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RESEARCH PAPER

Conceptualizing the Design Space of Artificial Intelligence Strategy: A Taxonomy and Corresponding Clusters

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Abstract As the real-world use of Artificial intelligence (AI) becomes increasingly pervasive, the interest of organizations in the nascent technology is currently at its peak. Although the scientific literature points out that a strategy is key to responding to technological breakthroughs, the three facets of autonomy, learning, and inscrutability that distinguish contemporary AI from previous generations of IT give rise to a novel and distinctive perspective on strategy. Particularly, the facets of contemporary AI lead to AI-induced market and resource shifts and, thus, to AI-related strategic challenges regarding the scope, scale, speed, and source from which organizations make strategic deliberations. This ultimately requires a strategic response from organizations in the form of an AI strategy. Against this backdrop, this study proposes a multi-layer taxonomy with 15 dimensions and 45 characteristics that unveils how organizations currently structure and organize an AI strategy. Conducting a cluster analysis on this foundation, this study further provides four clusters that delineate predominant design options for developing a new AI strategy or evaluating an existing one. In this way, the results contribute to a fundamental understanding of the design space of an AI strategy and enrich recent discussions among researchers and practitioners on how to advance the real-world use of AI.

Keywords Artificial intelligence · Strategy · Taxonomy development · Cluster analysis

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1 Introduction

Artificial intelligence (AI) – the ever-evolving frontier of computational advancement – is currently causing an undeniable wave of excitement among researchers and practitioners alike (Benbya et al. 2021; Berente et al. 2021; Ågerfalk et al. 2022). The gaining momentum of AI to innovate products, services, and business models is driving incumbent firms (i.e., established organizations in an industry or market – henceforth referred to as "organizations") across all industries to establish AI projects (i.e., endeavors that aim to deliver a software product or service with AI functionality to be used in a productive environment) as a strategic response to unfold the underlying value potential of AI (Enholm et al. 2022; Shollo et al. 2022; Grebe et al. 2023). However, AI projects often do not achieve the aspired outcomes or even fail (Vial et al. 2022; Weber et al. 2023; Stohr et al. 2024). One reason is that organizations establish AI projects in an unstructured manner rather than following a distinct strategic direction

(Faraj and Leonardi 2022; van Giffen and Ludwig 2023; Sagodi et al. 2024). To succeed with AI and sustainably strengthen the competitive position in the market, organizations should implement an AI strategy (i.e., guidelines for courses of action and sets of decisions) that guides their AI projects in line with firm-specific goals as well as with internal and external constraints towards a distinct strategic direction.

Responding to technological breakthroughs at a strategic level to remain competitive is not a new phenomenon and has been thoroughly discussed in the established strategy discourse (e.g., in the context of a digital strategy) (Bharadwaj et al. 2013; Woodard et al. 2013). However, recent work in information systems (IS) indicates that AI differs considerably from traditional information technology (IT) (Benbya et al. 2021; Ågerfalk et al. 2022). Contrary to previous generations of IT, contemporary AI is characterized by the facets of autonomy, learning, and inscrutability (Berente et al. 2021). In fact, these three interrelated and interdependent facets may even exacerbate in the future as the methods and techniques at the core of AI continue to grow at an astonishing pace (Benbya et al. 2021; Ågerfalk et al. 2022). As a result, AI represents an ever-evolving frontier of computational advancement that is not only leading to a shift in market and resource conditions (Rajagopalan and Spreitze 1997; Ward and Peppard 2002) but also presents organizations with strategic challenges that affect the scope, scale, speed, and source from which they set courses of action and sets of decisions (Bharadwaj et al. 2013). Hence, organizations that aim to thrive in the competitive environment require a strategic response to AI-related strategic challenges and, thus, to AI-induced market and resource shifts in the form of an AI strategy. In this context, the rise of generative AI in general and the release of Large Language Models in particular as the current frontier of computational advancement has recently reinforced this necessity (Banh and Strobel 2023; Dell'Acqua et al. 2023; Feuerriegel et al. 2024). Recognizing this, some organizations have already moved beyond opportunistic and tactical decisions towards a more strategic direction with AI (Keding 2021). For example, MTU Aero Engines, a leading global engine manufacturer, has implemented an AI strategy as a strategic response to unfold the underlying value potential of AI and, thus, to sustainably strengthen its competitive position in the market (appliedAI Initiative GmbH 2022). For MTU Aero Engines, an AI strategy provides a coherent target picture for the strategic use of AI that specifies the necessary organizational and technical framework conditions for the exploration of AI use cases, sets the focus for the identification of AI use cases (e.g., virtual engine and test support in product development), and provides the roadmap for the scaling of AI use cases, among others.

Despite the consensus among researchers and practitioners about the strategic relevance of AI, knowledge of the emerging phenomenon of AI strategy is still in its infancy in the scientific literature (Collins et al. 2021; Enholm et al. 2022). Recent work focuses rather on the definition of a cognitive strategy (Davenport and Mahidhar 2018), the convergence of AI and corporate strategy (Kitsios and Kamariotou 2021), the integration of AI into organizational strategy (Borges et al. 2021), or the components of a data science strategy (Reddy et al. 2022). Although these valuable contributions have paved the way for investigating the emerging phenomenon of AI strategy, no study has condensed the extant knowledge in a comprehensive manner. Accordingly, there is not yet a shared understanding of what the design space of an AI strategy entails (i.e., how organizations can shape a strategic response to AI-related strategic challenges and, thus, to AI-induced market and resource shifts). This results in a twofold challenge: On the one hand, it poses issues for researchers seeking to understand how to describe the design of an AI strategy in general or to analyze the design of an AI strategy across multiple real-world instances. On the other hand, it poses issues for practitioners aiming to understand the predominant design options to consider when identifying a new AI strategy or classifying an existing one. Hence, we pose the research question:

"What is the design space of an AI strategy in the context of incumbent firms?"

To answer the research question, we developed a taxonomy and derived corresponding clusters (i.e., typical combinations of characteristics that co-occur in real-world objects) of AI strategy in line with the organizational systematics approach (Bozeman and McKelvey 1978). This approach is consistent with Gregor (2006), who characterizes both a taxonomy and corresponding clusters as a theory for analyzing (i.e., Type I), and with Gregor and Hevner (2013), who consider the classification of an emerging phenomenon such as an AI strategy as a foundation for further sense-making and design-led research. Following the methodological guidance of Kundisch et al. (2022), we iteratively applied conceptual-to-empirical (C2E) and empirical-to-conceptual (E2C) iterations to build a multi-layer taxonomy that characterizes the design space of an AI strategy along 15 dimensions and 45 characteristics. Thereby, we relied on knowledge from scientific and professional literature as well as fifteen semi-structured interviews. To ensure that the taxonomy reflects the properties of an AI strategy in practice, we further drew on empirical evidence from a sample of 51 real-world objects, which we sorted into the taxonomy to identify four clusters (i.e., Technology Navigator, Innovation Explorer, Business Enhancer, and Operations Stabilizer) via cluster analysis (Ketchen and Shook 1996). While the taxonomy unveils how organizations currently structure and organize an AI strategy, the clusters delineate predominant design options for developing a new AI strategy or evaluating an existing one.

The taxonomy and the corresponding clusters of AI strategy provide researchers and practitioners with a shared understanding of what the design space of an AI strategy entails. From a theoretical perspective, the results add descriptive knowledge to the scientific discourse at the nexus of IS and strategic management, which is lacking evidence on the design of an AI strategy. In addition, we lay a solid foundation for fellow researchers to further theorize on the design of an AI strategy in general by means of higher-level theories (i.e., explaining, predicting, and design and action). From a practical perspective, the results help organizations to establish AI projects with a distinct strategic direction. Particularly, we support managers (i.e., high- and mid-level decision makers) in designing an AI strategy in line with firm-specific goals as well as with internal and external constraints. In this way, the results contribute to a fundamental understanding of the design space of an AI strategy and enrich recent discussions among researchers and practitioners on how to advance the real-world use of AI.

The remainder of the paper is structured as follows. In Sect. 2, we provide the theoretical background on strategy fundamentals in general and AI strategy in particular. We then outline the research method in Sect. 3 to present the taxonomy of AI strategy in Sect. 4 and the corresponding clusters of AI strategy in Sect. 5. In Sect. 6, we first elaborate on the intricacies of an AI strategy before amplifying the theoretical contributions and practical implications of the work as well as future research opportunities. We finally conclude with limitations and extensions of the study of the design of an AI strategy in Sect. 7.

2 Theoretical Background

2.1 Strategy

A strategy is a key factor for the success of organizations (Pidun 2019). To understand the role of AI in the established strategy discourse, it is crucial to comprehend the fundamentals of a strategy (Keding 2021). Building on a long history, researchers take different perspectives and units of analysis in the scientific literature to elucidate a strategy (e.g., Porter 1980; Ansoff 1987; Mintzberg 1994; Chandler 1995). In the present work, we follow their understanding that a strategy gives organizations and their endeavors a distinct strategic direction through guidelines for courses of action and sets of decisions.

At the core of the established strategy discourse, organizations define a *business strategy* that is strongly interwoven with the overarching vision and mission of organizations (Bowman and Ambrosini 2007; Dhlamini 2022). This means a business strategy describes how organizations intend to compete in a market or industry to gain or maintain a competitive advantage and, thus, secure future existence (Pidun 2019). Accordingly, organizations align their managerial practices with their business strategy to ensure financial stability, carry out operations, and achieve desired goals (Bowman and Ambrosini 2007; Dhlamini 2022). In tandem, organizations craft an *IT strategy* that delineates how to utilize IT resources in an optimal manner to support overarching business objectives (Ward and Peppard 2002; Rathnam et al. 2005). As such, an IT strategy deals with key elements of IT management, such as hardware and software management, data management, risk management, and vendor management, to ensure a stable and reliable operation of the IT environment (Mithas and Rust 2016).

While research and practice have long regarded a business strategy and an IT strategy independently of each other, the digital interconnections among products, services, and processes increased the importance of business for IT and vice versa (Bharadwaj et al. 2013). To this end, the scientific literature has proposed to advance the fusion of a business strategy and an IT strategy towards a *digital strategy* (Bharadwaj et al. 2013; Woodard et al. 2013). A digital strategy refers to a strategy that is "[…] formulated and executed by leveraging digital resources to create differential value" (Bharadwaj et al. 2013, p.472). In other words, a digital strategy delineates the approach that organizations follow to gain a competitive advantage and promote growth in the digital age by leveraging digital technologies. Thereby, a digital strategy integrates market and resource perspectives to take equal account of technological breakthroughs and market demands when formulating strategic aspirations (Bharadwaj et al. 2013; Woodard et al. 2013).

