extension of ADR. The fifth and sixth components are data collection and data analysis techniques. Regarding the former, group discussions and interviews were used to collect data, while thematic analysis was employed for the latter.

Keywords Action design research · Elaborated action design research · Research methodology · Wilson's Honeycomb

E. Steyn et al., *Programmable Decisions for Business Organizations*,
https://doi.org/10.1007/978-981-95-0724-5_2

JEL Classification M10 · O30

2.1 Introduction

The previous chapter provided an overview of this book's aim and objectives. This chapter will outline the underlying research and design process used to achieve these goals. Singh (2006) defines key research characteristics as a sound philosophy, insights and imagination, a transdisciplinary approach, and a desire to improve. These characteristics underscore the importance of creativity, problem-solving, and knowledge in managing multidisciplinary teams. Ultimately, the book's applied research approach is expected to contribute to understanding the interplay between the programmability of management decisions and artificial intelligence (AI)-driven initiatives within the context of an actor-network theory (ANT) environment.

2.2 Methodological Justification

2.2.1 Introduction

This initiative adopted the honeycomb approach (per Wilson, 2014) to explain the different components of the approach applied in this book, as illustrated in Fig. 2.1.

Figure 2.1 outlines the six integrated research components. The first three (i.e., the philosophy, approach, and strategy) are considered foundational core concepts, while the remaining three (i.e., the design, data collection, and data analysis) encompass the execution aspects.

2.2.2 Philosophy

Research philosophies reflect the researcher's views, influencing the approach applied, with the underlying paradigms crucial for providing focus and guiding the research efforts as unpacked below:

- Epistemology involves assumptions about knowledge, i.e., what is considered acceptable, valid, and legitimate, and how it can be communicated. In this context, *positivism* asserts that different

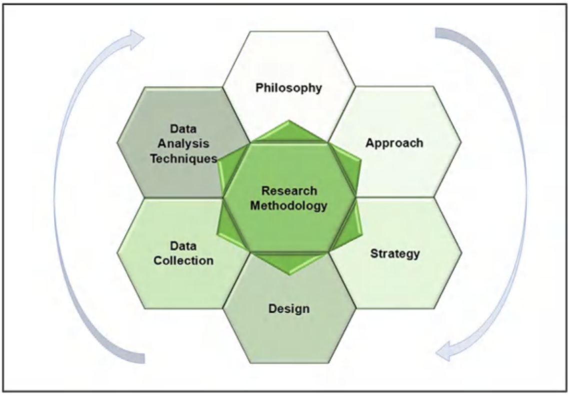

Fig. 2.1 Honeycomb methodology (Adapted from Wilson [2014])

researchers will reach the same conclusions; *post-positivism* acknowledges that knowledge is shaped by social conditioning while *interpretivism* argues that social actors and their perceptions construct reality and seek to uncover the deeper meaning of social phenomena (Wahyuni, 2012). In contrast, *pragmatism* does not align with any specific paradigm but focuses on pragmatic approaches to solving real-world research problems (Kelly & Cordeiro, 2020). This initiative adopts the latter approach, recognizing the value of diverse perspectives and qualitative data in understanding a real-life scenario.

- Ontology, in the context of management studies, reflects on how the world operates. O'Gorman and MacIntosh (2015) explain ontology through *objectivism*, which views social reality as external to the researcher and participants and aims to identify causal explanations and fundamental laws, and *subjectivism*, which asserts that the perceptions and actions of participants shape reality. Considering the objectives of this initiative, our approach required interactions with participants to gather qualitative data, thereby positioning the book within a subjective ontological framework.
- Axiology: The final aspect of axiology focuses on the role of values and ethics. The ethical considerations pertinent to this section are outlined in *Sect. 1.6: Ethical Considerations*. Fundamentally, this initiative employs a subjective philosophical approach, which epistemologically aligns with a pragmatist view, treating information

as the unique opinions of knowledgeable participants. Ontologically, it assumes that reality is understood through interaction with these participants. As such, the axiological approach is value-bound, ensuring the researcher ethically engages with participants.

2.2.3 *Approach*

Wilson (2014) suggests that research can follow either an inductive approach, which moves from specific observations to broader generalizations, or a deductive approach, which starts with general principles and narrows down to specific instances. Given the objective's focus on explaining findings from specific cases to broader conclusions, rather than retesting data, an inductive approach will be used. This method aligns with previous research, such as Petersson et al. (2022), who successfully employed an inductive approach to studying the implementation challenges of AI-based technologies.

2.2.4 *Strategy*

The third element of the honeycomb methodology is strategy, typically categorized as either *quantitative*, explaining phenomena through numerical data and mathematical evaluation, or *qualitative*, producing findings that are not based on statistics or quantification (Yilmaz, 2013). Therefore, quantitative research aims to generalize outcomes, whereas qualitative research explores processes or phenomena in-depth to support theory building (Cruz & Tantia, 2017). In justifying the approach followed herein, quantitative research in technology supports theory testing, while qualitative research is better suited for theory construction (Pearse, 2021). Given our approach to technology research and the specified book objectives, seeking to comprehend decision-making models in AI-based technologies rather than measure them, a qualitative approach is most appropriate. While quantitative approaches focus on measuring social phenomena, qualitative approaches aim to understand the meaning behind them.

2.2.5 *Design*

The choice of research method depends on the needed information, and understanding the philosophical assumptions helps guide the research process (Al-Ababneh, 2020). An action design research (ADR) approach provides procedural guidance, conceptual frameworks, and techniques for documenting project tasks (Cronholm & Göbel, 2022). It typically follows four stages, each guided by principles that form the foundation of the ADR design, as illustrated in Fig. 2.2.

The illustrated stages entail the following:

- Stage 1 identifies a perceived problem and is guided by two principles, requiring the research to be *practice*-inspired, to generate knowledge applicable to the broader class of problems, and to integrate new artifacts with *theory*, ensuring that they take on a socially recognizable form by embedding theoretical elements.
- Stage 2 uses the earlier problem identification and theoretical assumptions to create artifacts developed through iterative cycles of collaboration between researchers and practitioners.

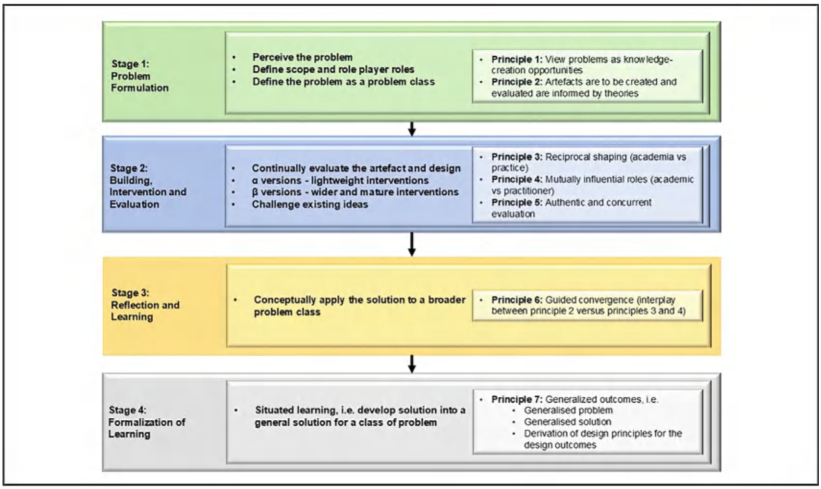

Fig. 2.2 ADR stages (Adapted from Sein et al. [2011])

- Stage 3 involves reflection and learning. During this stage, the research team reflects on the problem and the theories employed, adjusting the process and theory as new insights emerge.
- Stage 4 is the formalization of learning, where the solutions developed are generalized to address broader classes of problems.

Figure 2.3 illustrates the iterative interactions between researchers and practitioners in the development of solutions through iterative processes.

Mullarkey and Hevner (2019) introduced critical interventions to make knowledge creation more explicit in the ADR process. Their interpretation, known as elaborated ADR (eADR), still recognizes ADR's iterative nature but adopts a multistage approach, as opposed to the single build, intervention, and evaluation stage used in conventional ADR, as illustrated in Fig. 1.5. In this context, the book's approach is grounded in a reciprocal research-practitioner approach, where both parties play influential roles. It utilizes theory-grounded models, such as ANT and socio-technical theory, to explore AI in decision-making. Artifacts will evolve through the design of research and organizational use,

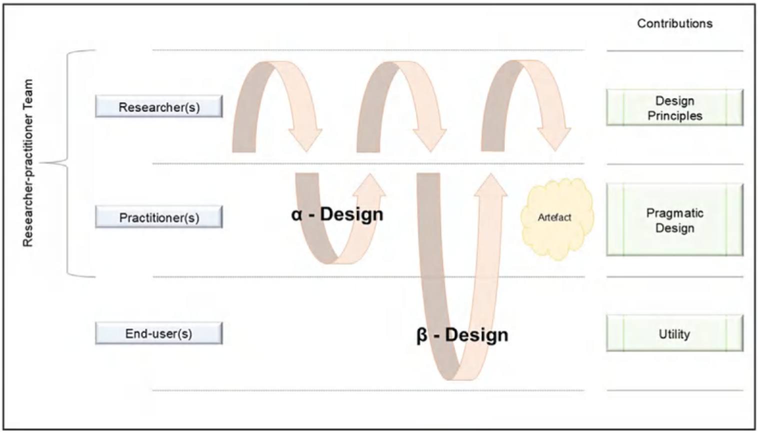

Fig. 2.3 Building, intervention, and evaluation cycles (Adapted from Sein et al. [2011])

reflecting a guided emergence. Adopting an eADR approach, the initiative will focus primarily on diagnosis and design iterations, as well as a pre-implementation iteration.

2.2.6 Data Collection

2.2.6.1 Introduction

Researchers should validate their chosen methods, recognizing both their strengths and limitations (Kairuz et al., 2007). In attaining the book's objectives, group discussions and interviews were the primary data collection methods, as elucidated below:

- Firstly, group discussions were used to define the industry practitioners' perceptions on a specific topic, yielding qualitative or quantitative data. Seven types of group discussions can be identified, each with a different approach, as follows:
  - *Single focus* groups, where participants interact on a specific topic.
  - *Two-way focus* groups in which one group discusses while another observes.
  - *Dual-moderator focus* groups, where two moderators, each with distinct roles, facilitate the discussion.
  - *Dueling-moderator focus* groups with moderators with opposing views.
  - *Respondent-moderator focus* groups in which a participant temporarily moderates.
  - *Mini-focus* groups entail a small group of experts.
  - *Online focus* groups that are conducted via the Internet and related technologies.

  According to T. O. Nyumba et al. (2018), larger groups can often be challenging to manage and limit data diversity. Hence, this initiative applied a *mini-focus* group approach to extract qualitative data from industry experts. According to Onwuegbuzie et al. (2009), a mini-focus group might involve three to four participants with specialized knowledge. As such, the mini-focus groups should strike a balance, offering enough diversity while creating a comfortable environment for in-depth discussion.

- Secondly, interviews are conversations designed to gather information (Joshi, 2018), which involve in-depth questions that describe participants' experiences (Cruz & Tantia, 2017). They are effective in data collection for ANT due to their focus on organizational processes (Zawawi, 2018). To meet the book's objectives, *structured* interviews with more specific questions and *unstructured* interviews with no predetermined questions were conducted, allowing for flexibility to explore new topic avenues as needed.

2.2.6.2 Application of Group Discussions and Interviews

Due to their interactive nature, group discussions were initially used for data collection, followed by interviews with senior participants to validate and expand the findings for the next eADR iteration.

Considering the sample size, researchers should determine and continuously assess its size. In qualitative research, there is no standard for sample size; instead, the concept of saturation is used. According to Malterud et al. (2016), saturation involves comparing new observations with prior analyses to identify characteristics. An approach supplementary to this is *informed power*, which states that the more information the sample holds that relates to the study, the fewer participants are needed.

This initiative will commence with a select group of participants chosen for their relevant expertise (Cruz & Tantia, 2017), followed by the recruitment of additional participants through snowball sampling. This method effectively reaches hidden populations and aligns with the need for smaller samples in specialized research (Etikan et al., 2016).

2.2.6.3 Verification and Validation

For this book, *verification* is defined as the evaluation of an artifact to ensure it meets the design conditions set at the start of a development phase, while validation is defined as ensuring the artifact meets the specified requirements and the needs of stakeholders, as per Ryan and Wheatcraft (2017), as conceptualized in Fig. 2.4.

As illustrated in Fig. 2.4, the approach followed entailed the continuous verification and validation throughout the overall development process. As such, the suggested AI model will align with initial design requirements and address the experienced business issue.

Regarding verification, the pertinent measurement criteria are whether the various eADR stages address the research objectives and whether

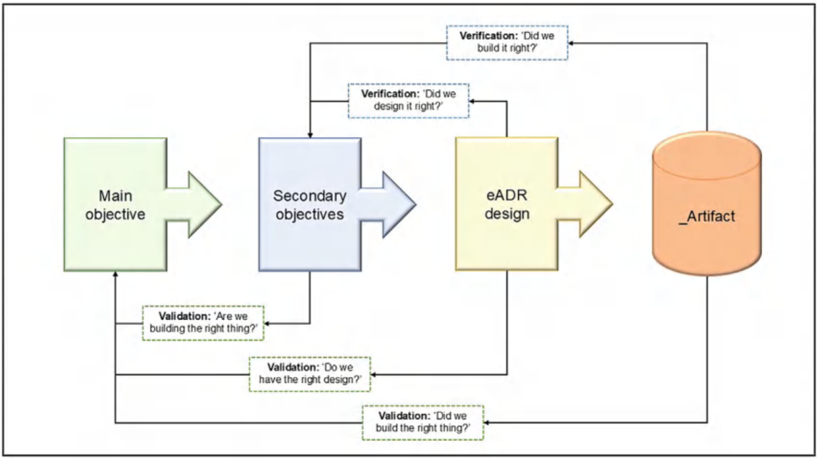

Fig. 2.4 Continuous verification and validation (Adapted from Ryan and Wheatcraft [2017])

the final framework meets them. Regarding validation, the measurement criteria revolve around whether the research objectives adequately address the problem, whether the eADR approach provides the necessary knowledge, and whether the final decision-support model effectively supports AI-driven decision-making environments.

2.2.7 Data Analysis Techniques

The final component of the honeycomb approach involves evaluating the collected data. After gathering data from interviews, the next step is to analyze it thoughtfully and communicate its insights clearly, in line with the book's objectives (Zawawi, 2018). Thematic analysis is the most suitable method for this task, as it systematically identifies and organizes themes from the data (Alhojailan, 2012; Braun & Clarke, 2012). This method is known for its accessibility, flexibility, and popularity in qualitative data analysis. Thematic analysis is arguably also easy to learn and accessible to researchers with limited experience, offering the potential for unexpected insights.

2.3 Summary

This chapter aims to justify the research approach employed in achieving the book's objectives. It details the research and design process, guided by the honeycomb methodology, which encompasses epistemological, ontological, and axiological assumptions. The approach adopted an inductive, qualitative approach with eADR as the applied research approach. Data collection methods included group discussions and interviews, which were analyzed thematically.

With the established methodological assumptions and theoretical foundations in place, the next chapter will present the underlying ANT foundations, elucidating the contextual actors and their respective roles.

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CHAPTER 3

Theoretical Foundation

Abstract This chapter aims to elucidate the concept of actor-network theory (ANT), which is valuable in systems and technology research, particularly where human and non-human actors are treated as equals. The contextual application of ANT in this book is illustrated in a socio-technical environment to better systematize the social aspects of technical work. Three progressive moments of translation stages are explained: problematization, interessement, and enrollment. Porter's value chain contextualizes the *problematization* stage by helping to identify possible key performance indicators in the organization's activities, explaining how decision-makers utilize artificial intelligence (AI)-based technologies as actors in the context of ANT applications. The *interessement* stage aims to lock human and non-human actors in their roles, illustrating decision-making in an AI environment where decision-support models are based on decision trees and the more advanced concept of fuzzy logic models. Furthermore, the technology acceptance model (TAM) and the value-based adoption model (VAM) are introduced as key models in the study of technology acceptance. Lastly, *enrollment* involves the coordination and alignment of actors' roles, illustrating how the concepts of socio-technical theory effectively integrate new technologies by addressing both human and technical aspects.

E. Steyn et al., *Programmable Decisions for Business Organizations*,
https://doi.org/10.1007/978-981-95-0724-5_3

Keywords Actor-network theory · Artificial intelligence · Decision-support model · Enrollment · Interessement · Problematization · Socio-technical theory · Value chain

JEL Classification M14 · M15 · O33 · O35

3.1 Introduction

Whereas the previous chapter provided insights into the research and development process, this chapter elucidates the underlying theories by identifying the contextual actors and their roles in relation to the concepts of problematization, interessement, and enrollment, thereby illustrating the integrated nature of the approach using socio-technical theory.

The underlying theories provide a lens through which to view reality, using explanatory concepts to understand events and actions. Actor-network theory (ANT) has proven particularly valuable in information systems and technology research, for example, by analyzing human and non-human social media actors (Hajli et al., 2022) or demonstrating its successful application in artificial intelligence (AI) across various fields (Pollack et al., 2013).

3.2 Actor-Network Theory

3.2.1 Basic Concepts

A key goal of ANT is to understand how networks of shared interests are formed and sustained and why some fail (Walsham & Sahay, 1999). Despite ANT's varied methodological and analytical approaches, certain concepts remain relatively stable, as shown in Table 3.1.

In the context of this book's objectives, ANT's effectiveness in information technology stems from its principle of general symmetry, where human and non-human actors are treated as equals. To qualify as an actor within ANT, non-human entities must be capable of acting; for example, Pollack et al. (2013) noted that project plans can inform, schedules can

Table 3.1 Key concepts of ANT

Concept	*Definition*
Actor/actant	Any material, human or non-human
Actor-network	Related actors in a heterogeneous network of aligned interests
General symmetry	The symmetrical treatment of humans and non-humans as a priori equals
Translation	The ordering of actors through negotiating or maneuvering others' interests to one's own
Inscription	Introduction of artifacts that would ensure the protection of interests

Adapted from Adaba and Ayoung (2017) and Jackson (2015)

dictate, budgets can constrain, and planning can limit. The concept, illustrated by Jackson (2015), involves a ball in a game actively shaping relationships between (1) the players themselves and (2) the players and the ball. This reflects the definition of an actor network, where related actors within a heterogeneous network (or system) share aligned interests. The formation or failure of a network occurs through a process called translation, which involves four progressive stages, as shown in Fig. 3.1.

Figure 3.1 illustrates the four moments of translation in network formation as follows:

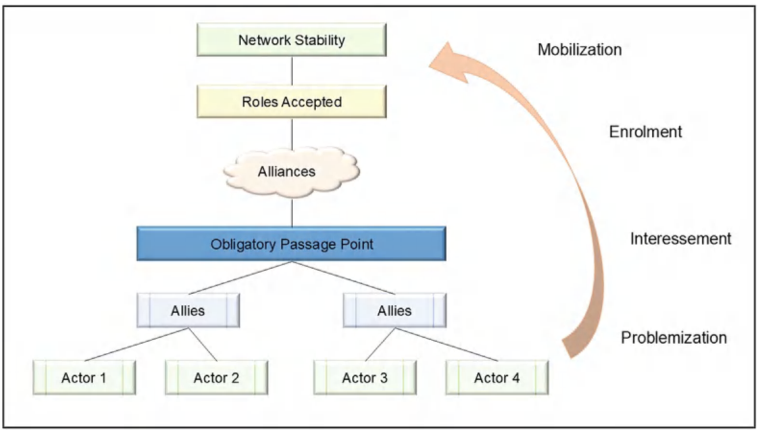

Fig. 3.1 Network translation (Adapted from Zawawi [2018])

- Problematization, as the starting point of the process, defines all the actors and formalizes the alliances pertinent to the scenario.
- Interessement occurs when the actors reach a pivotal point, convinced that their alliances can fulfill their collective interests and secure their roles in the network.
- enrollment, where actors' roles are defined and coordinated.
- Mobilization ensures that actors are adequately represented, creating a stable network.

3.2.2 *Contextual Application of ANT*

In alignment with Gumede and Tladi (2023), who proposed the contextual application of ANT in a socio-technical environment to better systematize the social aspects of technical work, Fig. 3.2 illustrates the contextual application of ANT in this book.

Figure 3.2 indicates the following:

- During the *problematization* stage, the focal point actor identifies the problem and proposes a potential solution, which enables the

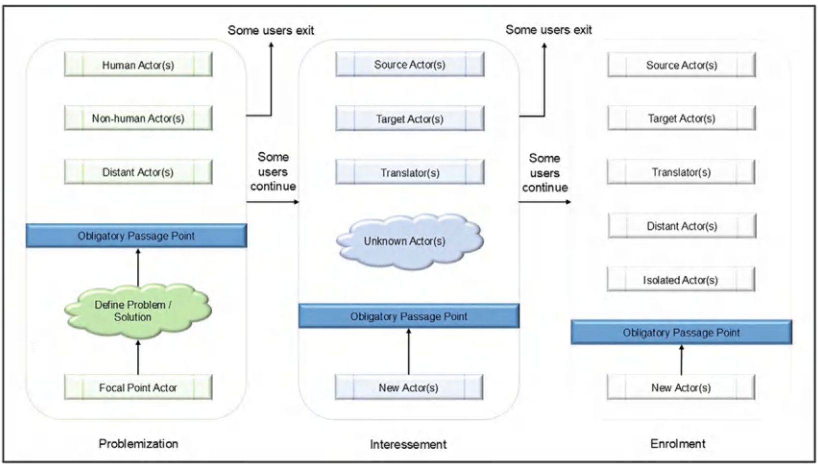

Fig. 3.2 ANT application (Adapted from Gumede and Tladi [2023])

identification of possible actors for the network. Initially, all human and non-human entities are considered equal in negotiation.

- During the *interessement* stage, roles are assigned to other actors within the network, which may include translators who mediate between source and target actors. This stage involves negotiations among actors to align their interests, suggesting that each moment in ANT development has its passage points that actors might navigate as the network evolves.
- During the *enrollment* stage, all actors have been identified, and their roles are confirmed within the network, recognizing that the network can achieve its intended goals while supporting their interests.

The following sections will integrate the underlying concepts within the ANT framework application, using the three moments of translation (as illustrated in Fig. 3.2) to demonstrate the creation of a network of humans and non-humans. Such networks, driven by aligned interests, will be used to develop the envisaged AI-enabled decision-support model.

3.3 Problematization

3.3.1 Porter's Value Chain

The first step in applying ANT is identifying all network actors, including decision-makers and technologies. Porter (2001) described the well-known value chain concept, which will be used to identify the initial decision-making actors and the connections between employees and technology.

In striving for a competitive advantage, Porter (2008) argues that organizations should be viewed as a series of distinct yet interrelated activities working together to deliver a specified outcome, such as a product or service. The primary activities add value at different stages as the incomplete deliverable progresses through these activities, while the support activities provide assistance. For the purposes of this book, Porter's generic value has been adapted to illustrate possible primary and support activities in an organization, as shown in Fig. 3.3. Analyzing each activity in context should arguably make it possible to identify the context-applicable key performance indicators (KPIs).

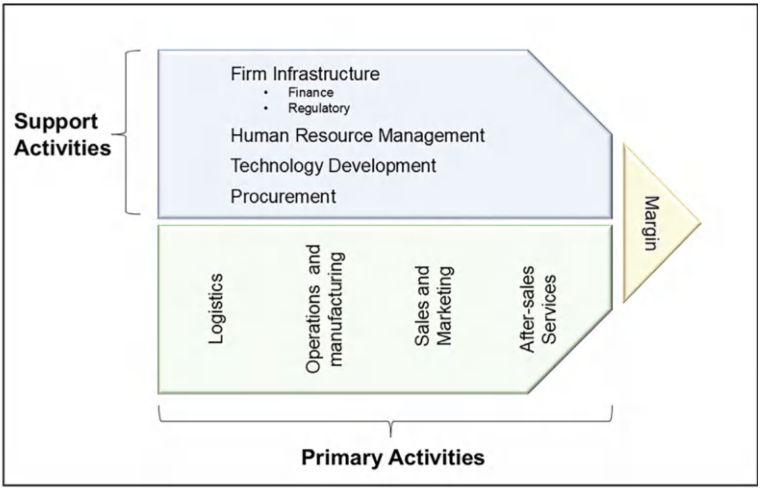

Fig. 3.3 Contextual value chain (Adapted from Porter [2001])

The value chain concept and its underlying philosophies have been adapted in areas and applications beyond individual firms (Zamora, 2016), as evidenced by its application in:

- The assessment of the impact of technological innovations (Moreno-Brieva & Merino-Moreno, 2021).
- The evaluation of industries with limited literature, such as the elderberry industry (Cernusca et al., 2012).
- The examination of how 5G technology can support the value chain (Rejeb & Keogh, 2021).