To provide a common ground, Bharadwaj et al. (2013) outline four core themes that guide the design of a digital strategy: First, the *scope* of a digital strategy refers to the activities that organizations perform within their direct control and ownership. Second, the *scale* of a digital strategy describes the key factors organizations must leverage to expand digital initiatives. Third, the *speed* of a digital strategy refers to the time and sequence in which organizations release products and services. Fourth, the *source* of a digital strategy describes how organizations create and capture value from products and services. Given that AI represents a manifestation of a digital technology, we build on the four core themes of a digital strategy to analyze the design space of an AI strategy (Benbya et al. 2021; Berente et al. 2021; Ågerfalk et al. 2022).

2.2 Artificial Intelligence Strategy

Together, these strategy concepts form the foundation for the successful use of digital technologies (Bharadwaj et al. 2013; Woodard et al. 2013). However, given the transformative impact of AI on the scope, scale, speed, and source from which organizations set courses of action and sets of decisions, there is a need to reflect on the present understanding of how to design a strategy in the age of AI (Buxmann et al. 2021). To assess the transformative impact of AI at a strategic level and, thus, the need for an AI strategy, we follow the chain of argumentation (see Fig. 1) that environmental and organizational conditions have an impact on the evolution of strategy (Rajagopalan and Spreitzer 1997; Ward and Peppard 2002). Hence, we argue that (1) the facets of contemporary AI lead to (2) AI-induced market and resource shifts, which, in turn, result in (3) AI-related strategic challenges. These AI-related strategic challenges require a strategic response from organizations in the form of (4) an AI strategy.

(1) Facets of contemporary AI: AI refers to a long-established research field in computer science devoted to making machines intelligent (Russell and Norvig 2021). To highlight how contemporary AI differs from previous generations of IT, Berente et al. (2021) point to three facets: *autonomy* (i.e., acting without human intervention), *learning* (i.e., improving through data and experience), and *inscrutability* (i.e., being unintelligible to specific audiences).

(2) AI-induced market and resource shifts: The facets of contemporary AI lead to shifts in both how organizations must operate in markets (i.e., *AI-induced market shifts*) and how organizations can access and leverage resources (i.e., *AI-induced resource shifts*). The following AI-induced market and resource shifts are evident in the scientific literature (for details, please refer to *"Appendix C"* – available online via http://link.springer.com).

Market shift 1: From narrow to pervasive AI applications: This shift is driven by the facet of learning, i.e., AI applications can autonomously analyze large volumes of data and perform complex tasks, allowing organizations to address a broader spectrum of tasks across multiple domains and implement ever-more pervasive AI applications (Berente et al. 2021; Faraj and Leonardi 2022; Reddy et al. 2022). Hence, the learning facet leads to a shift from domain-specific applications that require extensive domain-specific data and are confined within isolated tasks to more pervasive applications across industry boundaries and to more generalized AI applications that are able to perform a variety of tasks (Berente et al. 2021; Faraj and Leonardi 2022; Guo et al. 2023). This shift substantially impacts organizations, as it enables them to leverage AI applications across all aspects of their operations, both through the widespread adoption of specialized AI applications and through the increasing capability of AI to handle different types of tasks, leading to innovation and competitive advantage (Berente et al. 2021; Li et al. 2021; Papagiannidis et al. 2023). For example, in the field of natural language processing, the use of specialized AI applications, such as sentiment analysis for customer reviews, shifted from isolated implementations to more expansive and diverse fields of application, while AI

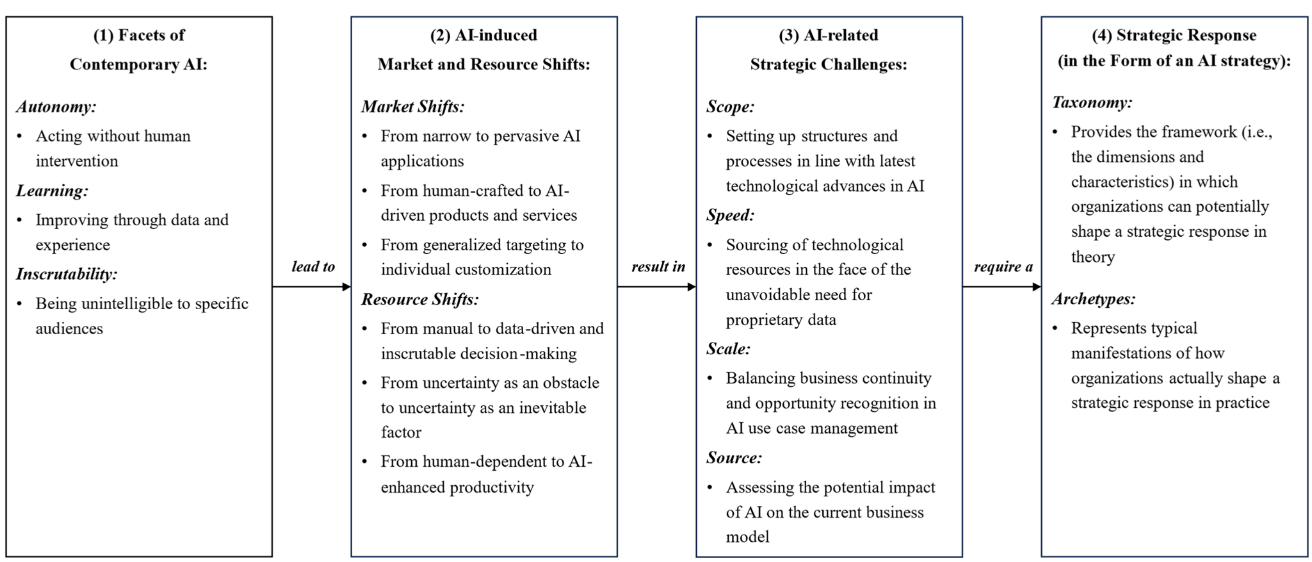

Fig. 1 Chain of argumentation for the need for an artificial intelligence strategy

applications themselves also shifted from narrowly focused functionalities towards broader, more versatile capabilities (Dong et al. 2023; Khurana et al. 2023).

Market shift 2: From human-crafted to AI-driven products and services: This shift is driven by the facets of autonomy and learning, i.e., AI applications can continuously learn from new information and integrate insights from the environment, allowing organizations to offer products and services that are more responsive to customer needs and market trends (Borges et al. 2021; Burström et al. 2021; Shollo et al. 2022). Hence, the autonomy and learning facets lead to a shift from relying mainly on human expertise and labor-intensive efforts for product and service optimization to autonomously predicting customer needs and market trends for the development of new product and service offerings based on data-driven insights (Burström et al. 2021; Lins et al. 2021; Shollo et al. 2022). This shift substantially impacts organizations, as it enables them to be continuously innovative in product and service development, giving them a competitive advantage by meeting customer needs and market trends even better (Borges et al. 2021; Burström et al. 2021; Krakowski et al. 2023; Papagiannidis et al. 2023). For example, in financial services, the creation and delivery of investment products and services shifted from human advisors relying on personal expertise to autonomous robo-advisors that analyze market data, predict market trends, and provide real-time investment advice (Hong et al. 2023; Zhu et al. 2024).

Market shift 3: From generalized targeting to individual customization: This shift is driven by the facets of autonomy and learning, i.e., AI applications can autonomously analyze large volumes of data and adapt to new customer information without human intervention, allowing organizations to understand individual customer preferences and predict individual customer behavior with a high degree of accuracy (Borges et al. 2021; Burström et al. 2021; Weber et al. 2022). Hence, the autonomy and learning facets lead to a shift from product offering strategies targeting broad customer segments to personalized experiences by addressing the specific needs and expectations of individual customers (Helfat et al. 2023; Kshetri et al. 2024). This shift substantially impacts organizations, as it enables them to deliver personalized offerings on an individual level, thus enhancing customer satisfaction and loyalty (Borges et al. 2021; Burström et al. 2021; Rowland et al. 2022). For example, Amazon or Netflix shifted from providing generalized recommendations based on broad customer categories to offering personalized suggestions tailored to individual customer preferences and behaviors (Perez-Vega et al. 2021; Kumar et al. 2024).

Resource shift 1: From manual to data-driven and inscrutable decision-making: This shift is driven by the facet of inscrutability, i.e., AI applications contain increasingly complex and sophisticated algorithms that allow more accurate decisions than those by humans, making it difficult for organizations to fully understand or trace decision-making processes (Baier et al. 2019; Coombs et al. 2020; Dietz et al. 2021; Jöhnk et al. 2021; Shollo et al. 2022). Hence, the inscrutability facet leads to a shift from comprehensible decision-making processes based on human expertise and transparent analytical methods to increasingly opaque decision-making processes driven by algorithms (Berente et al. 2021; Dietz et al. 2021; Shollo et al. 2022; van Giffen and Ludwig 2023). This shift substantially impacts organizations, as it enables them to enhance their competitiveness through more accurate decision-making with the aid of AI applications (Coombs et al. 2020; Li et al. 2021) but also requires them to address challenges in the decision-making processes related to transparency, accountability, and trust (Baier et al. 2019; Dietz et al. 2021). For example, AI applications shifted medical diagnosis from relying on the expertise of healthcare professionals and transparent diagnostic criteria to utilizing complex data analyses that can surpass human accuracy but present challenges of interpretability and validation for medical professionals (Markus et al. 2021; Alowais et al. 2023).

Resource shift 2: From uncertainty as an obstacle to uncertainty as an inevitable factor: This shift is driven by the facets of autonomy and inscrutability, i.e., AI applications contain algorithms that get more autonomous but harder to comprehend, forcing organizations to accept increasing uncertainties as an inevitable factor to navigate complex and dynamic environments (Dietz et al. 2021; Rowland et al. 2022; Vial et al. 2022). Hence, the autonomy and inscrutability facets lead to a shift from prioritizing predictability and control through established processes to embracing uncertainty as a crucial element by accepting the unpredictability of AI applications to experiment with novel approaches (Dietz et al. 2021; Vial et al. 2022). This shift substantially impacts organizations, as it enables them to become more agile and adaptable, fostering innovation and resilience in the face of unpredictable challenges and rapidly changing environments (Stecher et al. 2020; Dietz et al. 2021; Vial et al. 2022). For example, organizations shifted from avoiding risky AI projects due to potential failure and resource wastage to embracing uncertainty as a catalyst for innovation, using AI applications to tackle complex problems, such as protein folding, with the potential for unprecedented scientific breakthroughs (Vial et al. 2022; Sedkaoui and Benaichouba 2024).

Resource shift 3: From human-dependent to AI-enhanced productivity: This shift is driven by the facets of autonomy and learning, i.e., AI applications can autonomously analyze large volumes of data and continuously learn from new information, allowing organizations to increase their productivity to an unprecedented level (Coombs et al. 2020; Li et al. 2021; Reddy et al. 2022). Hence, the autonomy and learning facets lead to a shift from relying on human expertise to drive innovations that are constrained by cognitive limitations and information processing capacity to leveraging AI applications that can process information, uncover insights, and optimize processes beyond human capabilities (Coombs et al. 2020; Krakowski et al. 2023). This shift substantially impacts organizations, as it enables them to open up new frontiers of efficiency and effectiveness, reduce costs, and relieve workforce burden (Shollo et al. 2022; Guo et al. 2023; Helfat et al. 2023). For example, logistics shifted from relying on human-operated machines to utilizing AI-based robots for tasks such as material handling or quality control, significantly enhancing precision and scalability (Javaid et al. 2022; Albrecht et al. 2024).

(3) AI-related strategic challenges: The AI-induced market and resource shifts result in AI-related strategic challenges, which are reflected in the four core themes of a digital strategy (Bharadwaj et al. 2013).

Scope: The shift towards pervasive AI applications, for example, confronts organizations with the strategic challenge of how to set up structures and processes that allow for continuous implementation and governance of the ever-advancing landscape of AI applications (Jöhnk et al. 2021; Krakowski et al. 2023; Papagiannidis et al. 2023).

Scale: The shift towards data-driven and inscrutable decision-making, for example, presents organizations with the strategic challenge of how to source relevant technological resources for the development and operation of AI applications, because any form of sourcing is dependent on data considerations (e.g., ensuring that commercial solutions allow for a seamless training with proprietary data) (Oberländer et al. 2021; Sjödin et al. 2021; Weber et al. 2023).

S*peed*: The shift towards uncertainty as an inevitable factor, for example, confronts organizations with the strategic challenge of how to balance business continuity and opportunity recognition when identifying and scaling AI use cases (Dietz et al. 2021; Vial et al. 2022).

Source: The shift towards AI-driven products and services, for example, presents organizations with the strategic challenge of how to assess the potential impact of AI on the current business model, both in terms of value creation and value destruction (Burström et al. 2021; Sjödin et al. 2021).

(4) Strategic response in the form of an AI strategy: The AI-related strategic challenges ultimately require a strategic response from organizations in the form of an AI strategy (Keding 2021). However, considering firm-specific goals as well as internal and external constraints, the design of an AI strategy differs across organizations (Hess et al. 2016; Becker and Schmid 2020). To better understand the bandwidth in which organizations can potentially shape a strategic response in theory, we develop a taxonomy. Building on the taxonomy, we further derive clusters that represent typical combinations of characteristics that co-occur in real-world objects to describe how organizations actually shape a strategic response in practice. Thus, the taxonomy and the corresponding clusters altogether form the strategic response of organizations to AI-related strategic challenges, which we refer to as the design space of an AI strategy.

2.3 Related Work

With unprecedented opportunities to design intelligent products, to devise novel services, and to invent disruptive business models, interest in the strategic use of AI has moved to the center of corporate agendas (Li et al. 2021). While the scientific literature points out that a strategy is key to responding to technological breakthroughs at a strategic level (Bharadwaj et al. 2013; Woodard et al. 2013), organizations need to revitalize the present understanding of how to design a strategy in the context of AI (Buxmann et al. 2021). While recent work has already invested much effort in the study of the strategic actions organizations can take in response to the emergence of digital technologies in general (Volberda et al. 2021; Faraj and Leonardi 2022), comparatively little is known about how to design an AI strategy. To date, the scientific literature offers only selective insights into the emerging phenomenon of AI strategy by synthesizing knowledge at the intersection of IS and strategic management. In this context, Borges et al. (2021) investigate the integration of AI into organizational strategy, whereas Kitsios and Kamariotou (2021) analyze the convergence of AI and corporate strategy. Despite both contributions emphasizing the need to formulate strategic plans for the successful insertion of AI, they neither specify the term AI strategy nor discuss its design. In this context, Keding (2021) is the first to explicitly point out the relevance of an AI strategy as an antecedent for the use of AI in strategic management but also does not elaborate on its design. Further, there are several studies that place an AI strategy at the center of their work but take a very specific perspective on the emerging phenomenon. For example, Zechiel et al. (2024) conceptualize a framework to grasp the intertwining of AI and sustainability from a strategy perspective, while

Chowdhury et al. (2024) develop a strategy framework for integrating generative AI into human resource management practices, and Vomberg et al. (2023) investigate the emerging phenomenon of AI strategy from the perspective of data network effects. Although these contributions offer valuable insights, they take a very nuanced perspective on the design of an AI strategy and do not further elaborate on its design. Nevertheless, there are a few studies that already provide a first outline of the design of an AI strategy. For example, Davenport and Mahidhar (2018) argue that organizations need to develop a strategy for cognitive technologies along the key levers of content, technology components, people, change management, and ambitions. Similarly, Reddy et al. (2022) motivate the need for a robust and well-crafted data science strategy and synthesize relevant components under the four core themes of content, context, intent, and outcome. While both contributions provide building blocks for the design of an AI strategy, they do not further explicate how organizations can shape it in line with firm-specific goals as well as with internal and external constraints.

In addition, there are studies on the strategic use of AI in organizations with reference points on the design of an AI strategy. In this context, the scientific literature points to the need to develop or acquire specific capabilities for AI implementation (Mikalef and Gupta 2021; Sjödin et al. 2021; Weber et al. 2023), lists antecedents for the conceptualization and operationalization of AI in organizations (Pumplun et al. 2019; Jöhnk et al. 2021; Laut et al. 2021; Duda et al. 2024; Stohr et al. 2024), identifies success factors required to facilitate AI implementation (Hamm and Klesel 2021; Merhi 2023), or focus on how organizations can proceed to diffuse AI in organizations and, thus, to unfold the underlying value potential of AI (Shollo et al. 2022; Grebe et al. 2023; Hansen et al. 2024; Keramidis and Shollo 2024). Although these contributions provide valuable insights into the elements of an AI strategy, they equally lack evidence on how organizations can proceed to formulate a strategic response to AI-related strategic challenges and, thus, to AI-induced market and resource shifts.

Further, research has already developed taxonomies and derived clusters with reference points to the study of the emerging phenomenon of AI strategy in the past. In seminal studies, Miles et al. (1978) and Morrison and Roth (1992) provide patterns of strategic behavior of organizations with a focus on business strategy, while Miller and Roth (1994) in manufacturing, Autry et al. (2008) in logistics, and Craighead and Laforge (2003) in IT, among others, conversely study functional strategies. Recently, Fischer et al. (2020) presented three strategy clusters as blueprints for digital transformation efforts, while Volberda et al. (2021) outline four types of digital transformation journeys. Finally, D'Ippolito et al. (2019) present four clusters that describe how incumbent firms can adapt their business models in response to digital innovation. In the context of AI, the scientific literature provides insights into the characteristics of platforms that offer discrete AI services to organizations (Geske et al. 2021) or the characteristics that are relevant for the strategic assessment of the business value contribution of AI use cases for organizations (Engel et al. 2022). With a focus on business models, recent work developed taxonomies and derived clusters to investigate how the business models of AI start-ups differ from IT-related business models (Weber et al. 2022), how the rise of AI impacts the business models of incumbent firms (Weber et al. 2024), or what constitutes business models that use machine learning at their core (Vetter et al. 2022). Finally, taking the human factor into account, Fabri et al. (2023) study the entangled interworking between human agents and AI-enabled systems. Taken together, these taxonomies and clusters provide valuable reference points for the study of the design of an AI strategy, as they integrate aspects regarding the scope, scale, speed, and source from which organizations make strategic deliberations. However, as isolated bodies of knowledge, these contributions lack a comprehensive perspective on the design space of an AI strategy.

In sum, despite the consensus among researchers and practitioners about the strategic relevance of AI, the study of the design of an AI strategy has received sparse treatment so far (Collins et al. 2021; Enholm et al. 2022). While there is a growing body of knowledge on AI in general, comparatively little is known about strategic tools surrounding AI, including taxonomies and corresponding clusters. As a result, organizations focus on different application areas and follow disparate paths to unfold the underlying value potential of AI (Faraj and Leonardi 2022; van Giffen and Ludwig 2023; Sagodi et al. 2024). In light of the facets of contemporary AI that lead to AI-induced market and resource shifts and, thus, to AI-related strategic challenges, organizations require a strategic response in the form of an AI strategy. However, to date, a shared understanding of what the design space of an AI strategy entails remains unexplored. Hence, we set out to develop a taxonomy and derive corresponding clusters of AI strategy.

3 Research Method

To answer the research question, we developed a taxonomy and derived corresponding clusters of AI strategy in line with the organizational systematics approach (Bozeman and McKelvey 1978). A taxonomy refers to a modular scheme for structuring and organizing a set of knowledge (Glass and Vessey 1995). Embedded in design science research, taxonomy research combines qualitative and quantitative research approaches and represents an artifact in the form of a model (Nickerson et al. 2013; Kundisch et al. 2022). Thereby, a taxonomy integrates conceptual and empirical approaches into one comprehensive perspective, thus fostering the iterative usage of both paradigms to explore nascent topics with little knowledge along dimensions and characteristics. Taxonomy research has already been successfully applied in various contexts to investigate transformative concepts in the field of AI. To study the design of an AI strategy, we consider taxonomy research appropriate for two reasons: First, recent work suggests that IS research benefits from structuring and organizing emerging phenomena, such as AI, in a taxonomy to provide a basis for convergent understanding (Nickerson et al. 2013; Kundisch et al. 2022). Second, seminal work in strategic management regards a taxonomy as a useful lens for studying strategy concepts, as it affords the integration of multiple dimensions and characteristics in a common construct (Hambrick 1984).

3.1 Taxonomy Development

For taxonomy development, we followed the methodological guidance of Kundisch et al. (2022), who build on Nickerson et al. (2013), and provide further details on rigorous taxonomy building and evaluation (for details, please refer to *"Online Appendix A"*). Overall, we proceeded as follows.