The mentioned studies demonstrate the applicability of value chain concepts in various industry contexts and technological investigations. By evaluating the activities within individual value chain activities, including the value chains that comprise a specific supply chain, we argue that a very pragmatic approach to understanding an organization can be developed.

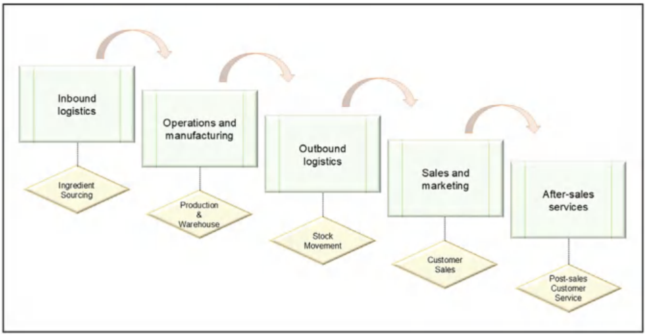

Fig. 3.4 Conceptual supply chain processes (Adapted from Mehralian et al. [2015])

3.3.2 Decision-Making

3.3.2.1 Value Chain Guided Decision-Making

By focusing on the supply chain, Mehralian et al. (2015) deepened the understanding of the role of the value chain concept in managerial decision-making and operational analysis. Figure 3.4 illustrates potential key factors herein.

Figure 3.4 illustrates the primary activities and the underlying decision contexts that may be found in a manufacturing and distribution environment. Analyzing these activities should greatly enhance contextual decision-making and KPI management. Understanding these factors should also enable the exploration of how AI can support decision-making.

3.3.2.2 AI as Actor

A significant challenge in AI-based technologies is mimicking the human ability to learn and adapt through reading, studying, and experience. As such, AI-based technologies strive to achieve machine intelligence, which is defined as the ability to compute and achieve the stated management objectives. According to González García et al. (2019), the current efforts aim to enable machines to recognize human language and replicate decisions based on logical, algorithmic-based rules. In applying such logic, AI mimics the human brain in solving industry-specific challenges, such as optimizing transportation (Abduljabbar et al., 2019), conducting sales and marketing analyses for market segmentation (Tiwari et al., 2020), or detecting fraud (Pallathadka et al., 2021). In doing so, it is used across various sectors, including data mining, expert systems, data classification (González García et al., 2019), gaming, language understanding (Pannu, 2015), and data management through machine learning (Jelley, 2022). Therefore, AI-based technologies can arguably be seen as actors in the context of ANT applications.

Specifically applicable to the context of this book, AI-based technologies are also applied to more complex operational processes (Wafa'H et al., 2021), with their application spanning a significant portion of the conceptual supply chain, as illustrated in Fig. 3.4. In this context, three key actors emerge, i.e., (1) the decision-makers within the value chain, (2) the AI systems, and (3) the organizations they operate within. Each actor influences the others as they work towards achieving specific objectives.

3.4 Interessement

The primary objective of the interessement stage is to lock the actors into their roles. For this to happen, human actors must understand how AI-based technology works. This understanding provides a framework for evaluating the programmability of decision-making within a specific context.

3.4.1 Understanding Decision-Making

To fully grasp decision-making in an AI environment, it is crucial to have a foundational understanding of the decision-making concept and, ultimately, how decisions are made. Martin et al. (2009) state that an essential aspect of decision-making is defining an objective and what the decision-maker aims to achieve. Bohanec (2003) argues that the essence of decision-making entails assessing the problem, identifying alternative solutions, making a logical evaluation between such alternatives, and selecting the preferred alternative. Through the progression of the *industrial revolutions*, the concept of decision-making has evolved to incorporate data-driven approaches, including machine learning and automated decision-making (Elgendy et al., 2022). Therefore, given the specific scenario's context, decision-making aims to pick the optimum alternative to achieve a specified objective.

3.4.2 *Decision-Support Models*

Early literature recognized *decision trees* as a pragmatic approach to modeling the decision-making process (Magee, 1964). Many contemporary studies, such as Avellaneda (2020) and Hu et al. (2019), have focused on their optimization. At its core, decision trees map out various decision routes leading to different outcomes, assessed against the objectives specific to the scenario, culminating in positive (P) or negative (N) outcomes. Figure 3.5 shows a simple decision tree illustration for a make-or-buy decision.

As indicated, the path for the decision will lead to one of four outcomes. The root node represents the initial question, with internal nodes connected by branches leading to leaf nodes representing outcomes (Lee et al., 2022). Best practice involves ensuring that each internal node has a corresponding leaf node to avoid excessive internal nodes and complex decision trees, which can impact reliability (Song & Ying, 2015).

Each internal node may also involve different considerations, which can be visualized using an influence diagram. As shown in Fig. 3.6, this helps to identify critical issues and support decision tree analysis.

Figure 3.6 shows the additional components to be included in the decision tree concept, further refining the alternatives. As such, these considerations may impact the decision's outcome, altering the decision path and leading to different outcomes. As illustrated, the total cost per product (as a KPI example) is linked to the make-or-buy decision,

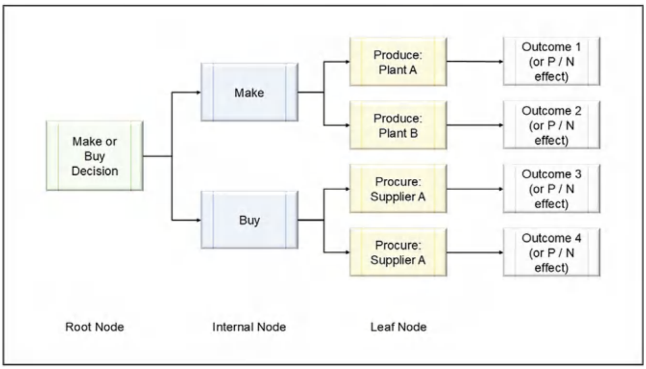

Fig. 3.5 Conceptual decision tree

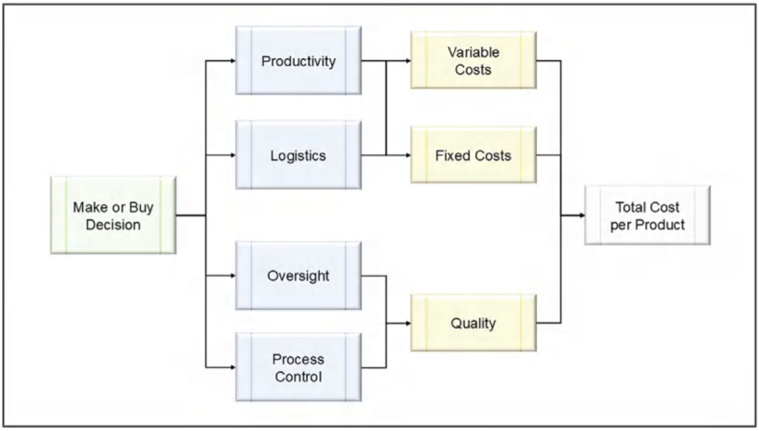

Fig. 3.6 Conceptual influence diagram (Adapted from Chelst [2013])

potentially influenced by various levels of influence such as productivity, logistics, oversights, and process controls, which in turn may be influenced by the next level considerations such as variable costs, fixed costs, and quality.

A criticism against the decision tree concept is a potential lack of flexibility. Since decision outcomes may not always be binary, as illustrated in Fig. 3.5, introducing additional variables in context after model development can be challenging. Fuzzy logic has emerged to address the limitations of traditional models that rely on binary outcomes. This approach can handle more complex outcomes and develop rule-based behaviors (González García et al., 2019; Phillips-Wren, 2012). Figure 3.7 contrasts a fuzzy logic approach with the traditional decision tree concept in the context of a knowledge rule base.

As illustrated, in a rule-based (fuzzy logic) approach, the outcomes range from "0" to "1," such as Very (0.9), Moderate (0.7), Slightly (0.25), or Not (0.1), compared to a binary (decision tree) outcome of Yes (1) or No (2). The rule-based system allows for some interpretation of user queries, such as determining whether it is cold outside, utilizing a so-called inference engine that contains the rules upon which the logic is based. This allows for more nuanced information for decision-makers.

The inference system evaluates users' input data or queries using the *knowledge rule base* parameters, upon which the outputs are formulated. A

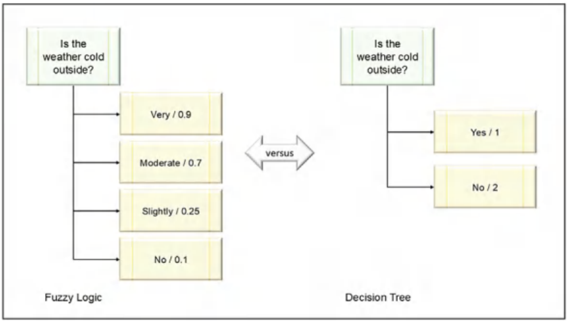

Fig. 3.7 Knowledge rule base concept (Adapted from Sarker [2022])

critical advantage hereof is adaptability, which, according to Phillips-Wren (2012), can be refined with new information, thereby enhancing control throughout decision-making. Fuzzy logic improves decision-making and performance management (Chan et al., 2002) and has been applied to specific analysis areas, such as:

- Financial and operational management, e.g., cost-volume analysis (Yuan, 2009).
- Indoor climate control based on external weather conditions (Meana-Llorián et al., 2017).
- Personal entertainment, such as video streaming services (Bagchi, 2011).

Thus, fuzzy logic is a viable approach for considering variables in decision-making, offering a framework for evaluating ranges of possible outcomes.

3.4.3 Decision-Making Within AI

As AI-based technologies become increasingly integrated into daily life, a critical issue is how these systems can effectively coexist with humans. This book focuses on coexistence in the context of business decision-making. To this effect, Shrestha et al. (2019) examined four AI decision-making approaches as follows:

- Full AI;

- Sequential AI to Human (S_AI - H);
- Sequential Human to AI (S_H - AI); and
- Aggregated Human to AI (A_H - AI).

These approaches were assessed across five areas as follows:

- Decision search space—between high and low.
- Interpretability—between high and low.
- Alternative set size—between large and small.
- Decision speed—between fast and slow.
- Replicability—indicated as its potential impact on either humans or AI.

These findings are summarized in Table 3.2.

As indicated, AI-based technologies increase the need for decision search spaces, while human intervention reduces it. AI also affects decision interpretability, potentially causing delays before implementation. Humans typically limit outcome options, constrain decision results, and slow decision-making by acting as bottlenecks in three approaches. Due to its algorithmic nature, AI facilitates replicable decision outcomes. Relevant to the book's objectives, Alami et al. (2020) identified AI readiness, stakeholder acceptance, technology alignment, and a business plan as important factors.

Regarding the programmability of decisions, Herbert Simon, a pioneer in decision-making theory, classified decisions along a spectrum from programmed to non-programmed (Pomerol & Adam, 2004). On this spectrum, programmed decisions are structured and predictable, whereas *non-programmed* decisions are more ambiguous. Saaty (1978) expanded

Table 3.2 AI approaches to organizational decision-making

Approach	*Decision search space*	*Interpretability*	*Alternative set size*	*Decision speed*	*Replicability*
Full AI	High	Low	Large	Fast	High: AI
S_AI - H	High to low	High	Large	Slow	Low: human
S_H - AI	Low to high	Low	Small	Slow	Low: human
A_H - AI	Low	High	Small	Slow	Partial: AI

Adapted from Shrestha et al. (2019)

this by introducing structured, semi-structured, and unstructured choices based on their outcomes. Structured decisions, therefore, would have more known outcomes, while unstructured decisions would involve higher levels of uncertainty.

3.4.4 Information Technology Acceptance Models

According to Pasmore et al. (2019), contemporary system design has shifted from *one-time optimization* efforts to *continuous*, agile approaches. In such an environment, implementing new technologies requires a *socio-technical* system design approach, rather than a purely technological design approach (Coiera, 2007), making it essential to understand the scenario-specific user culture. Several so-called technology acceptance models (TAM) aim to elucidate the relationship between users' attitudes and the actual practical application of technology. In the context of this book's objectives, the TAM and the value-based adoption model (VAM), per Erasmus et al. (2015), are arguably the most relevant in our context. Sohn and Kwon (2020) state that although TAM is widely used to study technology adoption behavior, it does not consider external factors. As an extension of TAM, VAM incorporates enjoyment, perceived benefits, and sacrifices, and is deemed applicable to AI-based scenarios.

3.4.4.1 Technology Acceptance Model

In response to the technology boom of the 1970s and subsequent adoption failures, a model was needed to predict system usage. Davis (1985) developed a model to measure potential users' attitudes toward new systems, as shown in Fig. 3.8.

As indicated, TAM posits that system usage is shaped by users' attitudes towards the system, which are affected by its perceived usefulness and ease of use. These perceptions are affected by various factors, indicated as X1, X2, and X3.

VAM emphasizes that technology adoption hinges on comparing unknown benefits against uncertain costs (Kim et al., 2007). The model assumes that the system will be adopted if users believe it will enhance job performance and that the benefits outweigh the effort required.

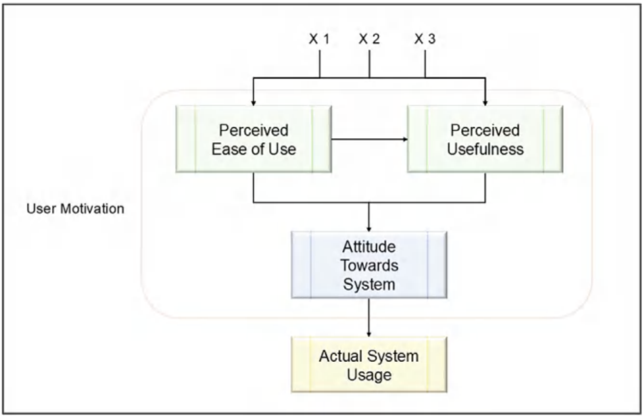

Fig. 3.8 Technology acceptance model (Adapted from Davis [1985])

3.4.4.2 Value-Based Adoption Model

The VAM approach was developed to complement the TAM approach, particularly in the adoption of new technologies (Lin et al., 2012). It is depicted in Fig. 3.9.

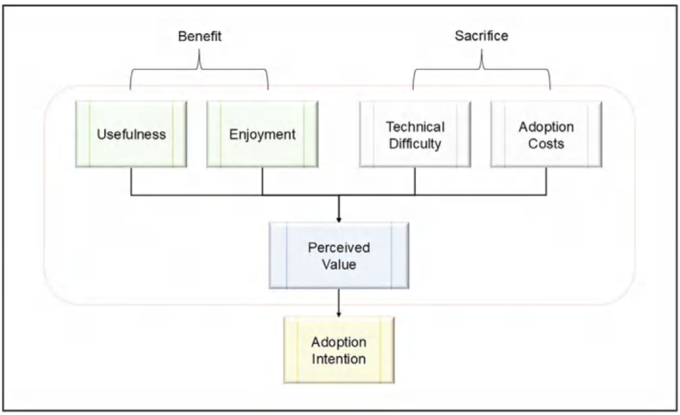

Fig. 3.9 Value-based adoption model (Adapted from Kim et al. [2007])

As illustrated, VAM considers two critical aspects: the *perceived benefits*, such as the system's usefulness and enjoyment, and the *perceived sacrifices*, including technical difficulty and adoption costs, associated with adopting the new system. While TAM focuses on user attitudes toward new technology, VAM also considers users' adoption intentions.

Therefore, in the contextual application of ANT, the interessement phase introduces human actors to decision trees to understand AI decision-making by applying TAM and VAM, which will also extend the user attitudes and adoption view assessments with the enrollment phase.

3.5 Enrollment

Enrollment involves coordinating and aligning the roles of the actors to achieve the network's objectives. To achieve this, a socio-technical framework will illustrate the integrated relationships between the human and the non-human actors.

3.5.1 Socio-Technical Theory

Research into both technical and social aspects has long recognized the profound impact of technological innovation on society. Furthermore, Pasmore et al. (2019) noted that the gap between technological advancements and organizational design, or alternatively, the gap between technological sophistication and societal acceptance thereof, has widened in recent times, making *socio-technical* theory more relevant as Industry 4.0 technologies continue to disrupt the business environment.

Applying socio-technical concepts is crucial for understanding how to effectively integrate new technologies, addressing both the human and technical aspects (Murphy, 2022; Sekgweleo et al., 2017). These conceptual interactions are illustrated in Fig. 3.10.

As illustrated, people within organizations interact with each other and with technological systems, which involve the physical system (i.e., the hardware) and the task aspects (i.e., the software).

Therefore, implementing a new system requires more than just technical considerations. Successful technology implementation requires considering the complex interaction between such actors and understanding how the organizational culture could better leverage technological resources (Pasmore et al., 2019). As such, socio-technical theory

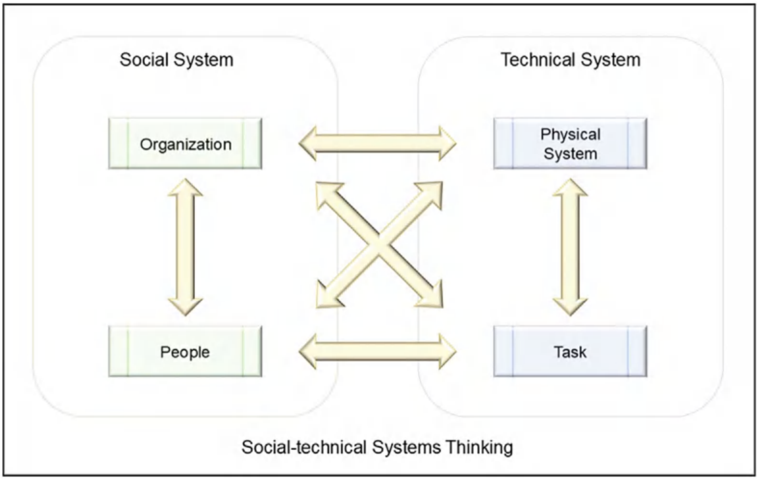

Fig. 3.10 Humans versus technology interaction (Adapted from Oosthuizen and Pretorius [2016])

involves using technology within a social structure to achieve specific objectives.

3.5.2 Socio-Technical Application

Building on the above, such integration triggers various levels of social and technical effects within the organization, as illustrated in Table 3.3.

Table 3.3 outlines the different interaction levels and key characteristics when implementing new technologies, evolving from the first level of algorithms through computer programming, the interaction between humans and computers, and ultimately a socio-technical system. The latter is ideally where the human and the technological actors work towards a common goal. In the context of this book's objective, we agree and note that the complex human interactions in contemporary industry make it particularly suitable for socio-technical theory. Furthermore, designing socio-technical systems requires a systems approach, as illustrated in Table 3.4.

Table 3.3 Socio-technical levels

Level	*Characteristic*
Algorithms	A formal representation of a process for accomplishing something
Computer program	Computer programs are the computational form of algorithms
Human–computer interaction	The physical and metaphorical ways users interact with computers
Socio-technical systems	Socio-technical systems analysis examines how human-technology interactions influence human interactions

Adapted from Coiera (2007)

Table 3.4 Socio-technical approach

System element	*Definition*
Boundaries	System boundaries are defined to ensure security and allow for system expansion
Internal structure	System internal structures ensure system reliability and flexibility. Internal structures ensure that the system is reliable and flexible
Effectors	System effectors utilize resources to respond to the environment, ensuring desired functionality and usability
Receptors	System receptors handle communication between systems, ensuring connectivity and privacy

Adapted from Whitworth (2009)

Socio-technical theory explores the interactions between humans and technologies to achieve specific goals. Table 3.4 illustrates these interdependencies in a systems thinking context. Therefore, with the actors, goals, and interdependencies confirmed and models such as TAM and VAM applied, the actor-network will focus on empowering management decision-making by advancing the understanding and utilization of technologies like AI.

3.6 Summary

This chapter justifies the theoretical foundations that support the development of the envisioned AI decision-support model, aligning with the book's objective. In doing so, it illustrated how an understanding of the programmability of decision-making within an AI environment can be influenced by socio-technical thinking. It also illustrated the roles of different actors within ANT, covering the first three translation moments. During *problematization*, actors were identified using Porter's conceptual value chain, and decision-making within this framework was examined. Under *interessement*, decision-making in AI environments was explored with decision trees, influence diagrams, and fuzzy logic to address decision programmability. Finally, *enrollment* was achieved by demonstrating interdependent relationships between human and non-human actors through socio-technical theory. The next chapter will elaborate on the finer details of the design science-based approach used to develop the envisioned AI decision-support model.

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CHAPTER 4

Diagnostics: Business Problem

Abstract This chapter presents the first diagnostic iteration per the elaborated action design research (eADR) approach and aims to identify and refine key performance indicators (KPIs). The first cycle involved discussions with mid-level managers to identify relevant KPIs across primary and support functions, classifying them into leading and lagging metrics. The second cycle refined and validated these metrics through validation with senior management, ensuring strategic alignment and relevance. A structured decision tree framework was developed to map the performance metrics to organizational decision variables, incorporating a thematic analysis approach. The findings underscore the need for a dynamic artificial intelligence (AI) decision-support model that considers both internal and external performance drivers. The final output, the _DecisionArtifact, consolidates these elements into a strategic framework and advances actor-network theory (ANT) interessement progression by identifying key actor roles and their influence in shaping the AI decision-support model.

Keywords Actor-network theory · Artificial intelligence · Decision-support model · Elaborated action design research · Key performance indicators

JEL Classification M13 · M16

E. Steyn et al., *Programmable Decisions for Business Organizations*,
https://doi.org/10.1007/978-981-95-0724-5_4

4.1 Introduction

The previous chapter contextualized actor-network theory (ANT) as underlying the development of the anticipated artificial intelligence (AI) decision-support model. This chapter covers the first of the three bespoke diagnostic iterations. This iteration consists of two cycles; the first identifies and considers the current key performance indicators (KPIs) through group discussions with mid-level managers, and the second refines the developed knowledge in collaboration with senior-level managers. Both cycles will follow the essential elaborated action design research (eADR) roadmap, which considers the problem, the build, and the evaluation of the in-process artifact building block, concluding with reflection and learning aspects.

4.2 Performance Metric Classification: First Cycle

4.2.1 Problem Formulation

According to action design research (ADR)'s first and second principles, artifact design must be based on practice-inspired realities and theory-ingrained research, drawing from real-world issues and science-based literature. With this in mind, considering the KPIs is necessary to understand the relevant metrics in the contexts of an organization's primary and support activities. Irfani et al. (2019) define the concept of *performance metrics* as metrics that quantify the effectiveness and efficiency of organizational actions. The following sections introduce illustrative performance metrics as a foundational framework for organizational performance analysis and decision support.

4.2.1.1 Primary Activities

The primary activities per Porter's value chain, refined for purposes of this book (refer to Fig. 3.3 as an illustrative guide) are considered as follows:

- Logistics activities ensure the movement of goods from origin to destination (Irfani et al., 2019) and help optimize inbound and outbound logistics in the value chain. Andersen and Fagerhaug (2003) emphasize the use of both quantitative and qualitative metrics to manage and enhance logistics functions, while Fawcett

and Cooper (1998) identify both *financial* and *non-financial* metrics. Examples of this may include logistics costs, inventory management, productivity, inventory levels, and shipping accuracy.
- Manufacturing activities include operations, defined by Porter (2001) as transforming inputs into final products. These activities encompass inbound logistics and manufacturing within the value chain, aiming to link manufacturing to outbound sales and marketing activities. Ahmad and Dhafr (2002) emphasize the need for a balanced mix of *financial* and *non-financial* metrics, including profitability, product quality, manufacturing flexibility, production speed, and customer satisfaction.
- Sales, marketing, and after-sales-support services encompass critical indicators of the organization's ability to generate revenue (Liu et al., 2015), emphasizing the need for integrated metrics. Such metrics could include *financial* indicators, with a focus on customer relationships, as well as non-financial metrics that hold sales teams accountable (Zallocco et al., 2009). These metrics also encompass sales volume, profitability, brand awareness, customer base growth, and customer retention (Clark, 2001).