Identify problem and motivate: In step (1), we specified the observed phenomenon as the emergence of AI strategy both in research and in practice. Thereby, we focused on incumbent firms that have sufficient structures, resources, and networks to advance the real-world use of AI (McMullen and Shepherd 2006). In step (2), we fleshed out the target user group as researchers from IS and strategic management along with high- and mid-level decision makers in charge of strategic deliberations on AI in incumbent firms (i.e., the definition of an AI strategy). We chose researchers as target users because we felt a strong obligation to encourage a more nuanced discussion on the intricacies of an AI strategy in the scientific literature. Most likely, however, it will be incumbent firms and their respective managers who will use the taxonomy to build or refine an AI strategy, which is why we include them in the compass of this study. In step (3), we specified the intended purpose as a shared understanding of what the design space of an AI strategy entails. Accordingly, for researchers, the taxonomy should allow to describe the design of an AI strategy in general or to analyze the design of an AI strategy across multiple real-world instances, while for practitioners, the taxonomy should allow to identify a new AI strategy or to classify an existing one.

Define objectives of a solution: In step (4), we defined the meta-characteristic of the taxonomy in line with the research question as the design space of an AI strategy in the context of incumbent firms. In step (5), we choose a set of objective and subjective ending conditions according to Nickerson et al. (2013), which we checked after each iteration to claim the formal correctness of the taxonomy development process. Regarding objective ending conditions, we specified that (a) each dimension is unique within the taxonomy, (b) each characteristic is unique within its dimension, (c) at least one object is classified per dimension and characteristic, (d) and an iteration does not imply further modification of the taxonomy. For subjective ending conditions, we decided to stop the taxonomy development process when all authors agree that the results are (a) comprehensive, (b) concise, (c) extendible, (d) explanatory, and (e) robust.

Design and development: For steps (6) to (10), we iteratively performed either a C2E or an E2C approach (Nickerson et al. 2013). In a C2E approach, researchers determine dimensions and characteristics based on extant literature or the knowledge and experience of the authors. Conversely, in an E2C approach, researchers analyze a sample of real-world objects to infer characteristics and dimensions. In this way, we obtained an initial or revised taxonomy of AI strategy after each round. We continuously consolidated the proposed changes within the author team to ensure a shared understanding and iteratively improve the applicability and usefulness of the taxonomy in line with the defined meta-characteristic. We continued the taxonomy development process until all authors agreed that the taxonomy met the objective and subjective ending conditions in line with steps (11) to (14). To assess the real-world fit of the taxonomy throughout the taxonomy development process, we further compiled a random set of eight real-world objects of AI strategy in advance (for details, please refer to *"Online Appendix F"*). The set consisted of two AI strategies extracted from scientific literature and six additional ones from professional literature, which we selected based on three criteria: (1) in-depth description of one or more building blocks of an AI strategy, (2) timeliness of available information, and (3) coverage of diverse organizational contexts (i.e., business model, industry affiliation). We classified the eight real-world objects of AI strategy into the taxonomy in each iteration (Nickerson et al. 2013). Overall, we conducted five iterations (see Table 1**)**. In the following, we provide an overview of the iterations (for details, please refer to *"Online Appendix B"*).

Table 1 Overview of iterations

#	Approach	Activity	Basis	Structure
1	C2E	Review of scientific literature	31 articles	13 dimensions and 34 characteristics
2	C2E	Interviews with AI strategy experts	10 participants	17 dimensions and 47 characteristics
3	C2E	Review of professional literature	19 articles	17 dimensions and 51 characteristics
4	E2C	Analysis of one-third of real-world objects	17 organizations	15 dimensions and 45 characteristics
5	E2C	Analysis of two-thirds of real-world objects	34 organizations	15 dimensions and 45 characteristics

In the *first iteration*, we adopted a *C2E approach* to identify dimensions and characteristics of an AI strategy from a structured literature review (Webster and Watson 2002). As both AI and strategy are abstract and elusive terms with broad interpretations, we deliberately started to extract knowledge of the design of an AI strategy from the scientific literature. Therefore, we selected the established databases AISeL, ScienceDirect, and Web of Science to search for relevant literature and only considered results published from 2010 onwards to ensure timeliness and focus on the recent scientific discourse. We deliberately limited the search for scientific literature to the research fields of IS and strategic management and only considered articles from high-ranked journals and conference proceedings. We then used an iterative process to derive a single search term, which we then applied to titles, abstracts, and keywords as follows: *(Artificial Intelligence OR Machine Learning) AND (Strategy OR Strategic)*.

The initial search yielded 252 articles. After removing 13 duplicate entries, 239 articles remained for further analysis. To determine the thematic fit of each article with the meta-characteristic, we defined inclusion and exclusion criteria. Thus, we only considered articles that describe one or more design elements of an AI strategy or the antecedents for successful AI implementation. At the same time, we neglected articles that focus on the consequences of AI in strategic management, as well as duplicates, editorials, and non-peer-reviewed articles. To rank the articles according to their relevance, we then used a three-point Likert scale and assigned a score to each article. If the title was irrelevant to the meta-characteristic, we discarded the article outright (rank 0; n = 164 articles). However, if the title was subjectively relevant, we proceeded with abstract and keyword screening. We then determined whether the article was only slightly related to the overall context of the paper (rank 1; n = 49 articles) or whether the article appeared in a context that was closely associated with the meta-characteristic and relevant for an in-depth investigation (rank 2; n = 26 articles). Applying a manual forward and backward search, we added five articles. Ultimately, the final literature sample comprised 31 articles relevant for further analysis (for details, please refer to *"Online Appendix C"*).

Afterward, we proceeded with a full-text screening of the literature sample to extract relevant information on the design elements of an AI strategy in a table. Thereby, we followed the well-established three-step coding approach of open, axial, and selective coding (Wolfswinkel et al. 2013). During open coding, we closely read each article to highlight all statements related to the characteristics of an AI strategy (n = 376 codes). Continuing with axial coding, we then grouped the characteristics of an AI strategy into overarching dimensions. Finally, for selective coding, we assigned the dimensions of an AI strategy to the four core themes that guide the definition of a digital strategy (i.e., scope, scale, speed, source).

In the *second iteration*, we applied a *C2E approach* to expand the results from the structured literature review with empirical evidence from semi-structured interviews (Myers and Newman 2007). To capture a rich database, we followed purposive sampling and recruited subject matter experts from our professional networks, where they hold key positions with touchpoints to the definition or execution of an AI strategy (Etikan 2016). Hence, the interview partners reported exclusively on real-world instances of an AI strategy. We also sought to interview partners from various industries and sizes to minimize potential biases. In sum, we spoke to ten experts (i.e., E.1 – E.10) (for details, please refer to *"Online Appendix D"*) with an interview duration between 42 and 66 min. The core structure of the interviews had four areas: (1) an introduction to the research project and the theoretical underpinnings, (2) a brainstorming on the building blocks that guide the design space of an AI strategy, (3) a discussion on the design space of an AI strategy linked with firm-specific insights, and (4) a conclusion including lessons learned for further elaboration. We recorded all interviews and transcribed them for further analysis (n = 142 codes), again following the good practices (i.e., open, axial, and selective coding) of Wolfswinkel et al. (2013).

In the *third iteration*, we returned to the literature to ground the observations from the semi-structured interviews with references, using a *C2E approach*. Specifically, we searched in gray literature that reflects the latest technological advances in the field of AI. Hence, we triangulated the results with professional literature following the key principles of Flick et al. (2004). For this purpose, we selected three overarching areas to search for gray literature: (1) leading consulting firms, as they often have various insights on different topics in multiple organizations, (2) leading technology organizations, as they are often the first to shape new topics, (3) and well-known management magazines (e.g., Harvard Business Review, MIT Sloan Management Review), as they report on new topics at the intersection of research and practice. We conducted an internet search on the keyword "AI strategy" and found 19 articles (n = 62 codes) that dealt with the design of an AI strategy (for details, please refer to *"Online Appendix E"*). Subsequently, we coded them again in line with the good practices (i.e., open, axial, and selective coding) of Wolfswinkel et al. (2013).

In the *fourth iteration*, we applied an *E2C approach* to analyze how the design of an AI strategy manifests in real-world objects. To ensure a consistent and transparent identification and selection of real-world objects, we defined the following criteria: First, we only considered organizations with substantial experience in an industry or market in line with the meta-characteristic. Second, we focused on organizations from the U.S. as the world's largest economy and Germany as the European largest economy, as we assumed that respective players have sufficient resources to advance the real-world use of AI. Third, we incorporated multinational organizations that dominate the Asian market (i.e., China as the world's second-largest economy and Japan as the world's third-largest economy) to account for global coverage. To represent the leading organizations in the economies mentioned, we selected the Dow Jones Index (n = 30) for the U.S. and the DAX40 Index (n = 40) for Germany. Further, we analyzed the Shanghai Stock Exchange for China and the Tokyo Stock Exchange for Japan. Next, to determine whether organizations in the individual indices provide sufficient publicly available information about the design of their AI strategy, we built on content from websites (e.g., company websites, industry forums) and industry reports (e.g., annual reports, press releases). We then used a three-point Likert scale to rank the quantity and quality of publicly available information (i.e., 0 = not appropriate as the company does not provide enough publicly available information; 1 = conditionally appropriate as the company offers publicly available but subjectively insufficient information; 2 = appropriate as the company provides comprehensive publicly available information). In sum, we compiled a sample of 51 real-world objects (for details, please refer to *"Online Appendix F"*) eligible for taxonomy building and evaluation. At that point, we randomly selected one-third of the real-world objects (n = 17) for this iteration and kept the remaining two-thirds of the real-world objects (n = 34) for further iterations. Then, we started sorting the real-world objects into the taxonomy, with the following two objectives: First, to review the taxonomy for additional or dispensable dimensions and characteristics. Second, to extract similarities and differences in the design of an AI strategy. For the in-depth analysis of the real-world objects, we set up an Excel spreadsheet. Again, building on publicly available information, we recorded at least one quote (with source) for each dimension to determine a distinct characteristic. Subsequently, two co-authors independently performed the classification. In the case of extreme and ambiguous statements, a third co-author was consulted. In this way, we were able to ensure a definitive assignment of all real-world objects to the taxonomy.

In the *fifth iteration*, we applied another *E2C approach* to classify the remaining two-thirds of the real-world objects (n = 34) into the taxonomy. This time, building on the firmly established definitions of dimensions and characteristics, we could assign at least one real-world object from the sample to each characteristic. Simultaneously, it was no longer necessary to add, revise, or remove individual elements of the taxonomy. After a review of the results within the author team, we agreed that all objective and subjective ending conditions were met and that no further revisions to the taxonomy were necessary. Hence, we terminated the taxonomy development process.