4.2.1.2 Support Activities

In supplementing the primary activities, the support activities may include the following:

- (Soft) Firm infrastructure provides a vital support activity that services the entire value chain. Although organizational infrastructure may vary from case to case, input from stakeholders should be obtained to define the most appropriate metrics in context. These may typically be finance metrics (Mihăiloaie, 2019) and regulatory metrics (Giordano, 2022).
- Human resource (HR) management adds value by managing human capital to achieve a return on employee investment (Gabčanová, 2012). It must continuously monitor its targets through both financial metrics, such as labor costs per employee and return on investment (ROI) on training, and non-financial metrics, including employee relations, skill development, and recruitment (Gabčanová, 2012).

- Technology development provides support by leveraging technology. Arden et al. (2021) highlight that Industry 4.0 technologies, including digitization, autonomous systems, robotics, and computing, can transform organizational performance; however, adoption requires overcoming challenges related to data and automation.

4.2.2 Action Planning

The current cycle aims to identify and evaluate organization-specific performance metrics, as elucidated below.

4.2.2.1 Performance Metric Identification and Evaluation

The previous section considered basic metric categories across different potential value chain activities. However, as noted above, identifying the metrics would require input from knowledgeable stakeholders. Hence, a pragmatic framework is needed to identify relevant organizational activity metrics. Table 4.1 presents the proposed approach used in this book.

The illustrated framework aims to classify and analyze metrics based on the pertinent value drivers of each function, which are then differentiated by internal or external comparison against industry standards or benchmarks. Subsequently, the analysis considers the *leading metrics*, which focus on future performance, while *lagging metrics* measure past results. Finally, the lagging metrics are classified as qualitative, providing categorical information, and quantitative, offering numerical information. Figure 4.1 illustrates a roadmap for using this framework in the metric identification and evaluation.

As illustrated, the process begins by identifying value-adding activities within a function, upon which (1) the leading metrics are based, acting as

Table 4.1 Performance metric identification framework

Value driver	*Focus*	*Leading metric*	*Lagging metric*	
			Qualitative	*Quantitative*
	Internal External			

Adapted from Gabčanová (2012)

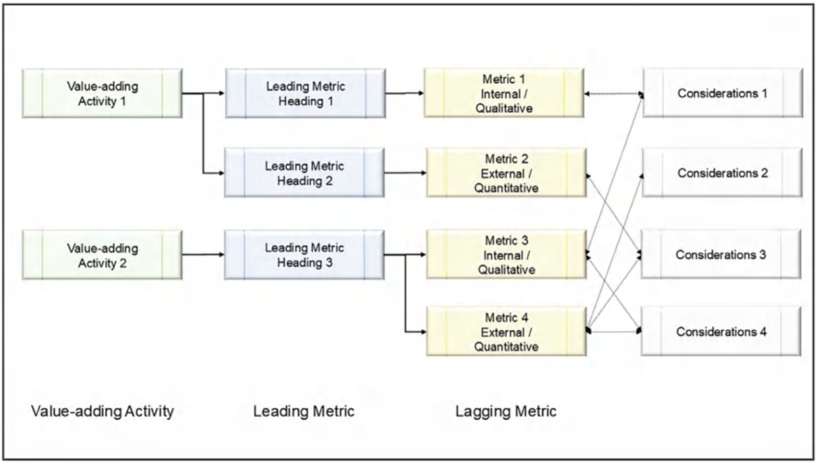


Fig. 4.1 Performance metric framework breakdown

categories for similar metrics, and (2) the lagging metrics are classified as either quantitative or qualitative. The latter's focus determines whether it is compared to internal standards or external benchmarks. Finally, factors that could potentially influence the actual performance must be considered. The accurate identification of these considerations enhances the development of decision trees.

4.2.2.2 Decision Tree Development

Corner and Corner (1995) proposed a three-dimensional analysis of decisions based on the problem structure, uncertainty in outcomes, and the decision-maker's preferences, laying a foundation for the decision tree concept. More recently, Kaul et al. (2022) highlighted the decision tree concept's applicability in the contemporary digital era.

Incorporating performance metrics into a decision tree involves charting each metric as a leaf node, representing the final decision point. The relevant metric's numeric or categorical outputs become internal nodes, branching into the root nodes and encompassing all internal node considerations. In context, it is therefore crucial to weigh each root and internal node, reflecting their significance (Song & Ying, 2015), as illustrated in Fig. 4.2.

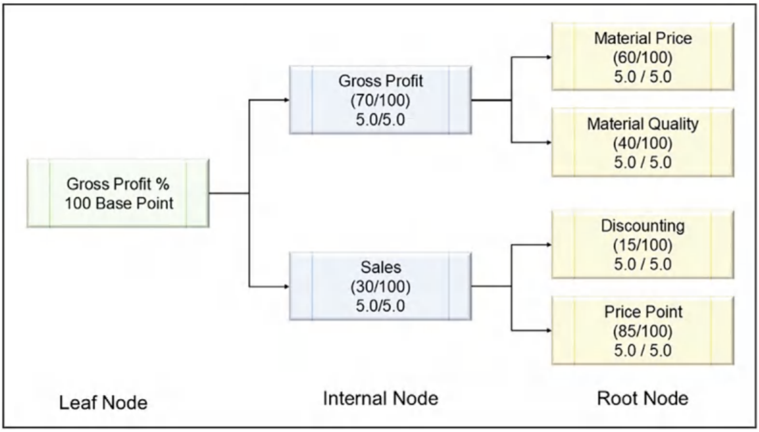


Fig. 4.2 Conceptual decision-making process

According to the illustration, the root nodes are considered individual factors that impact the overall performance; each is assigned a weighted rating (out of 100) and a base rating (out of 5.0). The various root nodes, in turn, contribute to the *internal node*, which is assigned to a base point and a weight rating, both of which can impact the leaf node and, consequently, affect the calculation of the metric. With a base rating of 100 points, any decision affecting such a rating must be assessed for acceptable variations to decide whether it should be implemented.

4.2.2.3 Data Collection

Specific details on applicable performance metrics and supporting considerations should be developed in collaboration with relevant experts, typically through discussions or workshops. The group discussions for the diagnostic iterations were planned per the guidelines of Nyumba et al. (2018), which entailed defining the research design, objectives, and data collection methods. A structured questionnaire guides the latter. After the data collection, thematic analysis will be applied to interpret and extract insights.

Group discussions using the said questionnaire involved up to four mid-level management participants per operational function across 11 organizational tasks. The participants identified value drivers for their respective functions, which represent their primary areas of responsibility. Relevant metrics were linked to these drivers and classified as lagging indicators, with further discussion determining their focus (i.e., internal or external) and measurement standards. The metrics were then categorized as qualitative or quantitative and grouped under broader headings for manageability.

4.2.3 Artifact Creation

Mullarkey and Hevner (2019) note that various artifacts can be created during the eADR cycles, depending on the iteration. For this book, the envisaged AI decision-support model requires data on industry decision-making processes and supportive considerations. As one of its building blocks, the applied framework, as outlined in Table 4.1, guides the identification and evaluation of relevant metrics and their underlying considerations.

The following sections outline the value drivers, leading, and lagging metrics in the context of primary and support value chain activities, as illustrated in Fig. 3.3.

4.2.3.1 Primary Activities

The following sections outline potential, illustrative primary activities, detailing the value drivers, leading and lagging performance metrics, and considerations that affect these metrics. Afterward, the thematic groups related to the leading metrics groups will be presented.

i. *Logistics (Inbound and Outbound)*

Table 4.2 illustrates the value drivers' leading and lagging metrics and their foci in the inbound and outbound logistics context.

Table 4.3 further clarifies the information in Table 4.2 by examining the thematic factors that influence the contextual metrics, detailing the value drivers and key metric groups.

ii. *Operations and Manufacturing*

Table 4.2 Logistics: value driver analysis

Value driver	*Focus*	*Leading metrics*	*Lagging metrics*	
			Qualitative	*Quantitative*
Logistics integrity	External	Compliance	Logistics compliance standards	–
Inbound logistics maintains the integrity of raw materials, while outbound logistics ensures the integrity of the supply chain from the supplier to the end user. Logistics integrity value driver measures compliance with potential industry standards, typically using metrics to assess qualitative adherence				
Supplier management	Internal	Relationship management	Supplier service level agreement (SLA) matrix compliance	
		Cost management	–	Cost comparison to budget
The supplier management value driver measures logistics suppliers' compliance with internal SLAs and industry standards, ensuring adherence to pricing, capabilities, communication, deliverables, and accreditations. Internally, logistics fees are compared to budgets to assess the value received				

Table 4.3 Logistics: thematic considerations

Value driver	*Leading metric group*	*Thematic considerations*
Logistics integrity	Compliance	Compliance/external compliance
Changes or deviations from industry standards could impact compliance with legislation and industry regulations, affecting the compliance metrics of the logistics integrity value driver		
Supplier management	Relationship management	Suppliers/internal standards
	Cost management	Supplier/cost management
		Logistics/logistic management
Supplier management involves establishing an internal SLA between the company and its logistics suppliers, and various factors influence compliance		

Table 4.4 illustrates the value drivers' leading and lagging metrics and their foci in the context of the operational activities.

Table 4.5 further clarifies the information in Table 4.4 by examining the thematic factors that influence the contextual metrics, detailing the value drivers and key metric groups.

iii. *Sales and Marketing*

Table 4.4 Operations and manufacturing: value driver analysis

Value driver	*Focus*	*Leading metrics*	*Lagging metrics*	
			Qualitative	*Quantitative*
Staff management	Internal	Production targets	–	Individual production targets
	External	Compliance	Professional qualification and CPD* compliance	–
Regarding staff management, qualifications, and ongoing professional development are tracked as qualitative metrics to ensure compliance. In production, staff or teams must meet output targets, measured as quantitative metrics against internal standards, and adaptable for automated environments				
Facility management	External	Housekeeping	Environment management	–
		Asset management	Equipment management	–
The facility management value driver ensures manufacturing facilities meet external standards for product safety. Performance metrics under housekeeping and asset management assess qualitative compliance, comparing facilities and assets against external requirements				
Production	Internal	Production	–	Production targets
		Planning	–	Planning delivery accuracy
	Internal/ external	Service levels	Product quality levels	
The production value driver measures actual manufacturing performance, including production targets and demand plan accuracy, expressed as compliance percentages against internal standards. Product quality must meet external legislative standards, and the final metrics assess compliance through both quantitative and qualitative measures				
Stock management	Internal	Stock level management	–	Obsolete stock levels
The stock management value driver ensures effective stock control by continuously monitoring levels to prevent obsolescence. Stock performance is measured as the percentage of obsolete stock relative to total stock and compared against internal standards				

*Continuous professional development

Table 4.6 illustrates the value drivers' leading and lagging metrics and their focus, specifically within the context of key sales and marketing activities.

Table 4.5 Operations and manufacturing: thematic considerations

Value driver	*Leading metric group*	*Thematic considerations*
Staff management	Compliance Production targets	HR/external standards HR/availability HR/internal skills available Business environment/internal environment
Effective staff management depends on factors that impact compliance and target achievement, including employee skills, educational levels, and changes in the business environment that influence production output		
Facility management	Housekeeping	Compliance/external compliance
	Asset management	Compliance/external compliance
The facility management value driver ensures compliance with industry standards, with metrics influenced by external regulatory changes and updates to facility hardware		
Production	Production	HR/availability HR/internal standards Stock management/availability Compliance/external compliance
	Planning	Production/planning Business environment/external trends
	Service levels	Compliance/external standards
The production process must comply with regulations and standards. Metrics influenced by HR availability, stock levels, and external trends impact production needs and planning accuracy		
Stock management	Stock level management	Business environment/external trends Stock management/external trends
The stock management value driver ensures stock does not become obsolete by considering external market changes and internal production capacities that impact stock demand and availability		

Table 4.7 further clarifies the information in Table 4.6 by examining the thematic factors that influence the contextual metrics and detailing the value drivers and leading metric groups.

iv. *After-Sales Service*

Table 4.6 Sales and marketing: value driver analysis

Value driver	*Focus*	*Leading metrics*	*Lagging metrics*	
			Qualitative	*Quantitative*
Customer relationship	Internal	Relationship management	Performance review	–
		Relationship creation	–	Number of new customer visits
	Internal/ external	Product placement	–	Store coverage of products
The customer relationship value driver focuses on building and maintaining client relationships. Organizations assess compliance qualitatively using a performance review matrix. Sales teams are evaluated based on new customer outreach and product range coverage in stores, with metrics tracking the percentage of stocked products to ensure proper distribution				
Departmental support	Internal	Stock availability	–	Stock planning (Infill report)
The sales function supports stock management by ensuring requested stock aligns with actual sales, with performance metrics measuring accuracy against internal standards				
Sales	Internal	Margin management	–	Various channel margin ratios
		External sales	–	Sales to the customer vs Budget achieved
			–	Sales go out to the consumer
The sales value driver ensures organizational profitability by managing sales and profitability ratios across channels. Performance metrics track financial ratios against internal standards and budgets. For wholesale sales, a metric monitors stock movement to final consumers				
Operational support	Internal	Staff management	–	Individual staff sales targets

(continued)

Table 4.6 (continued)

Value driver	*Focus*	*Leading metrics*	*Lagging metrics*	
			Qualitative	*Quantitative*
			–	Company policy compliance
			–	Commission management
		Staff training	Margin management training	
The operational support value driver ensures effective sales and HR management through the tracking of key metrics, including individual sales targets, policy compliance, and commission alignment with budgets. Staff training is also evaluated qualitatively to ensure the maintenance of required skills				
External brand awareness	Internal	Training	–	Number of training sessions
			–	Number of trainees
		Once-off support	–	New product sales support
			–	Obsolete stock movement targets
	Internal/ external	Sales Support	–	Specific sales targets
For external brand awareness support, the education function tracks training sessions for external staff to enhance sales effectiveness and ensure compliance with capacity targets and internal standards. Performance metrics also measure the sales performance of new or campaign-driven products and provide ad hoc support to address market changes, preventing stock obsolescence by converting it into sales				
Digital footprint	Internal/ external	Digital platforms	–	Product/ brand awareness
			–	Customer conversions

(continued)

Table 4.6 (continued)

Value driver	*Focus*	*Leading metrics*	*Lagging metrics*	
			Qualitative	*Quantitative*
The marketing function measures the quantity and quality of interactions with new products or brands under the brand awareness value driver. The goal is to ensure that sentiment initiatives reach a target audience, with performance metrics used to quantify their potential reach and compare it to internal standards				
Commercial measures	Internal	Innovation	–	Cost of goods sold (COGS) Support
		Renovation	Marketing investment levels	
The final value driver, commercial measures, enhances product profitability by optimizing commercial factors. Performance metrics include COGS savings compared to internal targets and financial investment assessed quantitatively against budgets and qualitatively against external benchmarks				

Table 4.8 illustrates the value drivers' leading and lagging metrics and their foci in the context of after-sales service activities.

Table 4.9 further clarifies the information in Table 4.8 by examining the thematic factors that influence the contextual metrics, outlining the value drivers, key metric headings, and relevant considerations.

4.2.3.2 Support Activities

i. *Finance*

Table 4.10 illustrates the value drivers' leading and lagging metrics and their foci in the context of the finance support infrastructure activities.

Table 4.11 further clarifies the information in Table 4.10 by examining the thematic factors that influence the contextual metrics and detailing the value drivers and leading metric groups.

ii. *Regulatory*

Table 4.12 illustrates the value drivers' leading and lagging metrics and their foci in the context of the regulatory support infrastructure activities.

Table 4.7 Sales and marketing: thematic considerations

Value driver	*Leading metric group*	*Thematic considerations*
Customer relationship	Relationship management Product placement	Customer/relationship Business environment/competitor analysis Stock management/availability Marketing/investment Business environment/business reputation Business environment/external trends
Key considerations for the customer relationship value driver include relationship history, internal and external factors, competitor actions, financial resources, product availability, market trends, and company reputation, all *of which influence* customer interactions and sales potential		
Departmental support	Stock availability	Stock management/availability Production/capacity Financial/cash resources Business environment/external trends
Departmental support considerations include supply planning accuracy, raw material availability, production capacity, and cash resources, all *of which impact* stock planning and the supply chain		
Sales	Margin management External sales	Sales/product mix Sales/pricing Customer/relationship Marketing/investment Business Environment/business reputation
The sales value driver considers factors impacting sales margins, including product mix, market and competitor trends, and company reputation, *which influence* pricing and profitability		
Operational support	Staff management	Stock management/availability Stock management/product mix Customer/relationship HR/internal standards

(continued)

Table 4.7 (continued)

Value driver	*Leading metric group*	*Thematic considerations*
For effective stock planning under operational support, sales must consider current stock levels, customer relationships, and adequate HR resources to optimize product mix and planning		
	Staff training	HR/availability HR/internal standards
The sales function's final value driver is staff management. The function ensures target achievement and policy compliance by considering staff availability for practical training		
External brand awareness support	Training	Business environment/ competitor analysis Business environment/ market Trends HR/availability HR/internal skills available
	Sales support Once-off support	Business environment/ competitor analysis Stock management/ availability Business environment/ business reputation Business environment/ time constraints
External brand awareness training is influenced by competitor strategies, internal skill shortages, staff availability, and market trends, all of which impact the content and delivery of training. For product sales and stock management support, business environment changes impacting product demand also affect performance metrics		
Digital footprint	Digital platforms	Marketing/internal standards Customer/pricing
Digital brand-building performance metrics rely on customer technical skills, factors that address customer needs, and influences on purchasing decisions		
Commercial measures	Innovation	Production/availability Business environment/ external trends
	Renovation	Business environment/ external trends Financial/cash resources
The commercial measures value driver is influenced by manufacturing costs, marketing's role in price reduction, financial resources, and market trends affecting product viability		

Table 4.8 After-sales service: value driver analysis

Value driver	*Focus*	*Leading metrics*	*Lagging metrics*	
			Qualitative	*Quantitative*
Pre-sales service	Internal	Customer satisfaction	Customer satisfaction index	
	External	Legality	Legality of sales	
The service department focuses on pre- and after-sales activities to ensure customer satisfaction. Pre-sales performance metrics assess compliance with industry regulations before a sale, while post-sales performance metrics evaluate customer satisfaction against internal standards during the ordering process				
After-sales service	Internal	Delivery management	–	On-time delivery
		Customer satisfaction	Customer satisfaction index	
	External	Delivery management	Delivery compliance	–
After-sales services focus on customer satisfaction with the product and delivery compliance. Satisfaction is measured against internal standards, while delivery time is assessed against customer agreements				

Table 4.9 After-sales service: thematic considerations

Value driver	*Leading metric group*	*Theme considerations*
Pre-sales service	Legality	Compliance/external compliance
	Customer satisfaction	Customer/preferences
Pre-sales services must comply with legal standards, requiring businesses to stay updated on regulatory changes. Customer satisfaction in ordering depends on various factors that companies must identify and understand		
After-sales service	Process management	Compliance/external compliance
	Delivery management	Logistics/logistic management Natural events/natural events Government/policies
	Customer satisfaction	Customer/satisfaction
After-sales services, like pre-sales, require regulatory compliance. Delivery performance metrics considerations include delivery type, destination, and unforeseen delays that affect timing		

Table 4.10 Finance: value driver analysis

Value driver	*Focus*	*Leading metrics*	*Lagging metrics*	
			Qualitative	*Quantitative*
Financial reporting	Internal	Reporting quality	–	Reporting quality
		Timely reporting	–	Timely reporting
	External	Compliance	Audit requirements	–
		Compliance	Listing requirements	–
		Compliance	Tax compliance	–
The financial reporting value driver focuses on meeting external financial requirements. Leading metrics emphasize the importance of reporting quality and timeliness to ensure high standards and punctuality. Qualitative metrics measure compliance by assessing adherence to audit, listing, and tax requirements				
Commercial finance	Internal	Commercial support	–	Reporting quality
		Commercial support	–	Timely reporting
	Internal/ external	Decision support	–	Various financial measures
Commercial finance supports the organization through timely, high-quality reporting to other functions. Key performance metrics in this context ensure proper reporting and include various business measures to guide decision-making, such as: • Statement of Profit or Loss (SoPL): – Sales vs. budget percentage – Gross profit margins – Fixed and payroll expenses – Rebates as a percentage of sales – Profit before and after tax • Statement of Financial Position (SoFP): – New working capital targets – Capital expenditure versus budget – Return on invested capital ratio				
Staff management	Internal	Staff measures	–	Staff productivity and service levels
Finance must effectively manage its HR resources to support other functions. The staff management value driver measures productivity to ensure timely report completion and compliance with internal standards				

(continued)

Table 4.10 (continued)

Value driver	*Focus*	*Leading metrics*	*Lagging metrics*	
			Qualitative	*Quantitative*
Supplier management	Internal	Relationship management	–	The volume of supplier complaints
In supplier management, the finance function oversees the processing of the accounting system, ensuring that inputs comply with internal standards measured by a quantitative metric. Supporting supplier relationships involves accurately reporting supplier documents, with quantitative metrics that track errors that may impact these relationships				

Table 4.13 further clarifies the information in Table 4.12 by examining the thematic factors that influence the contextual metrics and detailing the value drivers and leading metric groups.

iii. *HR Management*

Table 4.14 illustrates the value drivers' leading and lagging metrics and their foci in the context of the HR support activities.

Table 4.15 further clarifies the information in Table 4.14 by examining the thematic factors that influence the contextual metrics, detailing the value drivers and key metric groups.

iv. *Technology Development*

Table 4.16 illustrates the value drivers' leading and lagging metrics and their foci in the technology development infrastructure activities context.

Table 4.17 further clarifies the information in Table 4.16 by examining the thematic factors that influence the contextual metrics and detailing the value drivers and leading metric groups.

v. *Procurement*

Table 4.11 Finance: thematic considerations

Value driver	*Leading metric group*	*Thematic considerations*
Financial reporting	Reporting quality/timely reporting	HR/internal skills available Hardware/availability HR/availability
	Compliance	Compliance/external compliance HR/availability
Financial reporting prioritizes report quality and timely delivery. Key considerations include HR skills for managing internal reporting, availability of HR resources, and access to necessary information technology (IT) hardware		
Commercial finance	Commercial support	Business environment/internal processes Business environment/data accuracy HR/availability
	Decision support	Business environment/financial indicators HR/internal skill availability
The commercial finance value driver is influenced by internal processes, such as interdepartmental communication, which impact the ability to deliver quality outputs. External factors include data accuracy, the ability to interpret data, and staff availability for producing accurate, timely reports Supporting other functions involves adjusting financial indicators, such as sales levels, rebate management, COGS, fixed costs, and balances for debtors, creditors, and inventory		
Staff management	Staff measures	HR/internal skill availability Hardware/availability
The staff management value driver considers factors affecting productivity, including employee skills, available time, and access to necessary hardware for task accuracy		
Supplier management	Relationship management	HR/internal skill availability Supplier/internal processes
Supplier management focuses on internal standards for processing supplier documents in accounting software. Considerations include factors impacting capture quality, which could lead to supplier dissatisfaction or the need to rework documentation		

Table 4.18 illustrates the value drivers' leading and lagging metrics and their foci in the context of the procurement activities.

Table 4.19 further clarifies the information in Table 4.18 by examining the thematic factors that influence the contextual metrics, and detailing the value drivers and leading metric groups.