Evaluation: After we met all objective and subjective ending conditions, we performed an external evaluation in steps (15) and (16) to ensure the applicability and usefulness of the taxonomy (Kundisch et al. 2022). To determine whether the taxonomy accounts for the intended purposes of the individual target user groups, we decided to conduct two evaluation rounds. First, we performed a focus group discussion with eight fellow researchers who have sufficient knowledge regarding the trajectory of AI due to their experience in IS and/or strategic management research. Second, we conducted semi-structured interviews with five subject matter experts (i.e., E.11 – E.15) who have extensive knowledge either due to their internal leadership role in the definition or execution of an AI strategy or due to their involvement in external consulting projects (for details, please refer to *"Online Appendix D"*). The external evaluation consisted of a brief introduction to the topic at hand alongside a discussion of the problems and needs of the participants regarding the design of an AI strategy. We then presented the taxonomy to the participants not only to substantiate the dimensions and characteristics but also to evaluate whether the taxonomy serves the intended purposes of researchers and practitioners. Specifically, we asked researchers to assess whether the taxonomy is applicable and useful for describing the design space of an AI strategy in general (i.e., to ensure the completeness of the taxonomy) and for analyzing the design space of an AI strategy across multiple real-world instances (i.e., to ensure the comprehensibility of the taxonomy). Likewise, we asked practitioners to assess whether the taxonomy is applicable and useful for identifying a new AI strategy (i.e., to ensure the robustness of the taxonomy) and for classifying an existing AI strategy (i.e., to ensure the real-world fidelity of the taxonomy). We encouraged the participants to carry out the evaluation not only based on previous knowledge of the design of an AI strategy but also to actively use the taxonomy to determine whether it is useful and applicable. Overall, the participants confirmed that the taxonomy covers all dimensions and characteristics that are relevant to the design of an AI strategy. The external evaluation further demonstrated that the taxonomy accounts for the intended purposes of researchers (i.e., analyzing or describing the design space of an AI strategy) and practitioners (i.e., identifying or classifying an AI strategy) in line with relevant evaluation criteria (i.e., completeness, comprehensibility, robustness, real-world fidelity) (Kundisch et al. 2022). Ultimately, the participants provided us with further intriguing insights into the design of an AI strategy, which we incorporated into the description of the taxonomy.

Communication: As the taxonomy met all evaluation criteria in step (17), we reported the final version with descriptions for dimensions and characteristics in step (18). We also documented the taxonomy evolution, including the approach and changes for each iteration (for details, please refer to *"Online Appendix B"*).

3.2 Cluster Analysis

Building on the taxonomy, we performed a cluster analysis to derive clusters of AI strategy (Ketchen and Shook 1996). A cluster analysis is a statistical technique that aims to group objects with similar characteristics into clusters, ensuring a high degree of homogeneity within each cluster and a high degree of heterogeneity between all clusters (Hair et al. 2010). Thus, a cluster analysis aims to derive an abstraction of a particular phenomenon. In the present case, the approach serves to better understand typical combinations of characteristics of an AI strategy that co-occur in real-world objects in the form of distinct clusters. To conduct the cluster analysis, we built on the sample of 51 real-world objects and followed the four steps of Sarstedt and Mooi (2016).

In the *first* step, we selected the variables for the cluster analysis. Therefore, we transformed the dimensions and characteristics from the taxonomy into dichotomous dummy variables (i.e., 0 or 1). In the *second* step, we choose the clustering approach. Since we could not determine the optimal number of clusters in advance, we decided to use hierarchical clustering (Ferreira and Hitchcock 2009). We then followed the method of Ward (1963) because this approach allows a stable analysis even for a smaller number of objects. This algorithm is a conventional approach when no information about the optimal size of clusters is available. We further used the Euclidean distance as the distance measure, a proven measure in combination with the method of Ward (1963). In the *third* step, we determined the optimal number of clusters based on the dendrogram and the elbow criterion (for details, please refer to *"Online Appendix G"*). As both measures suggested an optimal number of clusters between three and five, we engaged in joint discussions within the author team to review all cluster solutions for their logical composition and meaningful interpretation. Ultimately, this resulted in an optimal number of four clusters.

In the *fourth* step, we validated the clusters to ensure their applicability and usefulness (Ketchen and Shook 1996). To do so, we calculated the absolute and relative frequencies of the characteristics in the clusters to better interpret and understand the specifics of the predominant design options of an AI strategy. Afterward, we applied the Q-sort method as a statistical tool to test the reliability and validity of the clustering (Nahm et al. 2002). We measured the reliability via Cohen's Kappa (Cohen 1960) and the validity via hit ratios (Moore and Benbasat 1991). For this purpose, we followed Carter et al. (2007), who recommend that two or more judges (P-set) with a clear understanding of the research topic classify a set of items (Q-set) according to predefined criteria and proceeded as follows. First, two co-authors who were not yet familiar with the clustering results intuitively and independently assigned the real-world objects from the sample to the clusters based on their qualitative assessment of the dominant dimensions and characteristics. When calculating the match with the results of the method of Ward (1963), we concluded that out of 51 real-world objects, we had 43 matches and eight mismatches, resulting in a hit ratio of 84.3% and a Cohen's Kappa of 81.2%. Second, we provided eight researchers divided into two groups with four clusters and a random sample of seventeen real-world objects (one-third of the sample), including a short description for both. We then asked them to assign them to each other based on joint discussions. Again, calculating the match, the researchers classified fourteen out of seventeen real-world objects to the right clusters, resulting in a hit ratio of 82.3% and a Cohen's Kappa of 83.6%. Building on the results of both evaluation rounds, we reached an almost perfect agreement, reflecting good validity and reliability of the clusters

Table 2 Taxonomy of artificial intelligence strategy

Layer	Dimension	Characteristics				Dominant AI-induced market or resource shift
Scope	Strategic ownership	Central staff unit	Separate department	Integrated team	Cross-functional unit	From narrow to pervasive AI applications
	Organizational anchoring	Corporate	Divisional	Functional	Proprietary	From narrow to pervasive AI applications
	Life cycle management	Centralized	Decentralized	Federal		From narrow to pervasive AI applications
	Governance level	Enterprise-wide	Portfolio-based	Application-specific		From narrow to pervasive AI applications
	Control mechanisms	Guiding	Restricting	No additional		From manual to data-driven and inscrutable decision-making
	Data governance framework	Isolated	Hybrid	Integrated		From manual to data-driven and inscrutable decision-making
Scale	Knowledge acquisition	Training	Hiring	Contracting		From uncertainty as an obstacle to uncertainty as an inevitable factor
	Technology sourcing	Make	Hybrid	Buy		From manual to data-driven and inscrutable decision-making
Speed	Use case identification	Systematical	Experimental			From uncertainty as an obstacle to uncertainty as an inevitable factor
	Use case expansion	One-to-many	Many-to-one			From uncertainty as an obstacle to uncertainty as an inevitable factor
Source	Technology aspiration	Established	Cutting-edge	Bleeding-edge		From human-crafted to AI-driven products and services
	Business model impact	Complementing	Extending	Renewing		From human-crafted to AI-driven products and services
	Risk tolerance	High risk	Limited risk	Minimal risk		From manual to data-driven and inscrutable decision-making
	Value creation	Frontstage	Backstage	Front- & backstage		From generalized targeting to individual customization
	Value recipient effect	Replacing	Reinforcing	Revealing		From human-dependent to AI-enhanced productivity

(Landis and Koch 1977). Hence, we conclude that the clusters are meaningful as we can notice external heterogeneities between the clusters and internal homogeneities within the clusters.

4 Taxonomy of Artificial Intelligence Strategy

In the following, we present the taxonomy of AI strategy (see Table 2). The taxonomy consists of 15 dimensions and 45 characteristics, which we defined in line with the meta-characteristic (i.e., the design space of an AI strategy in the context of incumbent firms). Building on Bharadwaj et al. (2013), we applied the four core themes that guide the definition of a digital strategy to the context of an AI strategy to structure the taxonomy into four overarching layers: scope, scale, speed, and source. Further, to justify the presence of a dimension in the taxonomy, we outline the dominant AI-induced market or resource shift for each dimension. For an in-depth comparison of IT-related strategic challenges with AI-related strategic challenges for each dimension, please refer to *"Online Appendix H"*.

4.1 Layer 1: Scope

The layer *scope* refers to the activities that organizations perform within their direct control and ownership to establish a digital technology in line with firm-specific goals as well as with internal and external constraints (Bharadwaj et al. 2013). As decisions about the scope play a central role in the context of an AI strategy, we focus here on the relevant aspects regarding the anchoring of responsibility and accountability for the strategic use of AI. This layer comprises six dimensions:

Strategic ownership refers to the entity that is in charge of the definition and execution of an AI strategy within an organization (Jöhnk et al. 2021; Li et al. 2021; Volberda et al. 2021). The challenge here is to determine an entity that keeps track of the ever-evolving technological advances in AI to adapt the strategic direction of an organization in an agile and dynamic manner when necessary (Berente et al. 2021; Faraj and Leonardi 2022). As a strategic response, Volkswagen, for example, installed an AI lab as a globally networked competence center (i.e., a cross-functional unit) that is responsible to sense the latest technological advances in AI and seize them within the entire organization (https://www.volkswagen-group.com/en/press-releases/volkswagen-group-establishes-artificial-intelligence-company-18105). In general, a *central staff unit* means that a special team reporting directly to the top management (i.e., CEO, CIO, CDO) is responsible for establishing an AI strategy with a respective vision, mission, and core values. Similarly, a *cross-functional unit* refers to a center of excellence that guides as a nucleus for all strategic endeavors with AI. In their role, both a central staff unit and a cross-functional unit set courses of action and sets of decisions regarding the strategic use of AI for an entire organization while equally supporting individual departments and teams to derive objectives and key results in line with an AI strategy. Further, a *separate department* means that an organization hands over the relevant activities related to an AI strategy to an existing department or founds a new one that operates independently. Lastly, an *integrated team* refers to employees in an existing department (e.g., business department, IT department) who take partial or entire responsibility for all strategic endeavors with AI.

Organizational anchoring describes the sphere of coverage of an AI strategy in line with the structures and processes of an organization (Borges et al. 2021; Kitsios and Kamariotou 2021; Mikalef and Gupta 2021). The challenge here is to determine a flexible and equally inclusive sphere of coverage for an AI strategy amidst the ever-evolving landscape of pervasive AI applications (Berente et al. 2021; Jöhnk et al. 2021). As a strategic response, MTU Aero Engines, for example, aggregates all efforts and activities related to the strategic use of AI on a corporate level to manage AI projects in a harmonized and integrated manner across the entire organization (https://www.appliedai.de/insights/mtu-aero-engines-stellen-weichen-wertschoepfung-mithilfe-ki). In general, defining an AI strategy on a *corporate level* means setting up courses of action and sets of decisions regarding the strategic use of AI for all departments and units in a unified manner. On a *divisional level,* an AI strategy is defined for one or more units in a specific industry (e.g., automotive, electronics) or market (e.g., America, Europe). Similarly, on a *functional level,* an AI strategy is defined for one or more departments that perform specific functional tasks (e.g., production, human resources). Finally, defining an AI strategy on a *proprietary level* means setting up courses of action and sets of decisions regarding the strategic use of AI partially or entirely detached from any hierarchical structures. Here, an AI strategy relates, for example, to a specific group of products or services to invariably consider their specific needs and unique requirements.

Life cycle management refers to the setup of teams responsible for the technical management of AI applications across the entire life cycle from development to operation within an organization (Baier et al. 2019; Stecher et al. 2020; Reddy et al. 2022; Shollo et al. 2022). The challenge here is to determine a team structure that is able to handle the ever-evolving landscape of pervasive AI applications in a technical manner (Stecher et al. 2020; Shollo et al. 2022). As a strategic response, Continental, for example, established a centralized AI lab in which experts from different areas develop together AI applications. In general, in a *centralized* team structure, all AI resources are grouped in a single unit that researches technological advances in AI technology and develops AI applications for the entire organization (https://www.continental.com/en/press/studies-publications/technology-dossiers/artificial-intelligence/). In a *decentralized* team structure, AI resources are distributed across several units within an organization, which manage AI applications separately from each other. A *federal* team structure combines elements of centralized and decentralized team structures. Here, for example, a global AI team sets guidelines and standards for AI applications, while satellite AI teams drive the trajectory of AI in individual units according to their specific needs and unique requirements.

Governance level describes the sphere of accountability that ensures that AI applications are developed and operated in line with social, legal, and ethical values (Volberda et al. 2021; Papagiannidis et al. 2023). The challenge here is to determine a level of governance that covers the life cycle of AI applications to the extent that the social, legal, and ethical values of an organization are constantly met in the ever-evolving landscape of pervasive AI applications (Papagiannidis et al. 2023). As a strategic response, SAP, for example, installed an AI Ethics Steering Committee, which is responsible for AI use cases across the entire organization and decides on compliance with the governance principles in quarterly meetings (https://www.sap.com/products/artificial-intelligence/ai-ethics.html?pdf-asset=940c6047-1c7d-0010-87a3-c30de2ffd8ff&page=1). In general, when the governance level is set *enterprise-wide*, the governance mechanisms apply to the entire organization and, thus, cover the entire portfolio and application landscape. Next, when the governance level is formulated as *portfolio-based*, the governance mechanisms apply only to a subset of applications with the same or similar characteristics. Here, an organization defines governance mechanisms per portfolio and assigns them to the respective applications to ensure a high fit with social, legal, and ethical values. Finally, when the governance level is set *application-specific*, the governance mechanisms apply explicitly to a specific application to ensure an optimal fit.

Control mechanisms refer to the guidelines and standards that govern the design of secure and reliable AI applications to avoid erroneous or discriminatory AI-driven decisions (Keding 2021; Papagiannidis et al. 2023; van Giffen and Ludwig 2023). The challenge here is to determine appropriate control mechanisms that not only apply to humans but also to autonomous AI applications (Keding 2021; Papagiannidis et al. 2023). Finding the appropriate kind of control mechanisms ensures required transparency and compliance with regulatory and ethical standards. As a strategic response, Mercedes, for example, established a set of four principles according to which they develop and operate AI applications across the entire organization (https://group.mercedes-benz.com/responsibility/compliance/digital/ki-guidelines.html). In general, *guiding* control mechanisms mean that an organization defines a set of indicative regulations in its AI strategy to steer AI development and operation processes, thereby reducing complexity rather than enforcing strict adherence. These control mechanisms can be tailored to the specific needs and unique requirements of an organization to promote innovation while maintaining a certain degree of consistency. Next, in the case of *restricting* control mechanisms, an organization defines a set of strict regulations in its AI strategy that AI applications must adhere to mitigate risks. This involves the installation of adequate control instances and the restriction of, for example, the use of certain algorithms or data sets. Finally, the existence of *no additional* control mechanisms means that an organization refers in its AI strategy to existing (IT) control mechanisms for the development and operation of AI applications.

Data governance framework describes whether the principles and practices for collecting, storing, and managing data within an organization are defined as part of an AI strategy (Jöhnk et al. 2021; Mikalef and Gupta 2021; Merhi 2023). The challenge here is to ensure a robust infrastructure and guidelines that foster data quality, privacy, and security for reliable databases used in AI applications (Dietz et al. 2021; Jöhnk et al. 2021). As a strategic response, Visa, for example, prioritized its data governance, which regulates the responsible use of data as the basis for the responsible development and operation of AI applications (https://usa.visa.com/visa-everywhere/blog/bdp/2023/09/13/30-years-of-1694624229357.html). In general, *integrated* means that data governance is an integral part of an AI strategy. Further, *isolated* implies that data governance is treated separately from an AI strategy. Hence, relevant standards and controls are defined in a distinct data strategy or data manifesto. Lastly, *hybrid* means that certain aspects of data governance are incorporated into an AI strategy while other aspects are defined separately. For example, critical data functions such as data compliance are defined in an AI strategy, whereas less critical data functions such as data accessibility or availability are addressed separately.

4.2 Layer 2: Scale

The *layer* scale describes the leverage effects (e.g., strategic alliances, partner ecosystems) that help organizations to establish a digital technology in a profitable way (Bharadwaj et al. 2013). Regarding an AI strategy, we subsume here how organizations can proceed to ensure the presence of relevant human capacity and technology resources. This layer comprises two dimensions:

Knowledge acquisition describes how an organization ensures the availability of relevant skills and competencies (Laut et al. 2021; Mikalef and Gupta 2021; Merhi 2023). The challenge here is to promote continuous learning in order to acquire human knowledge that is necessary to develop and operate AI applications in view of the latest technological advances (Pumplun et al. 2019; Reddy et al. 2022; Weber et al. 2022). As a strategic response, E.ON, for example, is involved in several investments and acquisitions, as it has been contracting with strategic partners for several years (https://www.eon.com/content/dam/eon/eon-com/Documents/en/new-energy/20191202-1022-in150-25039-yearbook-artinelli-170x240-online-5.pdf). In general, *training* implies that an organization provides its employees with education measures to acquire relevant knowledge. Further, *hiring* means that an organization gains relevant skills and competencies by attracting or recruiting specialists from another organization or the free labor market. Finally, *contracting* implies that an organization purchases relevant knowledge from one or more service providers (e.g., consultancies or start-ups).

Technology sourcing describes how an organization acquires the relevant technical resources to develop and operate AI applications (Baier et al. 2019; Lichtenthaler 2020; Lins et al. 2021). This encompasses the availability of software services (i.e., ready-to-use applications or pre-trained models and platforms), developer services (i.e., tools for supporting the coding process, such as frameworks and libraries), computing power (i.e., computational capacity for building and training algorithms, such as physical servers or virtual machines), and proprietary data (i.e., network and storage resources for data management, such as data lakes or NoSQL databases) (Lins et al. 2021). The challenge here is to decide on how to source complex and sophisticated algorithms, as the development and operation of AI applications requires in any case proprietary data, thus striking a balance between make or buy (Guo et al. 2023; Helfat et al. 2023). As a strategic response, Microsoft, for example, pursues a make approach to technical resources through in-house research and development (https://news.microsoft.com/source/features/ai/microsoft-approach-to-ai/). In general, with a *make* approach, an organization aims to develop and operate AI applications with internal resources from start to finish. Here, for example, an organization builds and trains AI models in-house, although it does not rely exclusively on internal resources and often includes external packages (e.g., frameworks and libraries of pre-trained algorithms). With a *buy* approach, an organization acquires complete AI applications from external vendors (e.g., AI start-ups, AI service providers) that require minimal customization or even allow for immediate use (e.g., ChatGPT Enterprise). With a *hybrid* approach, an organization aims to combine a make and buy strategy. Here, for example, an organization sources pre-built or pre-trained models or entire development modules (e.g., machine learning services from Amazon Web Services) to develop and operate AI applications.

4.3 Layer 3: Speed

The layer *speed* refers to the time and sequence in which organizations release products and services related to a digital technology (Bharadwaj et al. 2013). As the speed with which organizations bring products and services with AI functionality in a productive environment plays a central role in the context of an AI strategy, we describe here how organizations proceed to establish AI use cases. This layer comprises two dimensions:

Use case identification refers to the strategic practice of how an organization proceeds to find relevant AI use cases in line with firm-specific goals as well as with internal and external constraints (Pumplun et al. 2019; Lichtenthaler 2020; Vial et al. 2022; Grashoff and Recker 2023). The challenge here is to choose from a large variety of opportunities amid uncertain value creation when implementing AI applications and to understand that AI applications vary in different contexts (Pumplun et al. 2019; Dietz et al. 2021). As a strategic response, Deutsche Telekom, for example, utilizes the Design Thinking Framework and CRISP-DM methodology as guiding approaches for a systematical use case identification (https://www.t-systems.com/de/en/artificial-intelligence/topics/ai-strategy). In general, in a *systematical* approach, an organization first thoroughly analyzes potential application areas in which they expect to achieve a benefit from the use of AI. Based on a well-founded understanding of individual application areas, they then institutionalize the most promising AI use cases (i.e., learn from thoughtful conception). In an *experimental* approach, an organization starts to immediately institutionalize AI use cases in individual application areas in which they expect to achieve a benefit from the use of AI. Based on a fast-tracked experience about what works, they then institutionalize the most promising AI use cases (i.e., learn from active use). Essentially, it is a strategic decision as to whether an organization tends to find AI use cases rather through careful planning or straight diving in and learning from hands-on experience as they go.

Use case expansion describes the strategic practice that an organization applies to disseminate AI use cases across different application areas (Sjödin et al. 2021; Reddy et al. 2022; Helfat et al. 2023; van Giffen and Ludwig 2023). The challenge here is to define how AI use cases can be optimally expanded to the entire organization, considering the uncertainty that the performance of AI applications varies in different contexts (Dietz et al. 2021; Sjödin et al. 2021; van Giffen and Ludwig 2023). As a strategic response, Deutsche Bank, for example, runs a large number of pilot programs to find the most promising AI use cases that they then transfer to other application areas (https://www.thewealthadvisor.com/article/deutsche-banks-ambitious-ai-drive-reshaping-banking-generative-technology). In general, in the *one-to-many* approach, an organization starts with a limited number of AI use cases (i.e., one or a few) that address specific needs or problems. Once these AI use cases prove valuable, they are expanded to other application areas. In the *many-to-one* approach, an organization launches several AI use cases simultaneously to leverage technological opportunities. As soon as promising AI use cases emerge, they are transferred to other application areas. Essentially, the one-to-many approach is about starting narrow and then gradually expanding, whereas the many-to-one approach is about starting broad and then narrowing down.