Table 4.12 Regulatory: value driver analysis

Value driver	*Focus*	*Leading metrics*	*Lagging metrics*	
			Qualitative	*Quantitative*
Product quality	Internal	Customer feedback	–	Number of recalls
		Customer feedback	–	Number of complaints
	External	Process management	Severity of adverse effect (Process impact)	
The regulatory function ensures compliance with government legislation and governing bodies. Key value drivers include product quality, safety, effectiveness, registration, development, and improvement. The product quality driver focuses on customer feedback, measured by the number of complaints or product recalls, compared against company standards. In cases of adverse customer effects, the metrics assess the manufacturing process's contribution, using quantitative and qualitative measures to identify its impact on negative feedback				
Product safety	External	Process management	The severity of adverse effect (Formulation)	
The product safety value driver addresses negative impacts resulting from product formulation, focusing on metrics that ensure compliance with external standards for formulation. In contrast, the product quality driver focuses on manufacturing-related adverse effects				
Product effectiveness	Internal	Financial indicators	Sales levels	–
	External	Research quality	Academic research	–
Two leading performance metrics measure product effectiveness. The first comparison quantitatively evaluates sales against competitors, attributing higher sales to the product's efficacy. The second ensures the formulation remains current by comparing it to the latest external academic studies				
Product registration	External	Compliance	Product registration compliance	–
The product registration value driver ensures all products comply with legislative requirements and are registered with relevant regulatory bodies for consumer safety. The performance metric qualitatively assesses adherence to local registration standards				
Product development	Internal	Trend reactions	Turnaround time	–
	External	Competitor analysis	Competitor analysis	–

(continued)

Table 4.12 (continued)

Value driver	*Focus*	*Leading metrics*	*Lagging metrics*	
			Qualitative	*Quantitative*
In dynamic market environments, organizations must quickly adapt to market trends. The product development value driver tracks competitive changes qualitatively and quantitatively measures the time from development to market				
Product improvement	Internal	Customer feedback	–	Change in the number of complaints
		Financial management	–	Product margin improvement
The product improvement value driver focuses on maintaining competitiveness by quantifying potential financial margin improvements and measuring them against actual economic changes. It also tracks the effectiveness of margin and product improvements through a reduction in customer complaints				

4.2.4 Evaluation

Based on the literature, Table 4.1 enabled the exploration of diverse performance metrics and outcomes. Data collection expanded participant perspectives on such metrics within their functions. As shown in Fig. 4.2, root and internal nodes can be weighted to manage lagging metrics. When a metric changes, additional scoring can be applied to the leading metrics and overall value activities.

Evaluating the artifact components against the earlier defined problem entailed identifying and analyzing literature-based performance metrics. However, being cognizant of the fifth ADR principle, confirming that evaluation is an ongoing process shaping design decisions (McCurdy et al., 2016: 3), feedback was continuously assessed after each interview to ensure well-rounded data. In line with the third ADR principle of reciprocal shaping, the dynamic evolution of the artifact and research process is shaped by industry experts and an industry-knowledgeable researcher to maintain relevance. These integrated aspects are presented in Fig. 4.3 as an initial building block artifact on the path to the envisioned AI decision-support model.

Figure 4.3 integrates a decision tree with previously created components. The themes serve as root nodes, influencing code groups (internal nodes), which in turn impact lagging metrics (leaf nodes). These

Table 4.13 Regulatory: thematic considerations

Value driver	*Leading metric group*	*Thematic considerations*
Product quality	Customer feedback Process management	Compliance/external compliance Business environment/external trends
Product recalls under product quality are influenced by compliance with external standards and changes in the business environment. Factors include alterations to product specifications, raw materials, or manufacturing standards, which can lead to customer complaints or product recalls due to failures		
Product safety	Process management	Compliance/external compliance Business environment/external trends Business environment/internal standards
Ensuring product safety requires compliance with legislation and academic standards in the initial formulation. Changes in external compliance requirements, internal manufacturing standards, and evolving consumer trends that impact perceived safety standards influence performance metrics		
Product effectiveness	Financial indicators	Business environment/external trends
	Research quality	Compliance/external compliance
Product effectiveness is measured externally by sales levels and internally by the quality of research. Key considerations include factors that impact the product's journey from manufacturing to shelves, as well as the organization's capacity to research and apply the latest trends effectively		
Product registration	Registration compliance	Compliance/external compliance
Changes in registration and compliance requirements set by authorities and governing bodies influence the product registration value driver		
Product development	Trend reactions	Business environment/internal processes Financial cash resources Human Resources/availability
	Competitor analysis	Business environment/competitor analysis
When considering product development, key factors include external market trends, product type, and internal resources such as financial and HR availability, which can impact the performance metric		
Product improvement	Customer feedback	Human Resources/internal skill availability Financial/cash resources

(continued)

Table 4.13 (continued)

Value driver	*Leading metric group*	*Thematic considerations*
	Financial management	Business environment/external trends Financial/cash resources
The product improvement value driver focuses on enhancing current products through innovation, with the first metric addressing external customer feedback to reduce complaints by tracking issues and implementing corrective actions. Additional metrics could target profit margin improvements through formulation updates, manufacturing processes, or packaging changes, relying on internal skills and financial resources. External trends also impact metrics, as failure to adapt to market or customer changes can hinder competitiveness		

contribute to a broader set of metrics affecting the leading metrics and, ultimately, functional value.

4.2.5 Reflection and Learning

Each eADR cycle's reflection and learning may trigger another cycle within the iteration, potentially leading to advancement to the next iteration or a move backward to refine problem understanding (Mullarkey & Hevner, 2019). These tables provide a foundation for an AI decision-support model but lack strategic inputs and oversight. Therefore, in the context of this book, before proceeding to the following diagnostic iteration (as outlined in Chapter 5), the validity of the value drivers presented in Tables 4.2–4.19 must be assessed.

Data validation is necessary to ensure accuracy and completeness; therefore, another diagnostic cycle is required to refine and validate the collected data before proceeding.

4.3 Performance Metric Classification: Second Cycle

4.3.1 Problem Formulation

Mullarkey and Hevner (2019: 4) emphasize that each eADR iteration's problem formulation should stem from the learning and reflection of the previous. The _DecisionArtifact, as the final output of this iteration, must be verified to confirm that it meets design iteration requirements.

Table 4.14 HR management: value driver activities

Value driver	*Focus*	*Leading metrics*	*Lagging metrics*	
			Qualitative	*Quantitative*
Staff pipeline	Internal	Workforce planning	–	Critical roles filled
			–	Leadership roles filled
HR creates value by managing talent to achieve a return on employee investment. Key value drivers include staffing pipeline management and ensuring continuity in the staff organogram. Relevant metrics measure the percentage of critical and leadership roles filled and the availability of successors for these positions				
Enablement	Internal	Onboarding	Role gap analysis	–
			–	Time to onboard
The enablement value driver ensures staff can meet job-specific targets and integrate successfully into the organization. HR conducts a qualitative role gap analysis to confirm staff have the necessary resources and training. The onboarding process is quantitatively measured to ensure it aligns with internal standards, enabling efficiency without overusing organizational resources				
Staff retention	Internal	Staff management	Staff development plans	–
	External		Employee benefits and value adds	
	Internal/external		–	Staff turnaround
After onboarding, HR ensures staff retention and maintains talent standards. The key metric for staff retention is the annual staff turnover rate, measured against internal standards and industry norms. HR evaluates employee benefits to minimize turnover, comparing them to market trends and internal budgets				
Learning and development	Internal	Supplier management	Supplier SLA matrix compliance	
		Staff development	9-box grid analysis	–
		Cost management	–	Learning and development cost management
			–	Government grant ROI management

(continued)

Table 4.14 (continued)

Value driver	*Focus*	*Leading metrics*	*Lagging metrics*	
			Qualitative	*Quantitative*
The learning and development value driver ensures staff skills remain relevant and aligned with industry standards. Training suppliers are evaluated using internal matrices to meet organizational standards. *A grid* framework qualitatively identifies staff members who need development. Development costs are assessed and compared internally to ensure compliance with standards. External factors, such as government grants for staff development, also impact this driver				
Labor compliance	External	Transformation	–	Transformation targets
	Internal/ external	Compliance	–	Legislation required reporting compliance
The labor compliance value driver ensures HR practices meet legislative and reporting requirements, including government transformation targets, reporting quality, and timeliness. These requirements align with stock exchange listing requirements and sustainability reports in annual financial statements; any changes to these requirements could impact compliance				

It encompasses a comprehensive set of performance metrics covering key organizational functions, supplemented by additional considerations. The artifact classifies metrics into leading and lagging categories, organizing considerations by theme and code, which supports its verification. While the decision framework identifies a range of concerns affecting these metrics, they are not exhaustive, as decision-making remains inherently dynamic and influenced by individual decision-makers.

4.3.2 Action Planning

The second cycle gathers additional industry feedback and validation on the performance metrics that support the objectives. Data collection and processing are discussed below.

4.3.3 Artifact Creation

Using the preceding tables as a guide, interviews will be conducted across 11 organizational functions, each involving one senior management

Table 4.15 HR management: thematic considerations

Value driver	*Leading metric group*	*Thematic considerations*
Staff pipeline	Workforce planning	Business environment/external HR standards Financial/budget constraints HR/internal processes
Factors affecting HR value drivers include market conditions that impact the availability and required skills, financial resources that influence the ability to maintain a skilled pipeline, and internal process complexity and compliance in hiring the right staff		
Enablement	Onboarding	HR/job specification HR/availability Financial/budget constraints HR/internal processes
During staff onboarding, key considerations include factors that impact the resources required for employees to perform effectively. Role complexity, availability of internal resources, and budget changes influence onboarding		
Staff Retention	Staff management	Business environment/external trends Business environment/external HR skills
Staff retention considerations include internal financial constraints that limit retention resources and external factors, such as the availability of skilled replacements in the market		
Learning and development	All leading performance metrics in the group	Financial/cash resources HR Resources/availability Government/grant management
Factors affecting learning and development metrics include internal financial resources and the availability of staff time for training. Externally, government incentives and grants influence ROI calculations and funding utilization for staff development		
Labor compliance	Transformation	Compliance/external compliance Compliance/internal compliance Financial/cash resources

(continued)

Table 4.15 (continued)

Value driver	*Leading metric group*	*Thematic considerations*
	Compliance	Compliance/external compliance
Changes in labor legislation or external reporting requirements directly impact the compliance metrics, affecting the company's adherence to labor compliance factors		

participant, to generate supportive knowledge and validate the current artifact. Each value driver required relevant performance metrics, categorized as lagging metrics. Participants discussed whether the metrics had an internal or external focus and whether they were measured against organizational or industry standards. The metrics were also classified as qualitative or quantitative and grouped under leading performance metric categories for better organization.

Once the performance metrics were confirmed, participants considered factors influencing them, following the thematic approach of the earlier iteration. After validating the data from the earlier iteration, industry participants provided additional insights, emphasizing a strategic perspective on the frameworks. Their input highlighted that decision frameworks align with the broader *business strategy*, as illustrated in Fig. 4.4.

Figure 4.4 shows that all nodes and value activities must align with the business strategy. Value drivers and performance metrics should support strategic objectives and remain relevant to the business environment. The findings emphasize that any AI-driven decision framework must be strategically designed to manage the relevant metrics effectively.

4.3.4 Evaluation

The final evaluation of the decision framework and data presented in Tables 4.2–4.19 informs the design of the _DecisionArtifact. Integrating business strategy further strengthens the artifact, enhancing support for the book's final objectives. The verification and validation of the _DecisionArtifact occurred in two steps: the design was confirmed to meet the specified requirements, and its ability to effectively address the defined *business problem* by identifying prevailing metrics in context was

Table 4.16 Technology development: value driver analysis

Value driver	*Focus*	*Leading metrics*	*Lagging metrics*	
			Qualitative	*Quantitative*
Infrastructure support	Internal	Service availability	–	Uptime
		Security	–	Applications levels
	External		Security standards	–
Infrastructure support is measured through service availability and security. Service availability ensures IT systems are operational and quantified as the uptime percentage against internal standards. Security is assessed qualitatively by comparing company practices to external standards, such as international organizational standardization (ISO), and internal security benchmarks				
Operational management	Internal	Hardware management	–	Warranty claims
			Asset life cycle management	–
		Software management	User applications availability	–
			Obsolete software review	–
Operational management metrics are measured against internal standards to ensure sufficient hardware and software for effective operations. It includes: • Hardware management: Measured by the number of warranty claims (quantitative) to assess brand reliability and asset lifecycle management (qualitative) to determine asset utilization before replacement • Software management: Assessed qualitatively against internal standards to ensure appropriate software availability for business functions while avoiding unnecessary use of obsolete software				
Staff support	Internal	Incident management	–	Ticket cycle
		Request management	–	Time to resolve a request
The staff support value drivers focus on addressing technology-related queries and requests to maintain organizational productivity. Leading metrics, grouped under incident and request management, are measured quantitatively by the resolution time for requests or incidents				
Supplier management	Internal	Relationship management	Vendor skill levels	–
			–	Supplier pricing

(continued)

Table 4.16 (continued)

Value driver	*Focus*	*Leading metrics*	*Lagging metrics*	
			Qualitative	*Quantitative*
			–	Turnaround time
The technology development function manages supplier relationships, *measuring metrics* against internal company standards. Qualitative metrics assess the skills and capabilities that suppliers should possess, while quantitative metrics include an internal matrix that evaluates factors such as pricing. A final metric measures average supplier turnaround times against internal standards to ensure timely service				

ensured. Hence, the _DecisionArtifact has been validated based on three key elements:

- Relevance—Does the eADR iteration support achieving the primary objective?
- Design—Does the diagnosis iteration follow the correct approach?
- Effectiveness—Does the final artifact address the problem under scrutiny?

The third ADR principle, reciprocal shaping, the fifth ADR principle, continuous evaluation, and the sixth ADR principle, guided emergence, balance the intentional intervention cycle with organic design evolution. The final artifact evolved through organizational and research perspectives, with internal shaping and external input from the researcher.

The current iteration's objective is to develop an AI framework that illustrates decision programmability. Data collection focused on industry-relevant performance metrics, with diagnostics cycles confirming the artifact's relevance. The final _DecisionArtifact includes all required components for the AI decision-support model, validating its correctness.

4.3.5 Reflection and Learning

Following the first eADR diagnostic cycle, translation has moved from problematization to interessement. During this process, identified actors passed through the obligatory point, recognizing that the proposed

Table 4.17 Technology development: thematic considerations

Value driver	*Leading metric group*	*Thematic considerations*
Infrastructure support	Service availability	Government/service Maintenance/planning Hardware/status
	Security	Compliance/external standards Compliance/internal standards
The infrastructure support value driver considers events that affect the availability of essential services, such as electricity or water, *and* maintenance cycles that impact service uptime. Hardware-related factors also influence the metrics based on various scenarios. For security, internal and external risks affect infrastructure integrity, requiring compliance with evolving ISO standards and internal processes to maintain security		
Operational management	Hardware management	Service standard/grouping Hardware/status Hardware/service history Hardware/standards Business environment/internal standards
	Software management	Software/status Software/pricing
Operational management support is influenced by factors affecting the availability and functionality of hardware and software • Hardware considerations include incident severity, service history, and internal standards. The business environment and evolving technologies also impact the metrics • Software, factors such as pricing and status, are key considerations		
Staff support	Incident and request management	Service standards/grouping Business environment/internal standards HR/availability Hardware availability
Staff support is influenced by factors that impact resolution time, including HR and hardware availability. The severity of the request also affects resolution time. Additionally, changing business conditions and evolving technologies can impact staff support		

(continued)

Table 4.17 (continued)

Value driver	*Leading metric group*	*Thematic considerations*
Supplier management	Relationship management	Suppliers/capabilities Supplier/pricing Service standards/grouping Business environment/ internal standards Business environment/ external trends
Supplier management involves interacting with suppliers in the technology development function. Key considerations include supplier capabilities, pricing, request urgency, and internal standards. Additionally, changes in the external environment can impact the supplier relationship		

Table 4.18 Procurement: value driver analysis

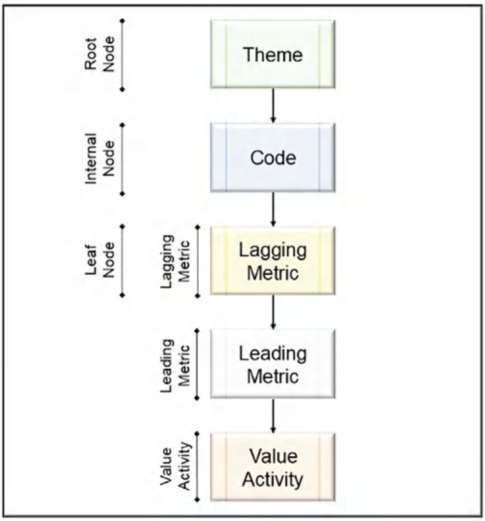
Value driver	*Focus*	*Leading metrics*	*Lagging metrics*	
			Qualitative	*Quantitative*
Strategic procurement	Internal	Demand supply	–	Demand planning delivery accuracy
		Supplier management	–	EBQ management
	External	Compliance	Quality compliance	–
	Internal/ external	Cost management	–	Price point management
The procurement function focuses on acquiring strategic raw materials and goods, measured by two value drivers: strategic procurement and supplier management. Under strategic procurement, metrics include cost management, which measures purchase prices against market trends and internal budgets Economic batch quantities (EBQ) are managed to avoid excess stock or shortages. Successful procurement ensures that the correct amount and quality of materials are available for manufacturing, requiring adherence to quality standards and performance metrics to ensure accurate demand planning				
Supplier management	Internal	Compliance	Supplier SLA matrix compliance	
All purchased items must come from approved suppliers to ensure compliance with industry standards and legislation. The supplier management value driver measures supplier compliance using an internal matrix, evaluating qualitative and quantitative standards against internal benchmarks				

Table 4.19 Procurement: thematic considerations

Value driver	*Leading metric group*	*Thematic considerations*
Strategic procurement	Cost management Supplier management Compliance Demand planning	Procurement/item classification Suppliers/pricing Logistics/logistics management Stock management/availability
Supplier management	Compliance	Stock management/external trends Stock management/complexity Natural events/natural events Government/policies Business environment/external trends Compliance/external compliance

The themes and codes illustrate how considerations integrate and impact various areas of the function. Factors such as the complexity of procured items, supplier pricing, and market trends can affect cost management metrics, supplier compliance, and demand planning. Supply chain or logistics changes can compromise item integrity, influencing supplier management and compliance. Availability issues, compounded by natural events, can affect pricing and supply

Fig. 4.3 Decision tree framework



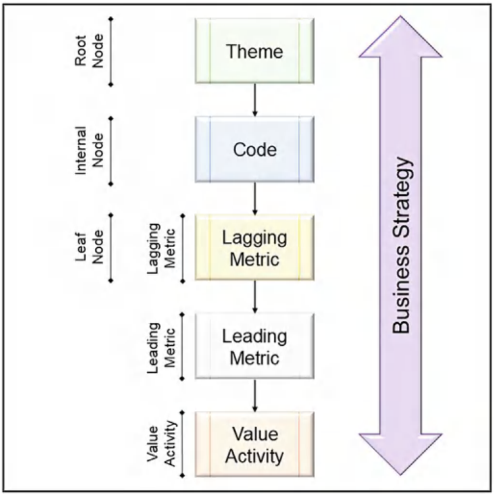


Fig. 4.4 _DecisionArtifact

solution supports both the network's broader goal and their interests. Figure 4.5 illustrates the updated ANT network post-diagnosis iteration.

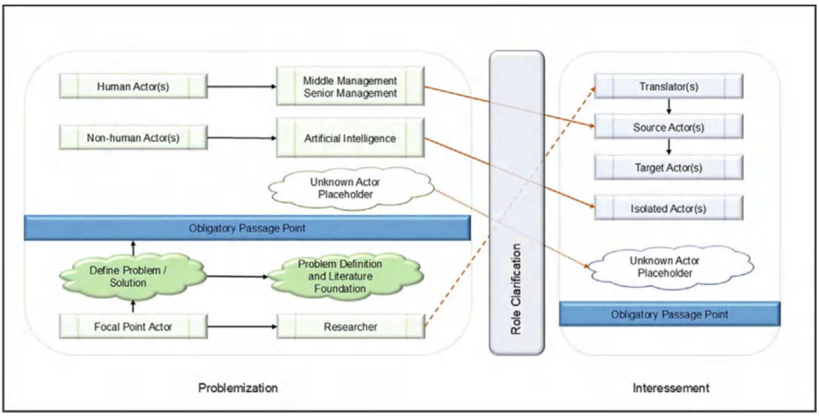


Fig. 4.5 ANT interessement progression (first diagnostics)

Figure 4.5 illustrates the translation from problematization to interessement in developing the ANT network. During this phase, actors assumed specific roles within the network.

The researcher, initially the focal actor, evolved into the network translator, facilitating communication between source actors and target actors. By engaging with the source actors, the researcher validated the viability of AI in decision-making. Once convinced, these actors influenced target actors, forming alliances that aligned individual interests with the broader goal of developing the envisaged AI decision-support model.

Non-human actors, including AI, became isolated network actors, meaning they could act without direct negotiation connections. AI, for example, influences the network but does not interact directly with other actors.

4.4 Summary

This chapter identified key performance metrics and their considerations using two eADR diagnostics cycles. The first cycle gathered metric data from mid-level managers, while the second cycle validated and refined the artifact in conjunction with senior-level managers. The final _DecisionArtifact outlines a decision-making framework incorporating industry-based metrics and their influencing factors.

Chapter 5 will conduct the second diagnostics iteration, focusing on socio-technical thinking aspects in context.

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CHAPTER 5

Diagnostics: AI Culture

Abstract This chapter presents the second of three diagnostic elaborated action design research (eADR) iterations, focusing on developing and validating a _SocialArtifact to support an artificial intelligence (AI) model in support of the envisaged decision-support model. By integrating the technology acceptance model (TAM) and value-based adoption model (VAM) into an enhanced action design research (eADR) process, the book addresses the challenges of AI adoption from a socio-technical theory perspective. Grounded in the design science's principle of solving practical problems, it examines user attitudes through TAM's perceived ease of use (PEoU) and usefulness (PU) and VAM's focus on perceived benefits and sacrifices. Qualitative data gathered from group discussions and interviews with mid- to senior-level management using a structured questionnaire informed the thematic construction of the _SocialArtifact, which is a further building block in the development of the AI decision-support model. Verification ensures the artifact accurately reflects the prevailing AI culture and supports the broader _DecisionArtifact. At the same time, validation confirms alignment with the primary objective of developing an AI framework that balances technical and social considerations. Finally, the chapter illustrates how actor-network theory (ANT)'s interessement stage progresses the evolution of the network, including interactions among actors and the influence of external actors on organizational change.

E. Steyn et al., *Programmable Decisions for Business Organizations*,
https://doi.org/10.1007/978-981-95-0724-5_5

Keywords Actor-network theory · Artificial intelligence · Decision-support model · Elaborated action design research · Socio-technical theory · Technology acceptance model · Value-based adoption model

JEL Classification M15 · O033

5.1 Introduction

The previous chapter introduced identifying and evaluating key performance indicators (KPIs) in support of structured decision-making. This chapter builds upon the key concepts introduced earlier and aims to establish foundational concepts about acceptance models in the context of artificial intelligence (AI) culture, condensed into a _SocialArtifact. Like before, knowledge development involves mid-level and senior-level industry participants. The iteration also aligns with the tenets of the elaborated action design research (eADR) approach, as it contextualizes the problem under consideration, plans for the development of the anticipated _SocialArtifact, and then reflects on the specific outcomes. After this chapter's diagnostic eADR iteration, the interessement moment in the actor-network theory (ANT) advanced as the researcher acted as a translator, aligning actors' interests with the AI decision-support model's goals.

5.2 Problem Formulation

5.2.1 AI Culture

The first action design research (ADR) principle, focusing on practically experienced problems, may, for example, investigate why technology projects fail. Regarding such a concern, Alami (2016) emphasized the importance of including diverse end-user perspectives in system design to prevent such failure, a core tenet of socio-technical systems thinking. In the context of rapid technological evolution during Industry 4.0, social and technical environments must be harmonized to maintain productivity.

This section examines the technology acceptance model (TAM) and the value-based adoption model (VAM) as frameworks for understanding AI culture among decision-makers.

5.2.2 Technology Acceptance Model

TAM evaluates how users perceive and adopt technology, focusing on perceived ease of use (PEoU) and perceived usefulness (PU) as key factors influencing their attitudes towards technological system usage. Developed by Davis (1989), the TAM enhances the understanding of the user acceptance process and examines the successful design and implementation of information systems. According to Chuttur (2009) and Alhashmi et al. (2019), TAM remains a widely used and evolving model for assessing technological adoption and clarifies three factor categories that explain a user's motivation for system usage:

- PEoU: The degree to which individuals believe that using a particular system would free them from physical and mental effort.
- PU: The degree to which individuals believe using a particular system would enhance job performance.
- External factors: These typically include aspects related to management, technology, operations, and various strategic elements that influence PEoU and PU.