4.4 Layer 4: Source

The layer *source* describes the mechanisms and activities through which organizations gain value from products or services related to a digital technology (Bharadwaj et al. 2013). Regarding an AI strategy, we subsume here the relevant aspects that serve as the cornerstone for organizations to achieve value with AI. This layer comprises five dimensions:

Technology aspiration refers to the strategic consciousness of an organization regarding the performance of AI applications (Reddy et al. 2022; Shollo et al. 2022; Weber et al. 2022). The challenge here is to balance the pursuit of competitive advantage with the feasibility and scalability of AI applications (Jöhnk et al. 2021; Grashoff and Recker 2023). As a strategic response, IBM, for example, decided to focus not solely on the latest technological advances in AI but rather on how they can leverage bleeding-edge AI technologies such as quantum machine learning (https://research.ibm.com/topics/quantum-machine-learning). In general, *established* refers to the aspiration of an organization to implement AI technologies that represent widely acknowledged technological advances. Related technologies (e.g., natural language processing) are already extensively validated and depict a proven track record of success in real-world applications. Further, *cutting-edge* denotes the aspiration of an organization to implement AI technologies that are at the forefront of current innovation, showcasing the latest technological advances. Related technologies (e.g., computer vision) have been extensively researched and developed and are already being deployed in stable and reliable practical applications with proven success. Lastly, *bleeding-edge* refers to the aspiration of an organization to implement AI technologies that represent even more speculative and experimental technological advances. Related technologies (e.g., neuromorphic computing) are, to date, only partly validated or tested as part of research or are at least not yet widely deployed in real-world scenarios but could provide a competitive advantage for an organization in the future.

Risk tolerance describes the risk level that an organization is willing to accept when developing and operating AI applications to achieve a desired return (Jöhnk et al. 2021; Rowland et al. 2022; Papagiannidis et al. 2023). The challenge here is to acknowledge the possibility of untraceable data breaches or algorithmic biases despite the fulfillment of relevant documentation requirements or human supervision to identify, assess, and address risks (Reddy et al. 2022; Merhi 2023). As a strategic response, American Express, for example, aims to leverage the potential of AI in invoice auditing, taking a high risk as it can have a critical impact on bank accounts and credit lines of customers (https://venturebeat.com/ai/amex-is-experimenting-cautiously-with-generative-ai-for-fintech/). In general, *minimal* risk means that an organization is only willing to implement AI applications that pose little or no risk to the rights or safety of users and are largely unregulated, so the value added by AI can be captured without significant risk. Further, *limited* risk indicates that an organization is willing to implement AI applications that may require specific transparency obligations (e.g., chatbots) to ensure users know they are interacting with AI applications but can leverage the corresponding added value. Finally, *high* risk means that an organization is even willing to implement AI applications that are subject to strict legal requirements due to their significant risks to safety or fundamental rights, including critical infrastructure, human workplaces, and private and public services. However, an organization accepts high risk to extract the transformative value from AI applications.

Business model impact refers to the potentially disruptive character of AI on the current business model of an organization (Burström et al. 2021; Sjödin et al. 2021; Weber et al. 2022). The challenge here is to continually understand the potential value creation and destruction mechanisms of recent technological AI advances on the business model and the resulting positioning and contrasting in the competitive environment (Shollo et al. 2022). As a strategic response, Toyota Motor, for example, focuses on complementing its core competencies with AI services, according to its CTO (https://pressroom.toyota.com/toyota-and-generative-ai-its-here-and-this-is-how-were-using-it/). In general, a *complementing* business model is present when an organization aims to use AI to enhance existing products and services. Related organizations understand "AI as a supporter" to increase the value proposition of their existing business model. Further, an *extending* business model is present when an organization aims to use AI to establish new sources of value within or beyond a market or industry. Referenced organizations see "AI as an enabler" to establish a new business model alongside the existing one. Finally, a *renewing* business model is present when an organization aims to use AI to transform the existing business model as it is not competitive in the long term or to ascend to a market leader. Related organizations understand "AI as a disruptor" to ensure continuance by establishing a new business model that contrasts with the existing one.

Value creation refers to the level at which an organization leverages AI to establish a value for themselves or others (Borges et al. 2021; Burström et al. 2021; Collins et al. 2021; Shollo et al. 2022). The challenge here is to leverage the value of AI through individual customization and to be capable of quantifying this value concurrently (Borges et al. 2021; Burström et al. 2021). As a strategic response, Johnson & Johnson, for example, aims to create value both frontstage to support surgeons in analyzing results and backstage to increase the discovery speed of new medicines (https://www.jnj.com/innovation/artificial-intelligence-in-healthcare). In general, we follow Beverungen et al. (2019) and argue that AI allows for dual value creation. First, the benefit of AI may arise *frontstage* through creating and capturing value-in-use for the respective user (e.g., direct value through monitoring or optimization). In the case of frontstage value, an organization uses AI for external purposes, focusing on delivering value for customers (e.g., by improving existing products and services or creating new ones). Second, the benefit of AI may arise *backstage* through creating and capturing value-in-use for the respective provider (e.g., indirect value through data analytics and aggregation). In the case of backstage value, an organization uses AI for internal purposes, focusing on enhancing effectiveness and efficiency (e.g., by increasing the performance of routines or processes).

Value recipient effect describes how the use of AI influences human capabilities and capacities (e.g., human intuition and creativity) (Coombs et al. 2020; Guo et al. 2023; Krakowski et al. 2023). The challenge here is to evaluate AI-enhanced productivity as performance gains as well as to take into account the changing role of humans in problem-solving (Coombs et al. 2020; Krakowski et al. 2023). As a strategic response, Chevron, for example, decided not to replace the expertise of its employees but rather to improve their workflows (https://www.linkedin.com/pulse/launch-enterprise-ai-chevron-embarks-new-qlpyc/). In general, *replace* means that an organization uses AI as a tool to automate tasks and activities that were previously performed by human beings. The benefits are often performance-driven, while the replaced tasks and activities are primarily mechanical. Further, *reinforce* indicates that an organization uses AI as a lever to empower and strengthen the actions and decisions of human beings. The benefits are often human-centered, while the reinforced actions and decisions are primarily analytical. Finally, *reveal* means that an organization adopts AI as a sonar to unveil hidden or latent trends and opportunities that were previously inaccessible or obscured to human beings. The benefits are often insight-driven, while the revealed trends and opportunities are primarily innovative.

5 Clusters of Artificial Intelligence Strategy

Building on the taxonomy, we performed a cluster analysis to derive clusters of AI strategy (Ketchen and Shook 1996). For this purpose, we classified the sample of 51 real-world objects into the taxonomy. In line with Nickerson et al. (2013), who state that the dimensions of a taxonomy should ensure mutually exclusive and collectively exhaustive characteristics, we chose the predominant characteristic in each dimension building on publicly available information. Ultimately, the cluster analysis resulted in an optimal number of four clusters (i.e., Technology Navigator, Innovation Explorer, Business Enhancer, and Operations Stabilizer), which we summarize hereafter (see Table 3). The clusters represent typical combinations of characteristics of an AI strategy that co-occur in real-world objects. We named the clusters according to the overarching sentiment of the underlying organizations regarding the strategic use of AI. Overall, we successfully assigned each of the 51 real-world objects to one of the four clusters. In this way, we were able to demonstrate the applicability and usefulness of the taxonomy.

By calculating the relative frequency of the characteristics in the dimensions, we gained overarching insights into how the sample of 51 real-world objects manifests itself in the taxonomy in total as well as in the clusters (see Table 4). Characteristics with a dark gray background were found in greater than or equal to sixty-six percent (rf $\geq$ 66.66%), while characteristics with a light gray background were found in less than sixty-six percent but greater than or equal to thirty-three percent (66.66% $>$ rf $\geq$ 33.33%), and characteristics with a white background were found in less than thirty-three percent (rf $<$ 33.33%). For more detailed information on the classification, please refer to "*Online Appendix I* and *J*".

For the presentation of the clusters hereafter, we provide for each cluster a description and interpretation of the classification results. Thereby, we delve deeper into the dimensions and characteristics that make a cluster unique or particularly distinguishable from another one. For more illustrative examples of how the sample of 51 real-world objects manifests itself in the taxonomy, please refer to *"Online Appendix K"*.

5.1 Cluster 1: Technology Navigator

Technology Navigators represent organizations that are the driving force behind the trajectory of AI, thereby pushing and shaping the frontiers of the ever-evolving performance and scope of AI applications. Regarding the scope of an AI strategy, Technology Navigators are the only ones that delegate the strategic ownership mostly to a *central staff unit* or alternatively a *cross-functional unit* and, thus, anchor the definition and execution of an AI strategy close to the senior management. This approach seems to reflect the practices of tech giants such as Microsoft or SAP that currently place AI at the center of their strategic deliberations. Consequently, it appears logical that organizations in this cluster set the scope of an AI strategy mainly at a *corporate* level and are the only ones that determine the governance level predominantly *enterprise-wide*. Further, Technology Navigators manage the technical aspects of the

Table 3 Clusters of artificial intelligence strategy

ID	Name	Description	Cluster	Number	Example
1	Technology navigator	Push the boundaries of AI through continuous research and development. Respective organizations undertake risky but rewarding projects to achieve technological breakthroughs at the forefront of AI	1	12	JPMorgan, Microsoft, Infineon, SAP
2	Innovation explorer	Delve into promising emerging and previously uncharted territories with AI. Respective organizations invest substantial resources in AI to unlock new value streams alongside existing products and services	2	18	American Express,Bayer, E.ON, Volkswagen
3	Business enhancer	Focus on improving the operational performance of processes or routines with AI. Respective organizations explore AI in initial use cases but are cautious about the widespread application	3	6	MTU Aero Engines, Procter & Gambler, Linde, Chevron
4	Operations stabilizer	Resort to AI to date in only a few isolated or scattered use cases. Respective organizations prefer stability and reliability over breakthrough innovations due to the potential risks and adverse outcomes of AI	4	15	Henkel, Nike, McDonald's, Coca-Cola