Therefore, TAM implies that the actual usage of a system will be influenced by the user's attitude, which, in turn, is controlled by the system's PEoU and PU, which are ultimately influenced by various external factors.

Figure 5.1 provides the general framework for this book's approach to investigating a user's attitude towards accepting new technological systems.

5.2.3 Value-Based Adoption Model

Where TAM explains the intention of using technology (based on the system's PeoU and PU), VAM assesses users' intentions to adopt technology by weighing *perceived* benefits, such as improved performance and user enjoyment, against *perceived* sacrifices, which typically include technical challenges and financial costs (Kim et al., 2017). VAM provides

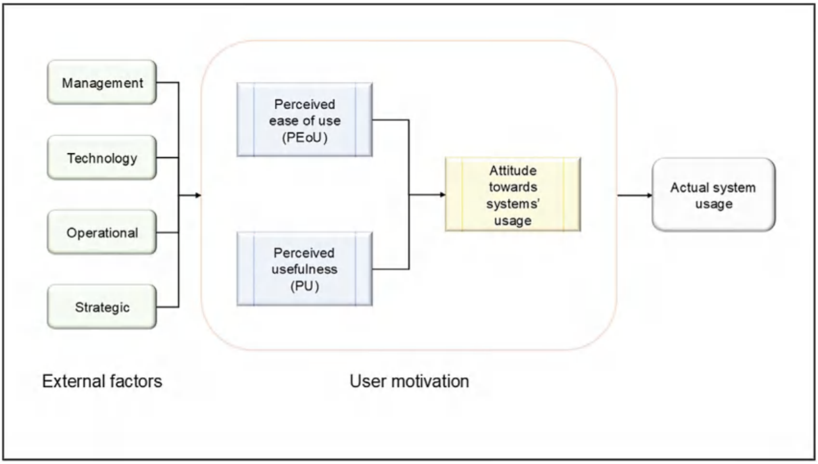

Fig. 5.1 Technology acceptance model (Adapted from Davis [1989] and Alhashmi et al. [2019])

insights into user perceptions of value, making it an effective tool for evaluating AI adoption, particularly in voluntary contexts. To design the AI decision-support model, the *benefits* of the technology will be investigated, examining the usefulness and enjoyment that users may experience. Meanwhile, the sacrifices will be analyzed in terms of the technical aspects of the system and the perceived costs that users might incur, as illustrated in Fig. 5.2.

As illustrated in Fig. 5.2, the benefits and sacrifices are considered primary factors in determining the system's perceived value. This perceived value will, in turn, affect the ultimate intention to adopt new technologies.

5.2.4 *Comparing TAM and VAM*

As elucidated above, TAM and VAM focus on different aspects of user adoption, which are clarified in Table 5.1.

Using TAM and VAM in tandem enhances qualitative insights into AI adoption. The models are complementary, with TAM assessing attitudes

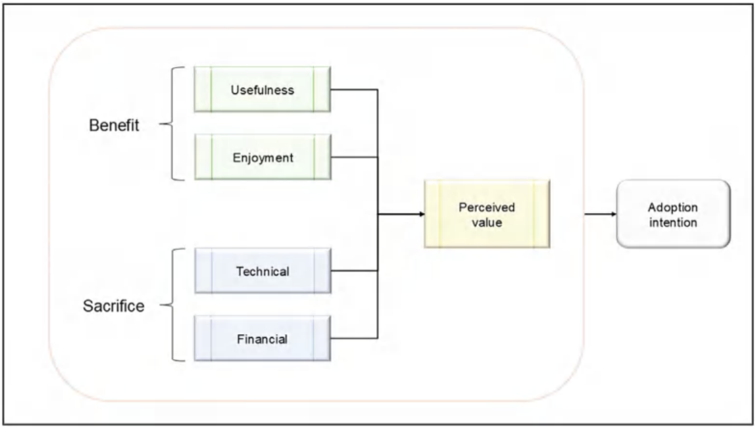

Fig. 5.2 Value-based adoption model (Adapted from Kim et al. [2017])

Table 5.1 Comparison of TAM and VAM

Focus	*TAM*	*VAM*
Subject	Employees in organizations	Individual users
Environment	Traditional technologies	New technologies
Features	Organizational work-related tech use. Costs of mandatory adoption. Usage created by an organization	Personal tech use. Costs of voluntary adoption. Usage created by individuals

Adapted from Kim et al. (2017)

and VAM evaluating perceived value. Together, they aim to comprehensively understand the contextual AI culture, bridging the gap between quantitative validation and qualitative knowledge.

5.3 Action Planning

Data for the TAM and VAM models were collected using a questionnaire adapted from Yigitcanlar et al. (2022), Sohn and Kwon (2020), and Kim et al. (2007), which investigated factors influencing the PEoU and the PU of an AI decision-support model. Despite its quantitative origins, the questionnaire was utilized during group discussions and interviews to gather qualitative insights. Participants were provided context on currently available AI models to support their responses to the guided questions, as outlined in Table 5.2.

Table 5.2 Guided questions breakdown

Model	*Focus area*	*Guided questions*
TAM	PEoU	• What factors would facilitate an AI decision model's ease of use and comprehensibility during interactions? • What factors make interacting with an AI decision model challenging? • What criteria would facilitate achieving the desired behavior from an AI decision model?
	PU	• Would using an AI decision model improve your daily performance? • Would using an AI decision model enhance daily work effectiveness? • Would using an AI decision model enhance overall effectiveness? • What factors could lead to an AI decision model being unreliable?
VAM	Benefit: usefulness	• Would an AI decision-making model enable you to accomplish tasks more efficiently? • Would an AI decision-making model improve your performance?
	Benefit: enjoyment	• Would it be fun to interact with an AI decision model? • Would using an AI decision model bore you?
	Sacrifice: costs	• What functions should the systems incorporate to ensure that the fees paid are reasonable? • What are your feelings regarding your organization's expenditure on an AI decision-making model?
	Sacrifice: technical	• What hardware would make interacting with an AI decision-making model easy? • What factors would impact the duration required to understand an AI decision-making model? • What perceived risks do you highlight regarding AI models making biased or incorrect decisions? • Do you harbor concerns or fears about the potential future displacement of human jobs by AI? • Do you believe that AI can release resources within your organization?

After data collection, the responses were analyzed, and the findings were interpreted to gain new insights. Using a thematic approach, recordings and notes from the sessions were reviewed, with longer recordings transcribed in Microsoft Word. Transcriptions were evaluated for accuracy, and feedback was manually analyzed to identify thematic codes. The knowledge derived from these codes and themes, based on interviews and group discussions, is presented in the following sections.

5.4 Artifact Creation: Technology Acceptance Model

5.4.1 TAM: Perceived Ease of Use

The first factor in assessing users' attitudes toward new technologies is their PEoU. Figure 5.3 summarizes the factors influencing PEoU in the possible use of an AI decision model.

Figure 5.3 highlights themes influencing a system's PEoU, each discussed below with relevant codes and user perceptions:

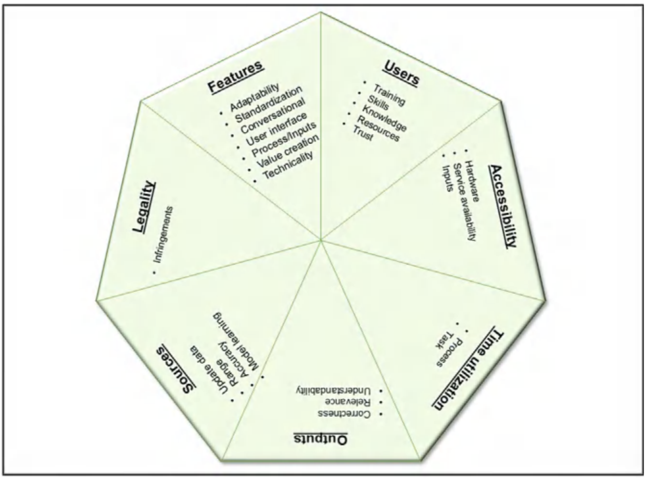

Fig. 5.3 PEoU influences

- Features: AI systems should minimize user effort through value-driven outputs, simplified interactions, and familiar interfaces. Efficient input–output cycles, system integration, and adherence to technical standards ensure intuitive and seamless usability.
- Users: Ease of use also depends on the user's skills, experience, and confidence; thus, practical training, HR support, and clear guidance are essential for effective adoption.
- Accessibility: Reliable uptime, AI-driven inputs, and broad hardware compatibility should enhance accessibility and usability, positively shaping user perceptions.
- Time utilization: Autonomous processes and task optimization should reduce input requirements, saving users time and improving ease of use.
- Outputs: Any output must be relevant, accurate, and understandable. It must combine clear text and contextual numerical data while avoiding unnecessary information that could overwhelm the user.
- Sources: A robust system ensures relevant, insightful outputs by drawing from accurate, up-to-date sources and actively identifying and addressing gaps to maintain relevance and reliability.
- Legality: AI systems must comply with legal standards by accurately distinguishing between lawful and unlawful actions to maintain trust and ensure compliance.

5.4.2 TAM: Perceived Usefulness

The second factor is the PU, which can be seen as the degree to which an individual believes using a particular system would enhance job performance. Figure 5.4 illustrates all the themes and codes influencing users' perceived performance.

As illustrated in Fig. 5.4, several themes influence users' perceptions of a system's usefulness, which are elucidated as follows:

- Features: To enhance perceived usefulness, an AI system must offer features tailored to user needs while demonstrating reliable, autonomous task performance that minimizes rework and upholds high standards. In regulated industries, standardized input forms and clear prompts support compliance and reduce confusion. Intelligent input processing helps overcome human limitations, such as

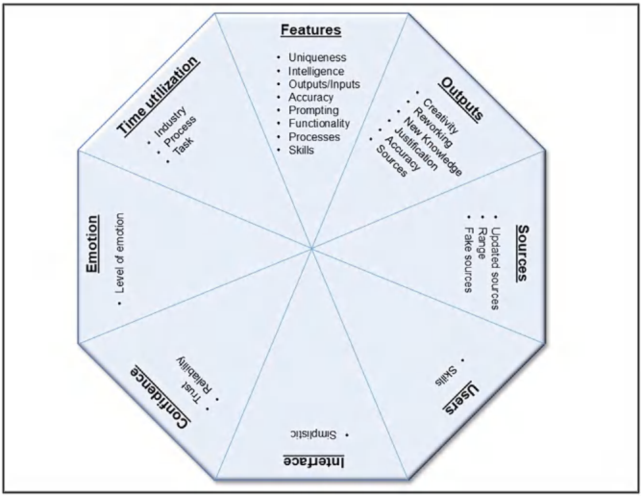

Fig. 5.4 PU influences

fatigue, and features like history logs promote transparency, trust, and ongoing training.

- Outputs: Ideal AI outputs should be accurate, ready-to-use, and require no further adjustments, offering creative insights beyond basic responses. They should fully address user queries, enrich data context, and introduce relevant additional information, while validation and source justification reinforce trust and confidence in the results.
- Sources: A system's perceived usefulness depends on access to reliable, credible data sources. To ensure accuracy, fake or suspicious content must be excluded. Continuous source updates are crucial to ensure compliance with current standards, particularly in regulated industries.
- Users: Individual attitudes toward technology shape perceived usefulness, so AI systems should complement user skills while minimizing required expertise to foster a positive perception.
- Interface: An intuitive interface is essential, as even a powerful backend is ineffective if users struggle to interact with the system. Simplicity and accessibility in design enhance both the user experience and perceived usefulness.

- Confidence: User trust is vital to perceived usefulness, built through consistent, reliable outcomes supported by transparent justification and dependable sources.
- Emotion: The ability to interpret and respond to emotional cues enhances system effectiveness, as emotionally intelligent outputs improve performance on sensitive tasks and boost user satisfaction.
- Time utilization: AI systems enhance productivity by automating repetitive tasks, streamlining workflows through process analysis and bottleneck resolution, and adapting to time-sensitive environments for improved responsiveness.

5.5 Artifact Creation: Value Adoption Model

5.5.1 VAM Benefit: Usefulness

The first aspect of VAM is the perceived usefulness, which refers to the extent to which a system enhances user performance. Figure 5.5 outlines the themes and codes affecting this perception.

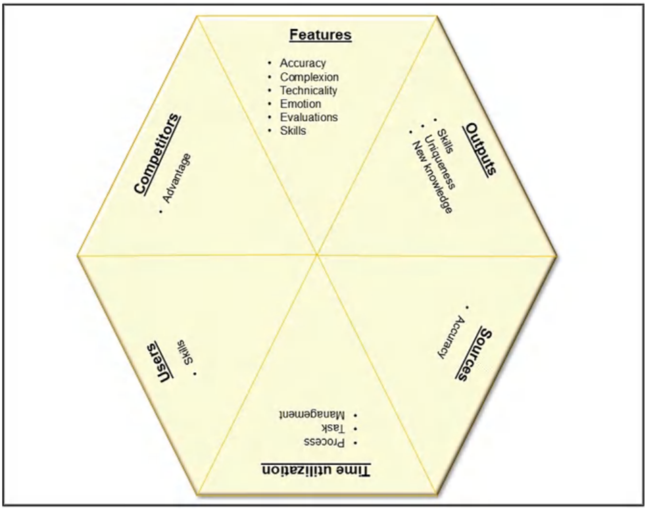

Fig. 5.5 Usefulness influences

Per Fig. 5.5, several themes influence users' perceptions of a system's usefulness in context, which are elucidated as follows:

- Features: A new system's effectiveness depends on its accuracy, versatility, and capacity to handle complex requests. Seamless integration with existing systems and consistent outputs ensure reliability. Recognizing system limitations and appropriately delegating non-processable tasks is equally important to avoid rework and maintain efficiency.
- Outputs: Users seek unique, actionable insights rather than generic data when adopting a new system. To be valuable, the system must deliver tailored solutions that generate new knowledge and opportunities, ultimately contributing to a competitive advantage.
- Sources: Accurate, reliable, and up-to-date sources are essential for system adoption and for ensuring robust, trustworthy conclusions.
- Time utilization: New systems must streamline workflows by minimizing delays from untested tasks, with well-trained models adapting to evolving needs to enhance time management and meet business deadlines.
- Users: Systems should enhance users' decision-making by offering comprehensive arguments and acting as decision-support tools or autonomous decision-makers.
- Competitors: Market competition drives adoption, as systems that offer competitive advantages compel businesses to adapt to stay relevant.

5.5.2 VAM Benefit: Enjoyment

The second VAM aspect is perceived enjoyment, which refers to the pleasure users derive from interacting with a system, influencing its adoption. Figure 5.6 illustrates the identified themes.

As indicated in Fig. 5.6, the various themes that influence a system's perceived ease of use and affect users are clarified below:

- Features: To ensure intuitive interaction and user satisfaction, systems should align with user preferences and mimic familiar habits. To enhance the experience further, socially aware and non-offensive communication should be integrated. Avoiding overly complex

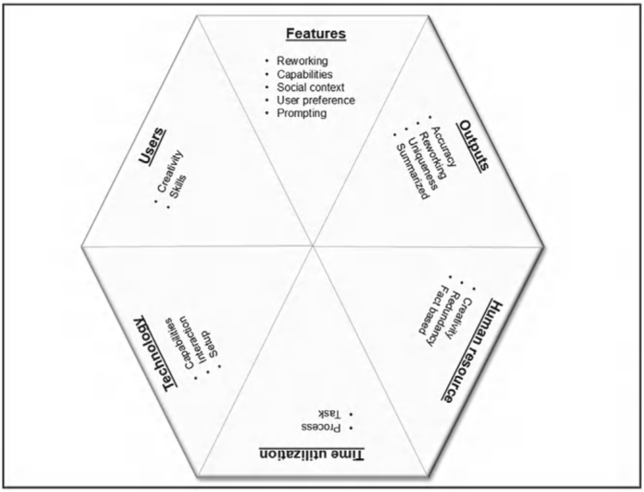

Fig. 5.6 VAM: enjoyment influences

forms or repetitive inputs helps maintain ease of use and preserve user enjoyment.

- Outputs: System outputs should be accurate, visually varied, easily presentable, and tailored to provide detailed and summarized responses, enhancing user enjoyment and overall experience.
- Human Resources: Concerns over redundancy and reduced creativity can diminish user satisfaction with AI systems, whereas fact-based, impartial decision-making fosters confidence and enhances the overall experience.
- Time Utilization: AI systems should enhance individual efficiency by reducing task completion time, improving time management and overall process effectiveness. Demonstrating these time-saving benefits upfront increases user satisfaction and supports system acceptance.
- Technology: AI systems can enhance user enjoyment by generating excitement through their emerging potential, particularly during testing and capability exploration. Although the initial setup may be tedious and reduce early enjoyment, it lays the foundation for greater long-term satisfaction.

- Users: Users value systems that challenge and enhance their skills and creativity while preserving human interaction. This analysis, grounded in the VAM, highlights key factors influencing AI adoption, particularly perceived usefulness and enjoyment, and offers essential guidance for artifact creation.

5.5.3 VAM Sacrifice: Costs

The costs associated with a new system often shape users' perceptions of the financial sacrifices required to adopt it. Figure 5.7 outlines the themes related to users' perspectives on system-related costs.

Figure 5.7 illustrates the themes that influence the cost-related aspects of operating the new system.

- Features: System features must align with user needs to ensure ease of use, trust, and effective task delegation. Paid systems should surpass free tools by offering personalized layouts, advanced functionalities, regular updates, automated learning for adaptability,

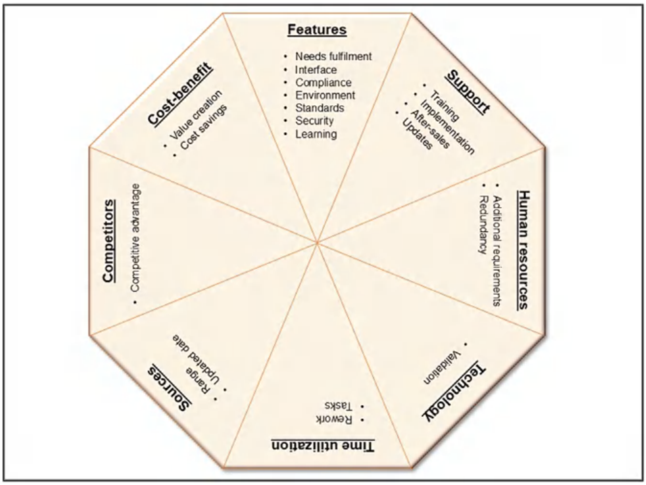

Fig. 5.7 VAM: cost influence

seamless integration with existing systems, and robust security to manage risks tied to emerging technologies.

- Support: Successful adoption depends on strong after-sales support, including well-planned implementation to minimize business disruption, comprehensive user training to maximize system utility, and ongoing updates with responsive customer service to address user needs effectively.
- Human Resources: AI systems must avoid creating redundancies or increasing human resource demands, as misalignment undermines cost-effectiveness and hinders staff adoption.
- Technology: Systems must be validated for compliance with relevant standards to ensure reliability and adherence to regulatory requirements.
- Time Utilization: New systems must improve efficiency and reduce workloads, as those that create redundancies or fail to enhance processing times may hinder adoption.
- Sources: AI systems must rely on accurate, up-to-date, and comprehensive sources to justify costs, and regular updates are essential to maintaining their value.
- Competitors: Competition often drives technological advancement, and organizations risk losing market relevance without comparable investments in AI.
- Cost–Benefit: Investments in new technologies must deliver measurable returns, such as cost savings, productivity improvements, or enhanced resource planning.

5.5.4 VAM Sacrifice: Technical

Technical factors influence users' perceptions of system complexity when they adopt a new system, as summarized in Fig. 5.8.

As indicated in Fig. 5.8, the factors influencing system adaptability in terms of technical sacrifices include themes that focus on various risk, resource, and support-related aspects, elucidated as follows:

- Risks: Technical risks, such as non-compliance, financial losses, security breaches, reputational damage, and complacency, can hinder adoption and must be proactively addressed during system design.

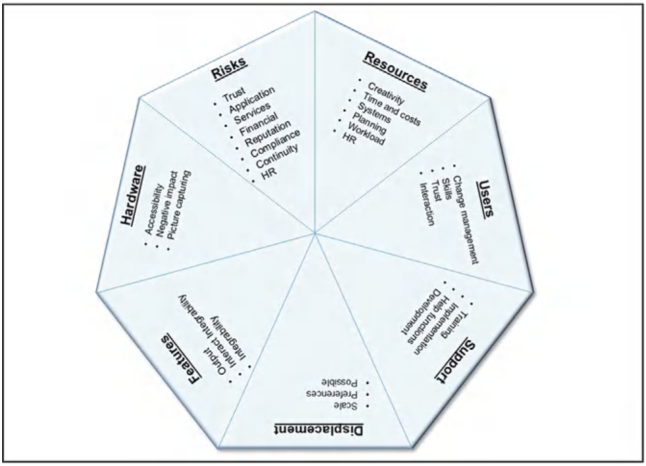

Fig. 5.8 Technical influences

- Resources: Effective AI systems free up resources, enabling better time management, cost savings, and enhanced creativity. Resource optimization should balance associated risks.
- Users: Users' willingness to adopt a system depends on their technical skills, generational differences, openness to change, and trust in the system. Positive interactions and minimal learning curves further promote adoption.
- Support: Effective support encompasses tailored training, user-friendly help functions, and iterative system enhancements informed by user feedback.
- Displacement: Concerns over job displacement can affect adoption. While automation may impact rule-based roles, history shows technology often creates new opportunities.
- Features: AI systems should offer flexible outputs, secure dashboards, and seamless integration, with successful adoption hinging on balancing system complexity with user benefits.
- Hardware: Systems should seamlessly integrate with existing devices and support advanced inputs, such as text, voice, and image recognition, while minimizing excessive demands on user hardware that could deter adoption.

5.6 Evaluation

5.6.1 Artifact Evaluation

The artifact creation in this iteration also followed the third and fourth ADR principles, emphasizing organizational involvement and the interdependence of researcher and practitioner roles. The researchers provided academic insights on TAM and VAM, while industry participants shared practical knowledge on factors influencing attitudes (TAM) and adoption (VAM) in their specific context. This collaboration resulted in the dual components of the _SocialArtifact, the first of which is presented in Fig. 5.9.

Figure 5.9 illustrates the factors and interrelationships influencing the TAM components, impacting the PEoU and PU aspects. In designing the AI decision-support model, stakeholders should be aware of these elements to mitigate the adverse effects on user attitudes.

The second component of the _SocialArtifact, presented in Fig. 5.10, focuses on the VAM aspects and highlights the factors that affect users' perceived value of new technologies. Perceived benefits and sacrifices influence adoption, and balancing these elements determines the system's overall perceived value. Aligning with socio-technical thinking,

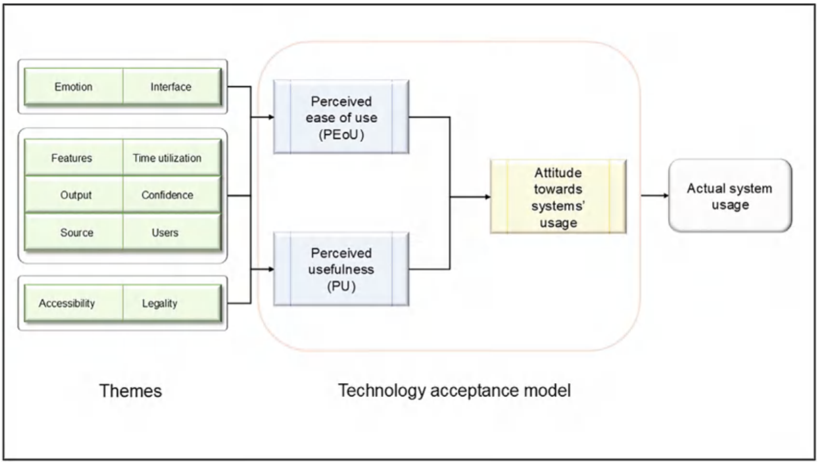

Fig. 5.9 _SocialArtifact: TAM influences' perspective (Adapted from Davis [1989])

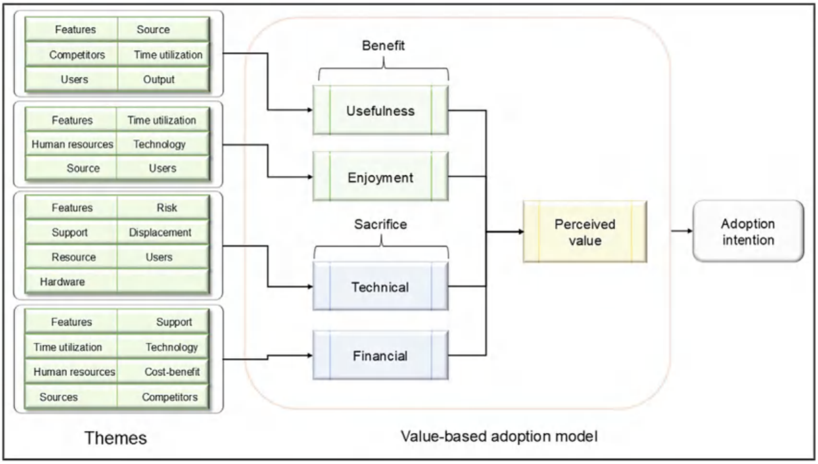

Fig. 5.10 _SocialArtifact: VAM influences' perspective (Adapted from Kim et al. [2017])

stakeholders must consider technical and social environments when implementing change.

Figure 5.10 demonstrates the factors and interrelationships that influence the VAM components, affecting both the benefit and sacrifice aspects. Figure evaluation confirms that addressing these influences is crucial for the effective adoption of technology.

For purposes of this book, the resulting knowledge, integrating the insights from Figs. 5.9 and 5.10, is termed the _SocialArtifact.

5.6.2 *Artifact Verification*

Verification of the final _SocialArtifact is conducted through a twofold process: first, ensuring the eADR iteration design meets the relevant sub-objective requirements; second, confirming that the _SocialArtifact was correctly constructed to establish the prevailing AI culture within the _DecisionArtifact.

This diagnostic iteration provided key insights into AI culture and facilitated the integration of TAM and VAM into the eADR process. Verification confirms that the _SocialArtifact addresses the key objective by identifying themes influencing AI adoption and use. Figures 5.9 and 5.10

illustrate the factors identified during artifact creation related to potential user adoption, further supporting verification.

5.7 Learning and Reflection

5.7.1 Artifact Validation

The final _SocialArtifact, depicted in Figs. 5.9 and 5.10, is validated by confirming the presence of key elements that ensure alignment with the primary objective. Validation serves two purposes: confirming that the design meets the objective's requirements and ensuring that the artifact effectively achieves its intended goal.

The primary objective is to develop an AI decision-support model that addresses technical and social challenges. Enabled by the eADR approach, comprehensive data collection informed the construction of the _SocialArtifact, which supports this objective by identifying critical factors influencing technology adoption and organizational change. This chapter successfully captures participants' perspectives on AI culture, synthesizing them into a _SocialArtifact that functions within the broader _DecisionArtifact.

5.7.2 ANT Interessement Progression

After the second diagnostic iteration, the interessement moment advanced as the researcher acted as a translator, aligning actors' interests with the AI decision-support model's goals.

After completing this iteration, the interessement moment continued with the researcher acting as translator and interacting with the source actors to achieve the goal of the network. During this moment of translation, new actors have passed through the obligatory point and can interact with other actors. Figure 5.11 illustrates the updated ANT network after completing the second diagnostic iteration.

In Fig. 5.1, ANT interessement progression illustrates the evolution of the network, including interactions among actors and the influence of external actors on organizational change.

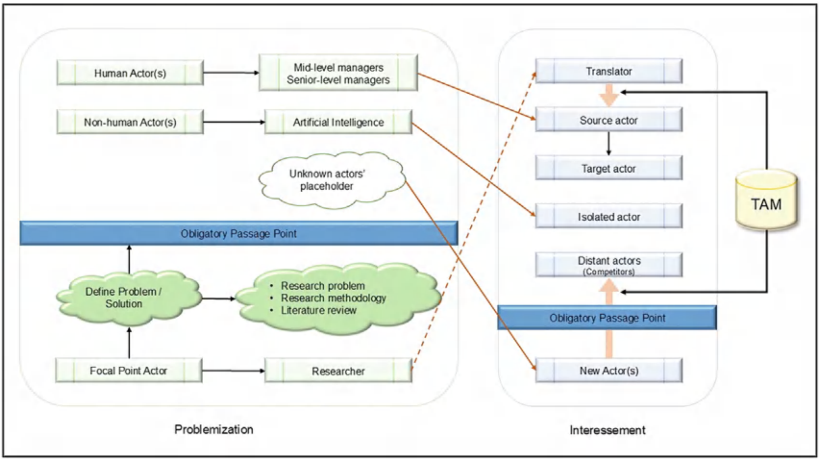

Fig. 5.11 ANT interessement progression (second diagnostic)

5.8 Summary

This chapter contributed to developing the envisioned AI decision-support model by further investigating the social environment, i.e., elaborating and expanding the knowledge developed during the earlier _DecisionArtifact. Using eADR diagnosis iterations, data from mid-level and senior-level management revealed additional aspects that may influence attitudes and adopting new technologies. The TAM and VAM models, culminating in the _SocialArtifact, provide a comprehensive framework for addressing the technical and social dimensions of change. The chapter will delve deeper into the programmability of decisions.

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CHAPTER 6

Diagnostics: Decision Programmability

Abstract This chapter concludes the diagnostics phase and assesses the programmability of the _DecisionArtifact within the context of the artificial intelligence (AI) decision-support model. Building on the socio-technical concepts from the previous chapter, this iteration aligns with action design research's (ADR) principles, combining practice-inspired realities with theory-based research. It emphasizes a systematic approach to AI-enabled decision-making, evaluating programmability across structured, semi-structured, and non-programmable decision types to highlight the need for a robust dataset. A literature-based dataset design framework was introduced in the first of two elaborated action design research (eADR) cycles, transforming the _DecisionArtifact into a dataset framework, enabling discussions with industry professionals on relevance, usability, and quality. The chapter demonstrates, in the context of the actor-network theory (ANT), the dataset's effectiveness in bridging the gap between the _DecisionArtifact and an AI environment. Evaluating the dataset on accuracy, completeness, and methodology validated its suitability for programming decision rules. The dataset was refined in the second eADR cycle, guided by industry insights, establishing it as the _DataSetArtifact.

Keywords Action design research · Actor-network theory · Artificial intelligence · Decision-support model · Programmability

E. Steyn et al., *Programmable Decisions for Business Organizations*,
https://doi.org/10.1007/978-981-95-0724-5_6

JEL Classification M13 · M16

6.1 Introduction

The previous chapter examined the socio-technical aspects of the envisioned artificial intelligence (AI) decision-support model, focusing on factors that influence attitudes and the adoption of new technology systems. Like the earlier diagnostic iterations in Chapters 4 and 5, this chapter follows the essential elaborated action design research (eADR) roadmap in two cycles by reflecting on the problem perspectives, the build and evaluation aspects, and concluding with a reflection on the realized outcomes. The chapter highlights the researcher's role as a translator in the context of the actor-network theory (ANT), engaging with source actors to enhance the programmability of decisions.

6.2 Programmability of Decisions: First Cycle

6.2.1 Problem Formulation

Action design research's (ADR) first and second principles require artifact design to blend practice-inspired realities with theory-based research, using real-world issues and scientific literature. In the context of this book's objectives, organizations must adapt to evolving technologies to remain efficient and competitive (Treacy, 2022). This chapter supports the book's objectives by exploring the programmability of the _DecisionArtifact through AI-driven decision-making.

6.2.1.1 Decision-Making and AI

The integration of AI in decision-making has been anticipated for some time. Licklider (1960) envisioned a man–machine symbiosis where computers support human decision-making. In the context of Industry 4.0, technology and automation are driven by data exchanges (Sarker, 2022), underscoring the importance of data as a key resource. As such, organizations must assess how AI models can enhance decision-making processes. However, effective AI-enabled decision-making requires an understanding of the decision-making process. Lassoued et al. (2020) define decision-making as a structured sequence of steps leading to the best alternative. Power et al. (2019) emphasize the role of people, methods, systems, and data in this process. Fülöp (2005) outlines an eight-step framework, with each step building upon the prior step, aligning with Power et al.'s (2019) view of decision systems as a combination of human, machine, and task elements. Figure 6.1 illustrates this process.

As shown in Fig. 6.1, the systematic decision-making process begins by identifying a trigger that necessitates a decision. This is followed by defining the proposal requirements, establishing the decision's goal, and focusing on desired outcomes beyond functional needs. Subsequently, possible alternatives to meet the goals and evaluation criteria are identified, after which the basis for the decision is set. Finally, alternative outcomes are evaluated, and the best option is implemented.

In our context, the AI decision-support model utilizes a knowledge base compiled by human experts to transition this process into an expert system (Sarker et al., 2021). Though initially static, AI-based technologies can enhance these systems by automating rule generation based on past trends (Sarker et al., 2021). Figure 6.2 conceptually illustrates such an expert decision model.

Figure 6.2 illustrates user interaction with a theoretical decision system. A decision is triggered (Step 1) and submitted via a user interface. The

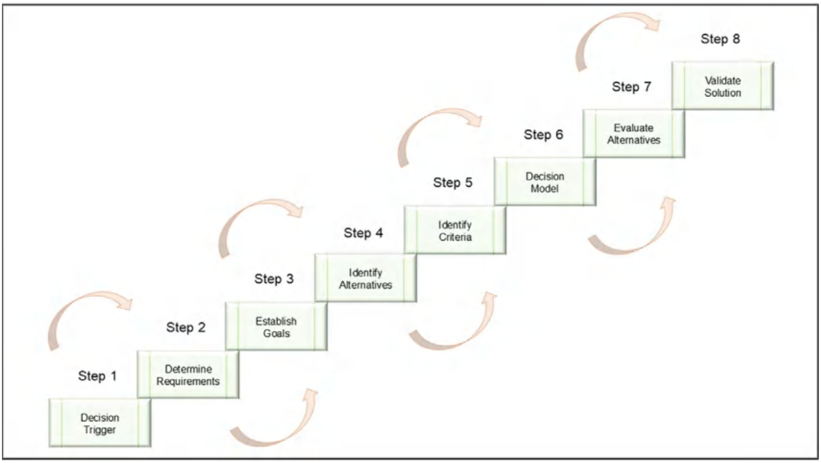


Fig. 6.1 Decision-making process (Adapted from Fülöp [2005])

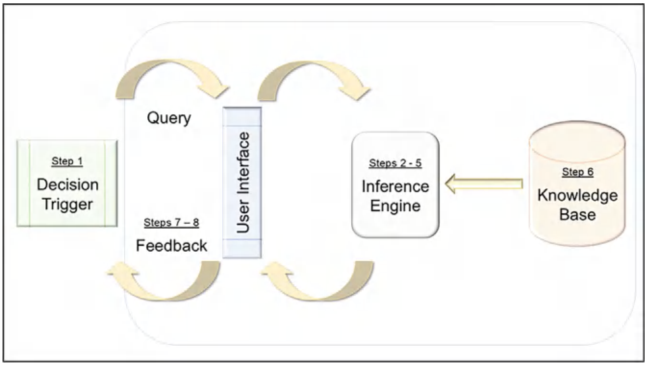


Fig. 6.2 Expert AI decision model (Adapted from Fülöp [2005] and Sarker [2022])

inference engine (Steps 2–5) processes the query, selecting relevant rules from the knowledge base to conclude (Step 6). The system then presents alternative solutions (Step 7), allowing the user to make an informed decision (Step 8).

Furthermore, ML can enhance the function and effectiveness of the knowledge base by identifying patterns and automating decision rules (Sarker, 2022) and improving decision-making by recognizing patterns linked to desirable and undesirable outcomes (Power et al., 2019). For the purpose of this book, the programmability of these rules must be examined to integrate the _DecisionArtifact into an AI environment. The following sections will explore how to achieve such integration.

6.2.1.2 *Programmability of Decisions*

The programmability of a decision involves understanding its nature and creating a framework to integrate various decision types into an AI environment. Historically, Donovan and Madnick (1977) classified decision systems into *structured* (routine, well-defined decisions), *institutional* (recurring but less structured decisions), and ad hoc (unanticipated, one-time decisions). More recently, Pomerol and Adam (2004) similarly classify decisions as *programmable* (routine, objective, and data-driven) or *non-programmable* (unique, subjective, and based on incomplete information). This book aligns with these classifications, viewing decisions as *programmable* (structured), *semi-programmable* (institutional), or *non-programmable* (ad hoc). In this context, programmable decisions rely on predefined rules or past outcomes, as noted by Uçaktürk and Villard (2013), which form the knowledge base that supports an inference engine. Furthermore, ML enhances this by automating rule generation (Power et al., 2019), reducing expert intervention. In contrast, non-programmable decisions require deeper exploration (Uçaktürk & Villard, 2013).

A framework is needed to structure decision types into a dataset that enables AI models to facilitate AI-based decision-making. Datasets simplify the implementation of AI models and enhance their capabilities (Zhou et al., 2020). The next step is to determine how to develop a dataset that supports the programmability of the DecisionArtifact.

6.2.2 Action Planning

This diagnostic iteration explores a literature-based approach to dataset design that supports decision programmability in an AI environment. The following sections will discuss data collection and processing. Before engaging industry professionals for dataset evaluation, it is essential to outline the dataset development process first. This understanding will facilitate effective communication between researchers and practitioners, aligning them with the objectives of the interview. This iteration follows Khan and Hanna's (2022) dataset development and implementation framework to ensure consistency, as shown in Fig. 6.3.

Figure 6.3 outlines seven steps for developing and implementing a dataset, ensuring its accuracy for AI applications. In line with the book's objective, the focus will be on applying steps one through four, discussed below.

- Problem Formulation: Framing problems as questions is vital for data science. This book's key question is how the _DecisionArtifact can be interpreted within an AI environment. The solution lies in developing a dataset framework for integration into the AI decision-support model.
- Data Collection: The step involves data mining to gather relevant dataset content. However, this study focuses on collecting data to guide dataset design rather than its specific content.

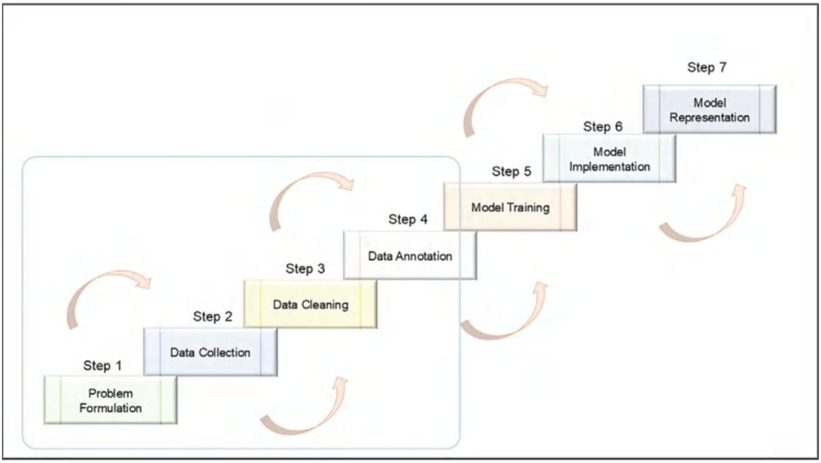


Fig. 6.3 Dataset development (Adapted from Khan and Hanna [2022])

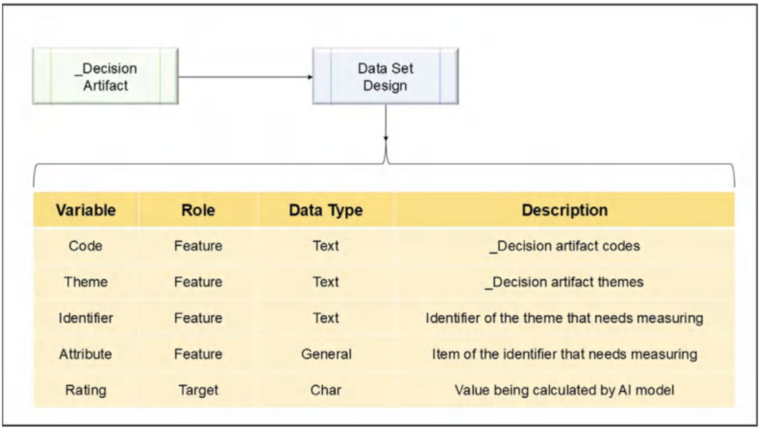
- Data Cleaning: After data collection, the data cleaning step structures unorganized data and fills in missing values to ensure completeness. In this book, the focus is not on cleaning dataset content but on refining collected data to guide dataset development.
- Data Annotation: Data annotation involves assigning labels to data, aiding the processing workflow. This book will apply annotations to processed data after step 3.

6.2.3 *Artifact Creation*

The four steps outlined above were used to create a framework data set, facilitating discussions with industry professionals on its viability for programming the DecisionArtifact into an AI environment, as shown in Fig. 6.4.

Figure 6.4 illustrates how the four steps converted the _ DecisionArtifact into a data set to support decision programmability discussions, clarified below:

- Problem Formulation: Real-world problems were reframed as questions for industry professionals, aligning with the book's primary



Variable	Role	Data Type	Description
Code	Feature	Text	_Decision artifact codes
Theme	Feature	Text	_Decision artifact themes
Identifier	Feature	Text	Identifier of the theme that needs measuring
Attribute	Feature	General	Item of the identifier that needs measuring
Rating	Target	Char	Value being calculated by AI model

Fig. 6.4 Conversion into data set framework

objective of understanding decision programmability in an AI context. This required gathering knowledge on decision-making and its influencing factors.

- Data Collection: The _DecisionArtifact guided dataset development, ensuring the inclusion of relevant data. For simplicity and adaptability, the dataset presentation followed established formats.
- Data Cleaning: Data refinement occurred in real-time during the interviews conducted during the first diagnostic iteration, eliminating the need for post-interview corrections.
- Data Annotation: Labels were attached to the _DecisionArtifact, improving dataset accuracy. Additional fields were introduced to capture company-specific details, forming identifier and attribute fields for customized thematic code and theme tracking.

The final dataset, shown in Fig. 6.4, integrates thematic codes and themes from the _DecisionArtifact. The identifier and attribute fields allow organizations to add unique data. In contrast, the target field enables machine learning to refine decision trees for performance metric-based recommendations.

6.2.4 Evaluation

The artifact from the current iteration resulted in a framework dataset to facilitate discussions with industry professionals on decision programmability. This dataset bridges the gap between the _DecisionArtifact and an AI environment, enhancing its programmability. As data entry is beyond the scope of this book, the focus is on evaluating the dataset's usability and identifying the necessary data types for AI integration.

6.2.5 Reflection and Learning

Each eADR cycle's reflection and learning can prompt another cycle within the iteration, advance to the next stage, or revisit a previous cycle for a deeper understanding of the problem (Mullarkey & Hevner, 2019). Based on current findings, the cycle progresses to a second diagnostic cycle, in which the framework dataset is assessed and validated with industry professionals, as discussed in the next section.

6.3 Programmability of Decisions: Second Cycle

6.3.1 Problem Formulation

It has been indicated earlier that each eADR iteration's problem formulation should build on reflections from the previous cycle. The framework dataset was developed using the _DecisionArtifact and literature-based dataset design data in the first diagnostic cycle. To align with the third ADR principle, a practitioner review is needed to assess whether the literature-based design is suitable for an AI environment. This evaluation will determine if the framework dataset can facilitate the integration of the _DecisionArtifact into AI. The approach to evaluating its programmability is discussed below.

The rapid increase in data availability has made it essential across various domains and professional roles. Data is increasingly used to enhance services, influence policies, create business value, and support informed decision-making. However, despite this abundance, challenges remain in finding, accessing, and evaluating data sources. To address this, Koesten et al. (2020) propose assessing data sets based on three key themes:

- Relevance assesses whether a data set aligns with the task, considering its scope and granularity.
- Usability evaluates how easily users can interact with the dataset, considering factors like format, language, and units of measurement.
- Quality encompasses subjective factors like accuracy and completeness used to assess a data set. These themes provide a framework for evaluating datasets and their effectiveness.

6.3.2 Action Planning

This cycle seeks practitioner feedback on the data set design to validate its applicability and relevance. Industry discussions will be based on the three evaluation themes: relevance, usability, and quality. The assessment will refine the framework data set and incorporate best practices. As the data population exceeds the book's scope, a qualitative evaluation will be conducted.

Data was collected from two perspectives: participants at an information technology (IT) company specializing in dataset development and an academic AI specialist. Both perspectives provided insights on programmability based on the three evaluation themes. The IT company participated in a group discussion, with eight participants who possessed expertise in AI, business management, system design, data administration, and database programming. The academic AI specialist was interviewed on a one-to-one basis.

Discussions began with a brief overview of the _DecisionArtifact, followed by a presentation of the framework dataset. Participants assessed its applicability for integrating the _DecisionArtifact into an AI environment, focusing on relevance, usability, and quality, with findings presented below.

6.3.3 Artifact Creation

6.3.3.1 Data Set Design Feedback

After the workshops, participants' feedback on relevance, usability, and quality was collected and summarized. The findings will be presented under three categories.

- Relevance (clarified in Table 6.1), was the first evaluation theme, assessing whether the framework dataset aligned with decision-making models. Key aspects included:
  - Scope: Assessing whether the dataset is suitable for decision-making.
  - Granularity: Evaluating its ability to capture detailed information.
  - AI Integration: Assessing its applicability within an AI model.
- Documentation: Ensuring the dataset was well-described.

The findings on relevance are discussed in Table 6.1.

- The second evaluation theme, usability (clarified in Table 6.2), was assessed through the following attributes:
  - Format and comparability: Ensuring correct data types and structure.
  - Language: Verifying industry-acceptable and compatible terminology.
  - Dataset Size: Discuss future considerations, as the final size remains undetermined.

Table 6.1 Relevance

Attribute	*Considerations*
Scope	Participants agreed that the proposed data set offered a strong foundation for decision support
Granular details	Identifier and attribute variables enable granular data capture for dataset integration, while the target variable sets the granularity and requires adjustments if the outputs lack meaning
Context	The context of the data set will be refined by comparing targets with their expected outputs. System outputs will guide AI integration, with suitability depending on the AI model's focus. Alignment with the model's context is crucial
Documentation	The proposed data set lacks detailed variable descriptions. Participants suggested adding more user-relevant details, which will be included in the final model

Table 6.2 Usability

Attribute	*Considerations*
Format	All data types, except the general type, were considered sufficient. As new data emerge, data types may evolve, with the final dataset refining the general type to a more specific format
Comparability	Clear documentation of units of measure is necessary for dataset comparability, which will be updated in the final dataset
Language	Participants emphasized the importance of clear headers and agreed that the current data set's headings were well-documented
Size	The dataset size affects model accuracy and requires iterative adjustments to the entry for balance. A balanced dataset ensures that all entry combinations are represented accurately for optimal ML outputs. Actual data is needed to evaluate the impact of the current dataset on accuracy

- As data sources are not yet available, the final evaluation theme and quality considerations will be addressed in the final model design. However, the analysis will be concluded in the context of three aspects (listed in Table 6.3), as follows:
  - Accuracy: Approaches to ensuring data accuracy.
  - Completeness: The impact of data completeness on dataset quality.
  - Methodology: Best practices for data collection.

Participant feedback also provided key considerations for future modifications to the framework dataset, as outlined in Table 6.4.

Table 6.3 Quality

Attribute	*Considerations*
Accuracy	Industry professionals should verify the accuracy of data sources. Advanced ML techniques can identify non-contributory features, requiring an iterative approach to refine dataset accuracy
Completeness	While ML techniques improve accuracy, completeness is more crucial, as dataset success relies on the volume of data. Ensuring source integrity is also key to filtering out irrelevant data
Methodology	Data collection methods differ for secure internal and unsecured external sources. Software-driven data entry enhances accuracy and ensures the correct data types are used

Table 6.4 Future considerations

Theme	*Attribute*	*Considerations*
Usability	Usability	Enhancing dataset representation with new features requires adding more data entries. Accuracy should be evaluated iteratively with each update
Quality	Accuracy	Avoid empty values when adding data entries to maintain dataset balance and accuracy
Quality	Accuracy	ML techniques, such as LIME and Shapley, enhance dataset accuracy and provide output explanations, thereby increasing confidence in the AI model

6.3.3.2 Final Data Set Design

Table 6.5 presents the final dataset design, incorporating the frameworks and discussion outcomes from the prior cycles.

The final dataset in Table 6.5 builds on the earlier cycles and feedback from Tables 6.1 to 6.3. Industry input resulted in minor structural adjustments, confirming the dataset's relevance, usability, and quality. Accepted for the following eADR stages, it will be referred to as the _DataSetArtifact in the next chapter's design iteration.

Table 6.5 _DataSetArtifact

Variable	*Role*	*Data type*	*Description*
Code	Feature	Text	Codes from the _DecisionArtifact findings should contain only text entries. These entries are flexible and can be updated as needed
Theme	Feature	Text	Themes from _DecisionArtifact findings enhance the explanation of Code variables and provide granularity. These flexible text entries can be updated as needed
Identifier	Feature	Text	The user-generated identifier provides granularity by describing the Code/Theme variables. It contains text values and offers flexibility, with no fixed list of entries
Attribute	Feature	Text	The attribute field captures the finest detail, explaining specific aspects of the identifier. It is text-based, user-generated, and has no fixed list of entries
Rating	Target	Char	The rating variable enables users to rate feature variables using integers (0–5) or a Boolean value ("yes"/ "no")

6.3.4 Evaluation

The artifact was developed following the third and fourth ADR principles, which emphasized the organizational involvement in shaping the artifact while acknowledging the collaborative influence of researchers and practitioners. The researcher provided academic insights based on the literature dataset, while industry professionals contributed practical considerations for dataset design. Their combined input shaped the final artifact, with the current cycle's findings highlighting programmability considerations through dataset design requirements. Successfully executing the eADR diagnosis iteration was essential for achieving the set objective. The first cycle contributed foundational knowledge of the dataset, while the second cycle refined the dataset within the eADR framework, reinforcing the study's understanding of AI applications. The _DataSetArtifact verified its role in enabling the programmability of the _DecisionArtifact within an AI environment. These findings confirm its usability in fulfilling the objective.

6.3.5 Reflection and Learning

The _DataSetArtifact was validated by ensuring three key elements: alignment with the primary objective, an appropriate design approach, and the effectiveness of the proposed solution. The aim is to design an AI framework that illustrates decision programmability. This necessitates a structured dataset to implement the DecisionArtifact in an AI environment. The current diagnostic cycles played a crucial role in developing this dataset, ensuring its relevance to the objective. The iterative eADR approach enabled dataset development, which was further refined through industry feedback. Literature-driven dataset design principles guided the creation and evaluation of the final _DataSetArtifact.

After completing the third diagnostics iteration, the interessement moment was finalized, with the researcher acting as a translator to align source actors with the network's goal. No new actors passed through the obligatory point, maintaining the focus on reaching enrollment. Figure 6.5 presents the updated ANT network post-diagnosis iteration.

Figure 6.5 highlights the researcher's role as a translator, engaging with source actors to enhance the programmability of decisions. During the third iteration of diagnosis, the researcher developed a dataset to bridge

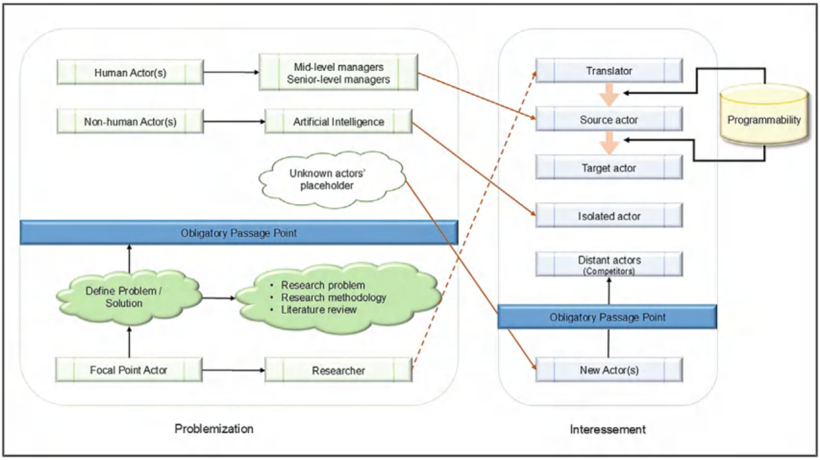


Fig. 6.5 ANT interessement progression (third diagnostic)

the decision-making of source actors with AI implementation, ensuring their understanding of the AI model's application.

This process strengthened the alliance between the translator and source actors, fostering belief in the network's goal. Seeing their inputs transformed into new knowledge and a functional dataset reassured source actors, enabling them to advocate for the network's success to target actors. With this alignment, the network is ready to progress to the following translation stage.

6.4 Summary

The chapter aimed to achieve the objectives by establishing a framework for programming the _DecisionArtifact within an AI environment. To accomplish this, a literature-inspired framework dataset was developed, incorporating elements of the _DecisionArtifact and a unique variable to enhance its functionality.

The framework dataset was then evaluated by industry professionals through a group discussion and interview, assessing its programmability against three literature-based themes. The feedback was positive, validating the dataset and providing best practices to future-proof the dataset and future data entries.

The _DataSetArtifact met the requirements, confirming its role in enabling the _DecisionArtifact's programmability. The chapter concluded the diagnosis phase, producing the final _DiagnosisArtifact. In the next chapter, the artifacts from the various diagnostic iterations will be integrated into the design iteration.

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CHAPTER 7

Design: Decision-Support Model

Abstract This chapter describes the elaborated action design research (eADR) design iteration, elucidating the design of the envisaged artificial intelligence (AI) decision-support model. This iteration integrates the earlier developmental diagnostic iterations' _DecisionArtifact, _SocialArtifact, and _DataSetArtifact into the _DesignModelArtifact, guided by a literature-based, stage-driven approach. This artifact encompasses two operational environments: technical and social. In the context of the actor-network theory (ANT), no new actors emerged during this stage, and the actor-network transitioned from interessement to the enrollment phase of transition. In the technical environment, the _DataSetArtifact serves as the knowledge base. User queries trigger specific codes that impact key performance indicators (KPIs), with the knowledge base assisting the inference engine in evaluating and providing feedback through the user interface. The social environment focuses on user adoption, with the _SocialArtifact serving as the foundation for the human experience. It emphasizes the technology acceptance model (TAM), particularly perceived ease of use (PEoU) and perceived usefulness (PU), as well as the value-based adoption model (VAM), which highlights benefits and sacrifices.

Keywords Actor-network theory · Artificial intelligence · Elaborated action design research · Key performance indicators · Technology acceptance model · Value-based adoption model

E. Steyn et al., *Programmable Decisions for Business Organizations*,
https://doi.org/10.1007/978-981-95-0724-5_7

JEL Classification M15 · O032

7.1 Introduction

This chapter outlines the design iteration focused on developing an initial artificial intelligence (AI) decision-support model that is both practice-inspired and theory-grounded, capable of operating within technical and social environments. Building on insights gained from earlier diagnostic iterations, the _DesignModelArtifact developed in this chapter integrates key knowledge related to the business problem (_DecisionArtifact), the organizational AI culture (_SocialArtifact), and the programmability of decisions (_DataSetArtifact). Consistent with previous chapters, this section applies the stages of the elaborated action design research (eADR) model to present the AI design approach (problem perspective), detail the data collection process (action planning perspective), and describe the design of the iteration-specific artifact. After completing the _DesignModelArtifact, the actor-network as described in the actor-network theory (ANT), was updated.

7.2 Problem Formulation

The first and second action design research (ADR) principles emphasize the importance of addressing both theoretical and practical field problems (Sein et al., 2011), a view supported by Charnley et al. (2011), who stress the need to incorporate multiple perspectives in system design. In alignment with this, the following literature-based approach ensures that diverse viewpoints are considered in developing the model. Kraus et al. (2022) contribute by proposing a stage-based framework for AI system development, as illustrated in Table 7.1.

Table 7.1 presents a literature-based approach outlining the key steps in designing an AI model following the objectives of this book. These steps include forming a team, defining goals, selecting appropriate tools, setting parameters, building and programming the model, training with user data, testing, and optimization. However, this book limits its scope to the initial design phase, explicitly focusing on team formation, goal definition, tool selection, and parameter setting. As industry input was

Table 7.1 AI design algorithm

AI setup stage	*Stage outcomes*	*eADR stage*
Team formation	Identifying the AI model development team	Problem formulation
Goal definition	Establish the AI model's objective	Problem formulation
Tool selection	Choose a model that fits the AI system's goal	Action planning
Model parameters	Configure system parameters	Artifact creation
Model training	Train the system using ML techniques	N/A
Model optimization	Test and optimize the model	N/A
Result analysis	Assess system performance	N/A

Source Adapted from Kraus et al. (2022)

already gathered during the three diagnostic iterations, the researchers will act as the sole team members for this phase.

7.3 Action Planning

This section discusses the tools used to develop the AI model in accordance with the tool selection step outlined above. This design iteration aims to integrate the _DecisionArtifact, _SocialArtifact, and _DataSetArtifact into a cohesive design model. These three artifacts are the foundational tools for constructing the AI decision-support model, which will be built using key components derived from earlier diagnostic iterations, including the decision-making framework, a structured and usable AI dataset, and insights into the social environment.

7.4 Artifact Creation

7.4.1 AI Decision-Support Design Model

The model parameters are visually depicted to highlight all components of the design. Figure 7.1 illustrates the integration of the three diagnostic iteration artifacts into a unified model.

Figure 7.1 presents the various components of the resulting _DesignModelArtifact, organized into two sections representing the environments in which the model operates: the social and technical domains.

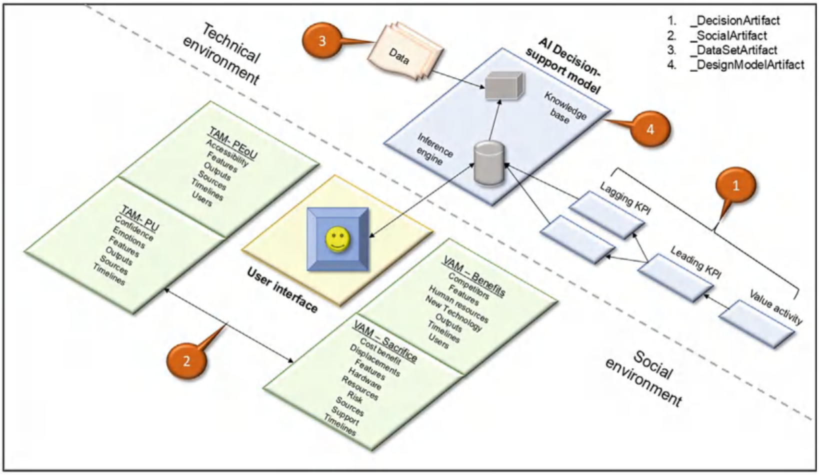

Fig. 7.1 _DesignModelArtifact

The figure highlights the contributions and applications of all relevant artifacts from the earlier iterations. The model's functioning within these environments will be further explained in the following sections, structured under technical and social headings.

7.4.2 Technical Environment

In this model, a user initiates a query through the interface, which is then processed by the inference engine. The engine accesses relevant rules and data from the knowledge base, applies them, and generates a response for the user. In the context of this book, the knowledge base is represented by the _DataSetArtifact. When a query is submitted, it activates specific codes linked to various key performance indicators (KPIs). The inference engine identifies the affected KPIs, assesses their impact, and formulates an appropriate response, which is then communicated back to the user. Figure 7.2 illustrates this process through an example of the firm's financial infrastructure activity.

Figure 7.2 illustrates a single value driver identified during earlier iterations. However, the _DesignModelArtifact consolidates all activities to reflect the interdependencies across multiple KPIs. The thematic codes

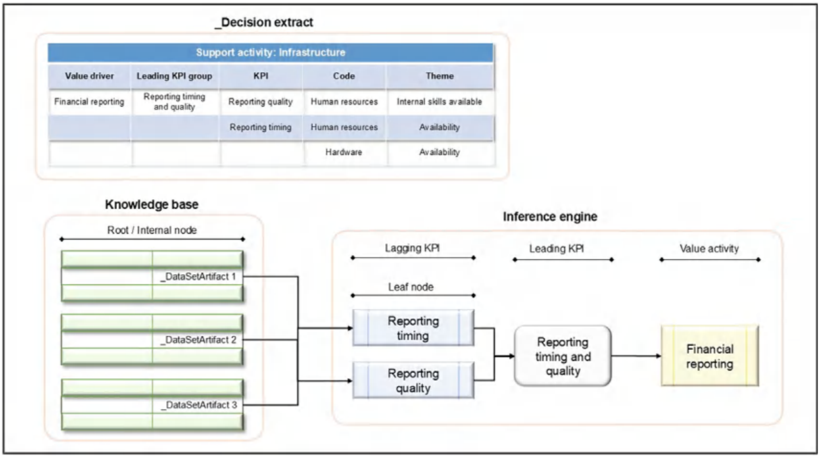

Fig. 7.2 Interworking of inference engine and knowledge base

and themes generated in the _DataSetArtifact are stored in the knowledge base. At the same time, decision trees, constructed from the relationships between value drivers and KPIs, are housed within the inference engine. For example, when a user queries the AI model about human resources (HR) resources, the inference engine accesses relevant information from the knowledge base, evaluates its influence across various KPIs, and determines its overall impact on the associated value driver.

7.4.3 Social Environment

AI system design must incorporate socio-technical considerations, ensuring that changes in the technical environment are aligned with social factors and contexts. This involves two key areas: the technology acceptance model (TAM), which focuses on perceived ease of use and perceived usefulness, and the value-based adoption model (VAM), which emphasizes the balance between perceived benefits and sacrifices. The following sections highlight the key social aspects evaluated during the development of the _DesignModelArtifact.

7.4.3.1 TAM: Perceived Ease of Use (PEoU)

A system's usability influences adoption. To enhance ease of use, the _ DesignModelArtifact incorporates:

- Multi-platform Accessibility: Ensures users can access the system from any device, at any time.
- Language adaptability: Supports key languages based on operational regions, with expansion as needed.
- User-friendly Interface: Mimics familiar platforms (e.g., social media, streaming services) for intuitive interaction.
- Efficient Query Processing: Optimized knowledge base and inference engine for fast, relevant responses.
- Contextualized Outputs: Prevents information overload by ensuring responses are relevant, unique, and tailored to the industry.
- Learning Capabilities and Training Support: Adapts through user interaction and provides robust onboarding resources.

7.4.3.2 TAM: Perceived Usefulness (PU)

A system must demonstrate value to encourage user adoption. Key design considerations include:

- Objective Decision-Making: Identifies situations where emotion-free decisions are necessary.
- Risk Identification: Detects potential risks within its operational scope.
- Contextual Insights: Enhances data interpretation by illustrating potential impacts.
- Justified and Trustworthy Outputs: Cites sources to build user confidence and minimize rework.
- Decision-Support and Collaboration: Facilitates discussions within organizations by providing well-supported recommendations.
- Source Validation: Identifies reliable information and filters out false data.
- Resource Efficiency: Saves time and effort, improving the perceived usefulness of the system.

7.4.3.3 VAM: Benefits

Users weigh the benefits of the system against potential sacrifices. Key advantages include:

- Competitive Edge: Enhances decision-making in a highly competitive industry.
- Seamless Integration: Reduces reliance on multiple systems.
- Advanced Data Processing: Generates detailed insights by analyzing large datasets.
- User Engagement: Encourages interaction with cutting-edge AI technologies.
- Personalized Outputs: Provides tailored recommendations beyond predefined rules.
- Continuous Improvement: Learns from user interactions to refine future outputs.
- Skill Development: Helps users enhance their expertise through AI-driven insights.

7.4.3.4 VAM: Sacrifices

To minimize adoption barriers, the system addresses potential concerns:

- Return on Investment: Justifies costs through financial savings and efficiency gains.
- Privacy and Security: Maintains data integrity, unlike free software alternatives.
- User-Friendly Learning Curve: Limits technical knowledge requirements.
- Workplace Flexibility: Accessible across multiple platforms, not restricted to office use.
- Hardware Compatibility: Operates on existing infrastructure without additional resource demands.
- Implementation and Training Support: Ensures smooth onboarding and ongoing maintenance.
- Risk Mitigation: Aligns with organizational compliance and industry regulations.
- AI Perception Management: Positions AI as a tool for augmenting human creativity, not replacing jobs.

This framework ensures the AI decision-support system integrates seamlessly into both technical and social environments, fostering adoption and long-term value.

7.5 Evaluation

7.5.1 Artifact Evaluation

The _DecisionModelArtifact was developed in line with the third and fourth ADR principles, emphasizing active organizational involvement and a collaborative relationship between researchers and practitioners (Sein et al., 2011). Researchers contributed academic expertise in system design. At the same time, industry participants enriched the process with practical insights gathered during the earlier diagnostic iterations, jointly shaping the _DesignModelArtifact.

Drawing on findings from the diagnostic iterations, the _DesignModelArtifact integrates AI system requirements into both its knowledge base and inference engine, thereby establishing the AI environment's social framework, which begins with a conceptual foundation in the _DecisionArtifact, designed to address the core business problem, and the _Dataset artifact, enabling the _DecisionArtifact to operate within an AI system while also anticipating future data needs.

Socio-technical factors were carefully embedded in the design, ensuring that any technical changes aligned with users' social contexts, as outlined in the _SocialArtifact. With these components in place, the _DesignModelArtifact is ready for verification and validation.

7.5.2 Artifact Verification

Verification of the _DesignModelArtifact required evaluating both the design process and the resulting artifact against the chapter's objective: to develop a practically informed, theory-grounded AI decision-support model that operates effectively within both technical and social environments. This verification focused on two aspects:

- Iteration Design: Confirming that the current iteration was appropriately structured to achieve the chapter objective.
- Artifact Alignment: Ensuring the final _DesignModelArtifact successfully integrates insights from preceding diagnostic artifacts.

The successful integration of these artifacts demonstrates that the design process effectively combined theoretical foundations with practical requirements to produce a robust AI decision-support model. Given that both the iteration design and the resulting artifact meet the intended objective, this design iteration is considered successfully verified.

7.6 Reflection and Learning

7.6.1 Artifact Validation

The _DesignModelArtifact was validated based on its alignment with the book's main objective, the appropriateness of the design approach, and the effectiveness of the final artifact.

The book's core objective is to develop a framework that illustrates decision programmability within an AI decision-support model to enhance decision-making strategies. The _DesignModelArtifact clearly supports this goal, demonstrating that the right solution is being built through a practical, theory-grounded approach.

By following the chapter's requirements and leveraging the design process's emergent nature, the iterative design approach successfully shaped a practical, theory-grounded AI decision model, affirming that the right design was applied to achieve the intended objective.

Finally, aligned with the chapter's goal, the final design model artifact provides a structured framework that informs industry discussions on empowerment and supports the development of a robust AI decision-making model. Its contribution to the overarching objective is confirmed through the eADR process, which validates its full validation.

7.6.2 ANT Enrollment Progression

With the completion of design iteration, the actor-network transitioned from interessement to the enrollment phase of translation (Fig. 7.3).

In this phase, the translator integrated findings from the previous artifacts into a unified _DesignModelArtifact, presented as a proposed solution to address the network's objectives. As no new actors emerged during this stage, all network participants are considered identified and confirmed. The enrollment process continues into the next chapter, where the _DesignModelArtifact is introduced into the network. Its success

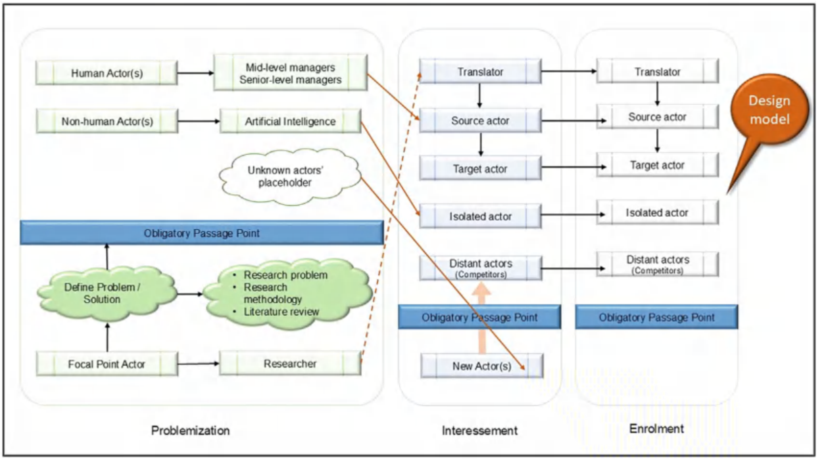

Fig. 7.3 ANT enrollment progression (design iteration)

relies on acceptance by source actors, who play a critical role in influencing target actors to enable broader adoption.

7.7 Summary

This chapter successfully met its objective by developing an initial AI decision-support model that is both practically inspired and theory-grounded, designed to operate within technical and social environments. This was achieved by integrating insights from the three diagnostic artifacts.

The chapter began with problem formulation and applied AI model design principles to construct the _DesignModelArtifact. The technical environment of the model was established by combining the _DecisionArtifact and the _DataSetArtifact, while the _SocialArtifact informed the model's social dimension. Following its creation, the _DesignModelArtifact was both validated and verified, confirming its alignment with the chapter's objective. It is now ready to progress to the next chapter, which will introduce the model to the original iteration _DecisionArtifact participants for final validation, resulting in the development of the _ValidatedModelArtifact.

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CHAPTER 8

Implementation: Validated Decision-Support Model

Abstract This chapter outlines the verification and validation of the _DesignModelArtifact, resulting in the final _ValidatedModelArtifact—an Artificial Intelligence (AI)-enabled decision-support model. Using the elaborated action design research (eADR) methodology, the model was reintroduced to the original participants to assess its alignment with five conceptual statements that cover verification and validation. Participant feedback confirmed the model's logical structure, practical relevance, and intuitive design. The _ValidatedModelArtifact integrates the _DecisionArtifact, _DataSetArtifact, and _SocialArtifact, forming a balanced framework that addresses both technical and socio-technical considerations. Aligned with action design research (ADR) principles, the artifact evolved through continuous participant input and embedded evaluation. Limitations include the pace of AI evolution, non-exhaustive coverage of key performance indicators (KPIs), and variability in decision-maker perspectives. The chapter also marks the completion of the actor-network theory (ANT) enrollment moment: with the model accepted, the researcher exits the network, and source actors engage target actors, initiating the mobilization phase. Future research may explore the model's applicability across various industries, expand the use of ANT in AI contexts, and examine the impacts of implementation.

Keywords Actor-network theory · Artificial intelligence · Elaborated action design research · Socio-technical thinking · Validity · Verification

E. Steyn et al., *Programmable Decisions for Business Organizations*,
https://doi.org/10.1007/978-981-95-0724-5_8

JEL Classification M15 · O032 · O033

8.1 Introduction

This chapter aims to elucidate the activities involved in verifying and validating the _DesignModelArtifact, culminating in the envisioned artificial intelligence (AI) decision-support model. This consists of presenting the _DesignModelArtifact to the original industry participants from the first diagnostic iteration (_DecisionArtifact), ensuring it aligns with the book's primary objective. The chapter follows the structured stages of the elaborated action design research (eADR) process, beginning with problem formulation, which outlines the need for validation and verification. This is followed by action planning, which introduces interviews with participant input, informing conceptual validation and verification statements. During the artifact creation section, participant feedback is incorporated to refine the model, resulting in the final _ValidatedModelArtifact. In the context of the actor-network theory (ANT), the chapter concludes by updating the actor-network, which entered its final phase of translation: mobilization.

8.2 Problem Formulation

The first and second principles of action design research (ADR) emphasize the importance of addressing both theoretical and practical problems (Sein et al., 2011: 40). In line with this, Charnley et al. (2011: 13) stress the need to consider the diverse interests of stakeholders, reinforcing the importance of ensuring that the _DesignModelArtifact accurately reflects the perspectives and insights of the participants involved.

8.2.1 Validation and Verification

The terms *verification* and *validation* are often used interchangeably, which can create confusion about their distinct roles in system development (Ryan & Wheatcraft, 2017). In this book, their meanings are clearly differentiated. Verification focuses on determining whether a system satisfies the conditions defined at the start of a development phase (IEEE, 2012). Davis (1992) outlines verification methods, including logical and mathematical verification, which ensures that algorithms and rules are error-free, and program verification, which confirms that individual components are implemented correctly. In contrast, validation assesses whether the system meets its intended requirements, with a particular emphasis on stakeholder needs (IEEE, 2012). Davis (1992) describes three types of validation: descriptive validity (evaluating whether the model accurately explains the phenomenon and organizes information meaningfully), structural validity (assessing the inclusion of appropriate model elements), and predictive validity (determining whether the model can accurately predict the desired system behavior). Both verification and validation are essential to ensure the reliability of a model, as undetected errors can undermine its effectiveness (Kleijnen, 1995). Notably, Davis (1992) also emphasizes that involving participants in the problem context enhances the verification and validation process, making it more relevant and robust within organizational settings.

8.2.2 Conceptual Design Statements

To ensure that the refinement of the _DesignModelArtifact into the _ValidatedModelArtifact, incorporating additional industry feedback and suggestions, meets established verification and validation standards, the following design statements were defined:

- **Verification:**
  - eADR iterations align with research objectives (*Logical verification*).
  - The final artifact supports and addresses research goals (*Program verification*).
- **Validation:**
  - The research objectives adequately address the problem (*Descriptive validity*).
  - The eADR research-practitioner approach provides necessary knowledge (*Structural validity*).
  - The final decision-support framework enables the manufacturing industry to adopt new technologies (*Predictive validity*).

8.3 Action Planning

This iteration focuses on gathering industry feedback on the _DesignModelArtifact developed in the previous phase, with the goal of refining it into a _ValidatedModelArtifact and advancing the model's development. The data collection and processing methods used to support this refinement are outlined below. The _DesignModelArtifact was reintroduced to participants of the _DecisionArtifact (first diagnostic iteration), using a working document to guide discussions around key conceptual statements. These included the book's primary objective, which was to conduct a unique eADR *pre*-implementation iteration to verify and validate the envisaged AI decision-support model and its underlying eADR design. Group discussions were held with participants, and the key feedback gathered is summarized in the following section.

8.4 Artifact Creation

8.4.1 Design Statement Feedback

Key insights from the industry participants include the following:

8.4.1.1 Verification

The verification encompassed two categories, as follows:

- Logical verification: Participants identified several aspects of the model that aligned well with the research objectives, reinforcing its logical soundness. Firstly, they emphasized the flow of information within the eADR process, noting that its iterative nature enabled knowledge to move forward and backward. Rather than following a linear path tied to task completion, the model allowed for continuous testing and refinement across stages, which enriched the quality of insights generated. Secondly, they emphasized the importance of knowledge creation across iterations, where findings were developed, critically evaluated, and refined before being progressed. This reflective process was essential for strengthening the eADR methodology and the organization's broader knowledge base. Lastly, participants valued the adaptability of the eADR model, observing that it need not rigidly follow the literature-defined phases of diagnosis, design, implementation, and evaluation. This flexibility was viewed as a critical attribute for any decision-support framework in fast-changing industries.

- Program verification: Participants provided targeted feedback on the _DesignModelArtifact, confirming its alignment with the book's objectives. They particularly appreciated the schematic representation of the model, which clearly and accessibly illustrated the distinction between social and technical components. This structured and visually coherent layout gave participants confidence that the _DesignModelArtifact accurately reflected the research objectives. Furthermore, the ease of understanding was a key strength noted across varying levels of technological expertise. Participants found the model intuitive and straightforward, reinforcing their belief in its practical applicability and overall effectiveness.

8.4.1.2 Validation

The validation encompassed three categories, as follows:

- Descriptive validity: Supported by the participants' feedback, it was confirmed that the objectives were clearly defined and effectively addressed the overarching book goal. Participants highlighted that the secondary objectives offered a structured and manageable breakdown of the research problem, enabling them to engage meaningfully with the study, particularly from a social perspective on the adoption of new technology. The sub-objectives were considered logical and necessary steps toward achieving the primary aim. Furthermore, the iterative refinement of the _DesignModelArtifact into a validated artifact, presented to the original participants, reinforced the internal coherence of these sub-objectives. By involving participants in both the early and final stages, the design process successfully *closed the loop*, ensuring that participant perspectives were accurately represented and validated throughout the research process.
- Structural validity: The participants reinforced the structural validity and emphasized the valuable contributions of the researcher-practitioner team. A key strength of this approach was the integration of insights from different managerial levels, each offering

distinct perspectives that collectively enhanced the depth, relevance, and applicability of the study's findings. Additionally, the team's composition, combining expertise from the manufacturing and information technology sectors, enabled a rich, multidisciplinary viewpoint. Participants emphasized the importance of minimizing translation loss when bridging social and technical domains, recognizing that effective communication across these areas is crucial for maintaining the integrity of insights. They also emphasized the importance of researchers' foundational understanding of the industry under investigation. The practical application of theoretical knowledge was considered essential to producing contextually grounded research, with participants warning that a lack of industry familiarity could lead to misinterpretation of key phenomena.

- Predictive validity: As was demonstrated through the benefits observed within the manufacturing industry, the predictive validity aspect was confirmed. A central factor was the active inclusion of participants throughout the research process, from initial diagnosis to the final *pre*-implementation stage, which fostered curiosity about the model's functionality and encouraged a sense of ownership. This engagement, facilitated through the eADR process, made the final _DesignModelArtifact feel organically integrated rather than externally imposed. Participants also highlighted the value of the model's clarity and logical structure, which enhanced their confidence in adopting new technologies. A well-articulated framework enabled them to assess potential risks and opportunities better, making the transition to new solutions more manageable. Furthermore, a recurring theme was the importance of understanding the origins of the technologies embedded in the model. When participants knew where system feedback originated, it reinforced their trust in the model's outputs and strengthened their willingness to engage with and rely on its recommendations.

8.4.2 _ValidatedModelArtifact

Based on the verification and validation feedback, the final AI decision-support model is confirmed as the _ValidatedModelArtifact, as presented in Fig. 8.1.

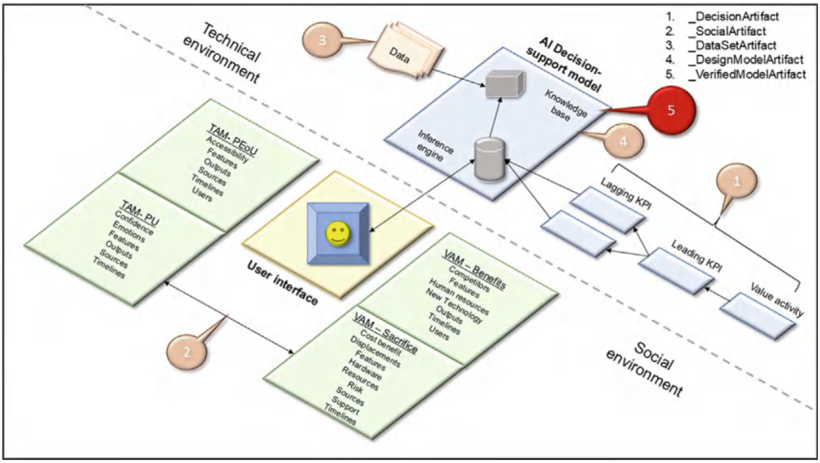

Fig. 8.1 _ValidatedModelArtifact

Figure 8.1 presents the final _ValidatedModelArtifact, which integrates the core concepts of the diagnostic, design, and implementation iterations.

8.5 Evaluation

The _ValidatedModelArtifact, refined through industry feedback, integrates key technical and social components to form a robust AI-enabled decision-support model. Verified by participants as aligned with conceptual statements, the model advances the main research objective of illustrating decision programmability. It builds on the _DesignModelArtifact, combining the _DecisionArtifact as the inference engine, the _DataSetArtifact as the knowledge base, and the _SocialArtifact, which embeds socio-technical considerations. This integration ensures a balanced framework, technically sound through its decision and programmability structures, and socially grounded by guiding factors for technology adoption. Practitioners identified the empowering impact of the approach in three areas: participatory design, adoption of new technologies, and understanding of AI feedback, with these outcomes validated through predictive statements, confirming the model's practical relevance and contribution.

8.6 Reflection and Learning

The final _ValidatedModelArtifact aligns with key ADR principles, demonstrating a rigorous and participatory design process. Evaluation was embedded through a unique eADR *pre*-implementation iteration, ensuring continuous participant validation. The model evolved iteratively, with the _DecisionArtifact, _SocialArtifact, and _DataSetArtifact, shaping the _DesignModelArtifact, which was refined into the final _ValidatedModelArtifact based on user input. While the model demonstrates strong contextual relevance, its broader applicability remains open to future exploration. However, the design process and context have limitations, including the rapid pace of AI evolution, which may affect the longevity of the _DataSetArtifact, the non-exhaustive nature of identified key performance indicators (KPIs), and the subjective influence of participant experience on decision considerations. Future research could investigate decision programmability in the context of industries with distinct KPIs, expand the application of ANT in other AI-related contexts, and conduct practical implementation iterations to better understand the socio-technical impacts on AI system development.

Following the completion of the *pre*-implementation iteration, the ANT enrollment moment initiated in the previous design iteration was finalized, marking the establishment of the _ValidatedModelArtifact as the definitive solution to support the network's goal. At this stage of translation, no new actors entered through the obligatory passage point, indicating the stabilization of the actor-network, as illustrated in Fig. 8.2.

After the *pre*-implementation iteration, the final _ValidatedModelArtifact was presented to source actors as the solution aligned with the network's goal, i.e., to explore how decision programmability in an AI-driven, socio-technical context empowers manufacturing organizations. Upon recognizing the model's value, source actors no longer required the researcher as a translator, marking the researcher's exit from the network and their disassociation as an active actor within the organization. With the translator's departure, source actors assumed responsibility for engaging target actors, thereby advancing the model's acceptance during the implementation iteration. This process occurs at the organizational level and is beyond the scope of this book. At this stage, the network entered its final phase of translation: mobilization. Meanwhile, isolated actors (such as AI systems) and distant

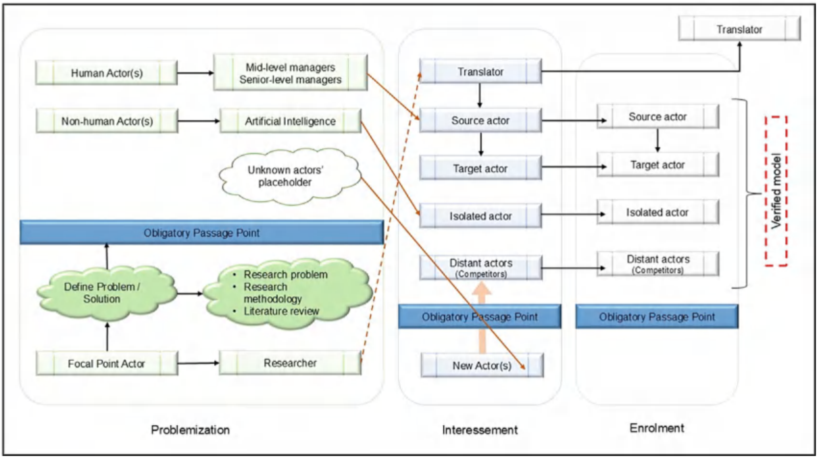

Fig. 8.2 ANT enrollment progression (*Pre*-implementation)

actors (such as competitors) continued to influence the network, interacting independently with source and target actors. The roles of these actors in future translation moments present opportunities for further research.

8.7 Summary

This chapter focused on reintroducing the _DesignModelArtifact to earlier participants for verification and validation against five key conceptual design statements, achieved through the *pre*-implementation eADR iteration. The chapter detailed the problematization and action planning phases, with artifact development and participant feedback evaluated according to these criteria. This process confirmed the model's alignment with the study's primary objective and research problem, resulting in the final _ValidatedModelArtifact. Reflection on the artifact's development highlighted the role of ADR principles and identified future research opportunities in AI decision-making and system design, as well as study limitations. With the *pre*-implementation complete, the next and final chapter will summarize the study's key findings and conclusions.

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CHAPTER 9

Conclusion

Abstract This chapter finalizes the empirical design of the artificial intelligence (AI)-enabled decision-support model by summarizing key components, outlining the methodology, and highlighting theoretical, methodological, and practical contributions. The book examines the integration of AI in decision-making within the socio-technical context of Industry 4.0, with a focus on balancing social and technical objectives. Actor-Network Theory (ANT) was applied to examine interactions between human and non-human actors through problematization, interessement, and enrollment phases. The elaborated action design research (eADR) approach was innovatively adapted through multiple diagnostic iterations and a *pre*-implementation phase, resulting in the creation of the _DecisionArtifact, _SocialArtifact, and _DataSetArtifact. These were integrated into the _DesignModelArtifact and validated to produce the final _ValidatedModelArtifact. The study contributes to theory by demonstrating the adaptability of ANT to AI decision-making, methodologically advancing eADR processes, and practically enhancing managerial decision-making through user inclusion, technology adoption, and transparency in AI models. Despite acknowledging potential technological and contextual limitations, the research promotes future studies on the application of ANT across various industries and the exploration of more advanced AI model implementations. The Validated Model offers a robust and adaptable framework for diverse AI decision-support contexts.

E. Steyn et al., *Programmable Decisions for Business Organizations*,
https://doi.org/10.1007/978-981-95-0724-5_9

Keywords Actor-network theory · Artificial intelligence · Decision-support model · Elaborated action design research · Socio-technical thinking

JEL Classification M13 · M16

9.1 Introduction

The previous chapter concluded the empirical design phases of the artificial intelligence (AI)-enabled decision-support model by performing the verification and validation tests of the _DesignModelArtifact, resulting in the _ValidatedModelArtifact. This chapter provides a brief overview of key components by recapping the background and literature review, followed by an outline of the applied methodology and the key objectives. The contributions are presented in three areas: theoretical (i.e., actor-network theory (ANT)), methodological (i.e., elaborated action design research (eADR)), and practical implications, before a brief concluding discussion.

9.2 Overview

Industry 4.0 integrates AI into daily life, driving significant societal and business changes. AI, defined as the creation of intelligent machines and software that mimic human cognition, has increasingly influenced decision-making, establishing algorithmic decision-makers (González García et al., 2019; Pannu, 2015). However, AI cannot function independently of humans, requiring a balance between social and technical goals—a concept rooted in socio-technical thinking. Such an approach emphasizes the reciprocal relationship between humans and machines, aiming to harmonize technical and social conditions for an efficient work environment. This highlights a knowledge gap in understanding AI-driven decision-making within its social environment to ensure effective integration of social and technical elements. The book examines how a deeper understanding of decision programmability within an AI context, informed by socio-technical thinking, can improve performance management and decision-making.

Since the 1980s, ANT has been widely applied in science and technology to analyze how networks form and how various actors interact to achieve shared goals. ANT considers networks as spaces where human and non-human actors collaborate through alliances and interactions. Network formation in ANT involves four translation moments: problematization, interessement, enrollment, and mobilization (Zawawi, 2018). For purposes of this book, the first three translation moments were relevant, clarified as follows:

- Problematization: For this book, the researcher acted as the focal actor, identifying the problem and developing a theoretical understanding. Mid-level and senior-level managers were identified as human actors, while AI was non-human, and both could influence the network.
- Interessement: Entailing three distinct diagnostic iterations, the focal actor assigned the actor roles:
  - The first instance designated the human actors as source actors, influencing the target actor (i.e., the organization). At the same time, AI, as a contextual technology, was considered an isolated actor because it could not *negotiate*. This resulted in completing the _DecisionArtifact, with all actors passing through the obligatory point, as per ANT.
  - The second instance explored the social environment using models like the technology acceptance model (TAM) and the value-based adoption model (VAM) to positively influence source actors regarding the benefits of AI, resulting in the creation of the _SocialArtifact. Competitors highlighted AI's role in maintaining competitiveness as distant actors but did not engage directly with other actors.
  - The third instance focused on the technical environment, developing a _DataSetArtifact that integrated the decision and social environment considerations into an AI model. This dataset strengthened the network by boosting the confidence of source actors.
- Enrollment: This entailed confirming all actors' roles and alignment with the network's goal, synthesizing the _DecisionArtifact, the _SocialArtifact, and the _DataSetArtifact into a schematic model called the _DesignModelArtifact. Finally, the _DesignModelArtifact

was validated in collaboration with designated source actors, resulting in a final _ValidatedModelArtifact, as the AI-enabled decision-support model.

The mobilization phase, which involves further research and implementation, was beyond the scope.

9.3 Objectives and Design Approach

9.3.1 Primary Objective

As indicated in Chapter 1, the primary objective was to develop an AI-enabled decision-support model to contextualize the programming of management decisions in an AI environment.

This entailed several sub-objectives that required investigating AI's *technical* and *social* environments. The former concluded in the _DecisionArtifact and _DataSetArtifact, while the latter was addressed through the _SocialArtifact, focusing on minimizing negative impacts when implementing new technologies. Integrating these artifacts resulted in the final _ValidatedModelArtifact, which showcased an AI-enabled decision-support model.

9.3.2 Research Design

An eADR approach was followed, using three iterations: i.e., diagnostics, design, and *pre-implementation* iterations, as clarified below:

- The first diagnostics iteration entailed two cycles, in which the first cycle primarily collected data and developed knowledge. In contrast, the second cycle confirmed accuracy, resulting in a decision framework (i.e., the _DecisionArtifact) suitable for an AI environment.
- The second diagnostics iteration contributed to understanding the social environment surrounding the _DecisionArtifact, resulting in the _SocialArtifact that supported socio-technical thinking.
- Similar to the first diagnostic iteration, the third diagnostics iteration also entailed two stages: investigating the programmability of the _DecisionArtifact and culminating in the _DataSetArtifact, which enabled the integration of the _DecisionArtifact into a decision tree AI model.

- The design iteration entailed the integration of the prior artifacts, i.e., the _DecisionArtifact, the _SocialArtifact, and the _DataSetArtifact, to develop the _DesignModelArtifact.
- The *pre*-implementation iteration verified and validated the _DesignModelArtifact, resulting in the final _ValidatedModelArtifact.

9.3.3 Data Collection and Knowledge Development

The data collection served as the foundation for the diagnostics iterations, as follows:

- **First Diagnostics Iteration:** Semi-structured and unstructured interviews, as well as group discussions, identified key industry performance indicators and supplemental themes and codes.
- **Second Diagnostics Iteration:** Similar methods were used to assess the current AI culture among participants and factors influencing AI adoption and usage.
- **Third Diagnostics Iteration:** Interviews and discussions evaluated the dataset's relevance, usability, and quality to enhance the programmability of management decisions.

The data collected were analyzed using a thematic approach, enabling the identification of key thematic codes as the foundation for knowledge development in the relevant iterations. To ensure data credibility, senior managers reviewed the data provided by mid-level managers for additional input, and industry professionals assessed the literature-derived data. The final _ValidatedModelArtifact was also presented to knowledgeable participants for verification and validation, ensuring the credibility of the data and the thoroughness of the artifact.

9.4 Contribution

9.4.1 Introduction

Research contributions should arguably aim to expand existing discussions rather than redefine a field. They should assess the entire research process, offering new approaches, contributing to theories, or generating new data and insights.

As such, the book presents original research on AI technology within the context of managerial accounting and performance management decision-making, integrating it with information technology. It adopted a creative approach using ANT, socio-technical thinking, and eADR methodologies. The book addressed the research gap by exploring AI decision-making models and the cultural environment needed to empower the pharmaceutical industry. Rather than aiming for generalization, it encourages readers to draw their connections to its components, as detailed below.

9.4.2 Theoretical Contribution

Applying ANT to the (re-)emerging field of AI and introducing it to managerial decision-making makes a significant academic contribution. Thus, incorporating socio-technical thinking to assist with actor identification and role allocation demonstrates ANT's adaptability, showcasing its versatility in integrating different theories.

The design approach employed ANT to explore network formation and analyze interactions between human and non-human actors. It enhanced AI research by assigning specific titles to unique actors within this context. These insights provide a foundation for future studies to identify new actors or explore interactions within the contexts of AI and management.

9.4.3 Methodological Contribution

The eADR process typically involves four iterative stages: diagnosis, design, implementation, and evolution, allowing forward and backward progression as needed. The standard eADR approach employs a single diagnosis stage, with repeated iterations within each stage until the desired artifact is achieved. This book introduced two innovative adaptations to the eADR process, i.e.:

- Multiple Diagnosis Iterations: Instead of a single diagnosis iteration, it applied three distinct and independent iterations. Each iteration produced a unique artifact that was integrated into a single artifact during the design iteration.
- *Pre*-implementation Iteration: Unlike the traditional approach, which moves directly from design to implementation, this study

included a *pre*-implementation iteration. This step focused on verifying and validating the concept design, ensuring a valid model was ready for implementation.

Continuous participant feedback during the various iterations emphasized the value of generating knowledge at each iteration stage. It highlighted the benefits of a researcher-practitioner team in enhancing research quality, particularly in complex research environments.

9.4.4 Practical Contribution

As mentioned earlier, the primary goal was to investigate how an AI-enabled decision-support model's technical and social environments empower managerial decision-making. The predictive validation findings highlighted three key empowerment levels:

- User Inclusion: Industry participants valued their involvement from initial diagnosis to the *pre*-implementation phase. This engagement fostered curiosity and reduced resistance to the final _ DesignModelArtifact, making it feel less *forced*. This suggests that including users in development stages helps integrate social considerations into technological products.
- Enhanced Technology Adoption: The _DesignModelArtifact's clear and logical structure increased participants' confidence in adopting new technologies. Understanding the model's components helped them identify threats and opportunities, promoting an investigative approach to new technologies rather than immediate rejection.
- Clarity of AI Model Sources: Participants felt empowered by understanding the sources within the AI model. Knowing where the system's feedback originated assured the model's outputs, enhancing trust and confidence in AI-driven decisions.

These findings demonstrate how understanding an AI model's social and technical aspects can empower users and lead to more informed, positive, and goal-oriented decisions about AI technologies.

9.5 Limitations and Research Recommendations

When evaluating the final _ValidatedModelArtifact and the applied theories and models in the context of this book, consider the following limitations:

- Due to the rapid pace of technological development, the current suggested artifacts may become outdated.
- The performance metrics are arguably not comprehensive and may differ across industries or organizations.
- The decision considerations reflect the views of specific participants and may vary with different decision-makers.

The following may be considered as possible future (research and design) endeavors in the context of AI-enabled decision-support models:

- Applying ANT in diverse industries and research contexts can identify more actors and refine their roles, thereby improving actors' management in emerging technologies like AI.
- Investigate an implementation phase for AI models to deepen understanding of actor interactions and the influence of socio-technical thinking on system development and deployment.

9.6 Concluding Discussion

As AI evolves in Industry 4.0 and organizations adapt to changing environments, research into the role of AI in managerial applications becomes highly relevant. This book elucidates a subjective approach with a pragmatic view of collected data. It employed an inductive, eADR process with three diagnostic iterations, a design iteration, and a *pre*-implementation iteration. These stages explored the social and technical environments of an AI decision-support model. ANT served as the theoretical framework, with the *researcher* acting as the focal actor and network translator. Human actors were classified as the source and target actors, while non-human actors, including AI, were also given full actor status. AI was designated as an isolated actor, while industry competitors were identified as distant actors.

The book aimed not to redefine the research field but to contribute to ongoing discussions by offering a new approach, supporting theoretical development, and providing fresh data. Rather than generalizing, it encouraged readers to find relevant connections within the various components. An empowering AI decision-support model may lead users to more positive adoption decisions and help them achieve their goals with new technologies. Three key empowerment factors were identified:

- Involvement in the Design Process: Participants felt included, reducing resistance to the final model.
- Encouraging Technology Adoption: A clear understanding of the model's design increased confidence in using new technologies.
- Understanding AI Sources: Knowledge of AI's data sources builds trust in the model.

The research also contributed to a methodology for studying AI in decision-making contexts and provided insights into specific actors within the AI network.

The book is grounded in reputable literature and uses established theoretical frameworks. New data from expert interviews strengthened the study's robustness. The _ValidatedModelArtifact supports knowledge transferability, allowing adaptation to other industries and research contexts. The rigorous and transparent methodology ensures reproducibility, and the iterative process consistently validates findings, demonstrating the study's trustworthiness and completeness.

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