AI life cycle in either a *centralized* or *decentralized* manner. Given the pioneering role of Technology Navigators, they are the only ones that usually apply *restricting* or alternatively *guiding* governance principles, displaying their high experience in how to control AI applications. They further take either a *hybrid* or an *isolated* approach to the data governance framework, indicating that they manage data aspects partially or even entirely detached from an AI strategy. For the scale of an AI strategy, Technology Navigators rely primarily on *hiring* employees to acquire relevant knowledge. Further, unlike the other clusters, they follow exclusively a *make* approach regarding technology sourcing as they develop and operate AI applications end-to-end with internal resources. This approach also seems reasonable, as it is typically tech giants that create technological foundations and make them available to other organizations. In terms of the speed of an AI strategy, Technology Navigators identify AI use cases predominantly in a *systematical* manner while expanding them exclusively through a *many-to-one* approach. As for the source of an AI strategy, Technology Navigators build mostly on *cutting-edge* or, in contrast to the other clusters, even *bleeding-edge* technologies. This reflects the aspirational and sophisticated approach of Technology Navigators. Correspondingly, organizations of this cluster aim to *extend* their business model while they tolerate *limited* or even *high* risk. This characterization is in line with the practices of tech giants that affirm a leadership role in technological advances with a risk-affine attitude towards AI. In doing so, organizations that belong to Technology Navigators create value in a mixture of *front- & backstage* value or even only *frontstage* value, which, in turn, emphasizes again the aim of tech giants to make technological foundations available to other organizations. Finally, unlike the other clusters, Technology Navigators are the only ones that exhibit *revealing* regarding the value recipient effect, which assumes that AI can take over tasks that were previously inaccessible or obscured to human beings.

5.2 Cluster 2: Innovation Explorer

Innovation Explorers represent organizations that embrace a forward-thinking approach to the strategic use of AI with the aim of transformative growth. Regarding the scope of an AI strategy, Innovation Explorers delegate the strategic ownership mostly to a *cross-functional unit*, albeit the other characteristics are present to a certain extent. The same applies to the organizational anchoring, where Innovation Explorers, unlike the other clusters, set the sphere of coverage of an AI strategy predominantly at a *divisional* level, with the other characteristics being also present. This seems to reflect the fact that Innovation Explorers, as the largest cluster, represent organizations from a wide range of industries (e.g., automotive, energy, finance, retail). Remarkably, in the scope layer, Innovation Explorers overlap with Technology Navigators as both manage the technical aspects of the AI life cycle either in a *centralized* or a *decentralized* manner and both take a *hybrid* approach regarding data governance. In contrast to Technology Navigators, Innovation Explorers define the governance level either *enterprise-wide* or alternatively *application-specific* and define *no additional* governance principles. Regarding the scale of an AI strategy, Innovation Explorers acquire the relevant knowledge mainly via *hiring*. Further, like Business Enhancers, they take a *hybrid* approach of make and buy for technology sourcing. This seems logical, as organizations such as American Express or E.ON are already investing extensive resources in setting up structures to leverage the business potential of AI but are not in

Table 4 Classification results

Layer	Dimension	Characteristics	Technology navigators (%)	Innovation explorers (%)	Business enhancers (%)	Operations stabilizers (%)	Total (%)
Scope	Strategic ownership	Central staff unit	41.67	11.11	0.00	0.00	13.73
		Separate department	8.33	27.78	50.00	33.33	27.45
		Integrated team	16.67	22.22	0.00	46.67	25.49
		Cross-functional unit	33.33	38.89	50.00	20.00	33.33
	Organizational anchoring	Corporate	83.33	22.22	50.00	46.67	47.06
		Divisional	16.67	38.89	0.00	26.67	25.48
		Functional	0.00	22.22	33.33	6.67	13.73
		Proprietary	0.00	16.67	16.67	20.00	13.73
	Life cycle management	Centralized	41.67	50.00	66.67	66.67	54.90
		Decentralized	50.00	38.89	16.67	26.67	35.30
		Federal	8.33	11.11	16.67	6.67	9.80
	Governance level	Enterprise-wide	75.00	44.44	16.67	33.33	45.10
		Portfolio-based	25.00	16.67	66.67	33.33	29.41
		Application-specific	0.00	38.89	16.67	33.33	25.49
	Governance principles	Guiding	41.67	22.22	33.33	13.33	25.49
		Restricting	58.33	22.22	0.00	0.00	21.57
		No additional	0.00	55.56	66.67	86.67	52.94
	Data governance framework	Isolated	33.33	27.78	16.67	46.67	33.33
		Hybrid	50.00	72.22	16.67	26.67	47.06
		Integrated	16.67	0.00	66.67	26.67	19.61
Scale	Knowledge acquisition	Training	16.67	0.00	83.33	0.00	13.73
		Hiring	83.33	83.33	0.00	20.00	54.90
		Contracting	0.00	16.67	16.67	80.00	31.37
	Technology sourcing	Make	100.00	27.78	0.00	6.67	35.29
		Hybrid	0.00	72.22	83.33	46.67	45.10
		Buy	0.00	0.00	16.67	46.67	19.61
Speed	Use case identification	Systematical	91.67	72.22	100.00	46.67	72.55
		Experimental	8.33	27.78	0.00	53.33	27.45
	Use case expansion	One-to-many	0.00	55.56	16.67	80.00	45.10
		Many-to-one	100.00	44.44	83.33	20.00	54.90
Source	Technology aspiration	Established	0.00	16.67	0.00	53.33	21.57
		Cutting-edge	66.67	83.33	100.00	40.00	68.63
		Bleeding-edge	33.33	0.00	0.00	6.67	9.80
	Business model impact	Complementing	0.00	38.89	83.33	73.33	45.10
		Extending	83.33	55.56	16.67	26.67	49.02
		Renewing	16.67	5.56	0.00	0.00	5.88
	Risk level	High risk	58.33	38.89	16.67	20.00	35.29
		Limited risk	41.67	27.78	83.33	20.00	35.29
		Minimal risk	0.00	33.33	0.00	60.00	29.42
	Value creation	Frontstage	25.00	22.22	0.00	26.67	21.57
		Backstage	0.00	5.56	100.00	40.00	25.49
		Front- & backstage	75.00	72.22	0.00	33.33	52.94
	Value recipient effect	Replacing	0.00	33.33	16.67	6.67	15.69
		Reinforcing	50.00	61.11	83.33	93.33	70.59
		Revealing	50.00	5.56	0.00	0.00	13.72

a position to do this entirely internally and standalone. In terms of the speed of an AI strategy, Innovation Explorers identify AI use cases predominantly in a *systematical* manner while they are the only ones expanding them through a *one-to-many* or alternatively a *many-to-one* approach. Remarkably, in the source layer, Innovation Explorers overlap again with Technology Navigators as both build on *cutting-edge* AI applications to mostly *extend* their business model. Thereby, Innovation Explorers are divergent as to whether they adhere either to a *high* or only a *minimal* risk tolerance. For value creation, Innovation Explorers, like Technology Navigators aim primarily for a mixture of *front- & backstage* value or even only *front-stage* value. This approach also seems natural, as respective organizations such as American Express and E.ON make dedicated investments in AI to unlock, for example, new value streams alongside their core business, thereby pursuing a penetration into untapped markets. Finally, unlike the other clusters, Innovation Explorers are the only ones that exhibit *reinforcing* next to *replacing* regarding the value recipient effect.

5.3 Cluster 3: Business Enhancer

Business Enhancers represent organizations that embrace a purpose-driven approach to the strategic use of AI with the aim of incremental growth. Regarding the scope of an AI strategy, Business Enhancers delegate the strategic ownership to either a *separate department* or a *cross-functional unit*, with the other characteristics not being present at all. The same applies to the organizational anchoring, where Business Enhancers set the sphere of coverage of an AI strategy either at a *corporate* or, unlike the other clusters, a *functional* level, with the other characteristics are absent or only present to a limited extent. This seems to reflect the fact that Business Enhancers, as the smallest cluster, represent a manageable number of organizations. Remarkably, in the scope layer, Business Enhancers overlap with Operations Stabilizers as both manage the technical aspects of the AI life cycle in a *centralized* manner and both define *no additional* governance principles. In contrast to Operations Stabilizers, Business Enhancers define the governance level *portfolio-based* and take, unlike the other clusters, an *integrated* approach regarding data governance. Regarding the scale of an AI strategy, Business Enhancers are the only ones that mainly acquire the relevant knowledge via *training*. Further, like Innovation Explorers, they take a *hybrid* approach of make and buy for technology sourcing. This seems logical, as organizations such as MTU Aero Engines or Linde are already investing extensive resources in setting up structures to leverage the business potential of AI but are not in a position to do this entirely internally and standalone. In terms of the speed of an AI strategy, Business Enhances identify AI use cases predominantly in a *systematical* manner while expanding them through a *many-to-one* approach. Remarkably, in the source layer, Business Enhancers overlap again with Operations Stabilizers as both build on *cutting-edge* AI applications to mostly *complement* their business model. Thereby, Business Enhancers adhere to a *limited* risk tolerance. For value creation, Business Enhancers, like Operations Stabilizers aim primarily for *backstage* value, emphasizing the focus on increasing the operational performance of routines or processes. This approach also seems natural, as respective organizations such as MTU Aero Engines or Linde make dedicated investments in AI to enhance, for example, product and service quality within their core business but are not pursuing a penetration into new markets. Finally, Business Enhancers exhibit *reinforcing* regarding the value recipient effect.

5.4 Cluster 4: Operations Stabilizer

Operations Stabilizers represent organizations that focus on the careful and thoughtful integration of AI through use cases that promise enhancements in operational efficiency performance, rather than breakthrough innovation or radical change. Regarding the scope of an AI strategy, Operations Stabilizers are the only ones that delegate the strategic ownership mostly to an *integrated team* or, in contrast to the other clusters, a *separate department* and, thus, anchor the definition and execution of an AI strategy detached from the management. This approach seems to reflect the practices of respective organizations such as McDonald's or Coca-Cola that have already delved into the business potential of AI but most likely have not taken far-reaching and structured strategic deliberations. Consequently, it appears logical that organizations in this cluster set the scope of an AI strategy differently, albeit mainly at a *corporate* level. Further, Operations Stabilizers manage the technical aspects of the AI life cycle in a *centralized* manner. Given the lagging role of Operations Stabilizers, it is not clear whether they determine the governance level *enterprise-wide*, *portfolio-based*, or *application-specific*, displaying their low experience in how to control AI applications optimally. Thereby, they apply usually *no additional* governance principles and take predominantly an *isolated* approach to the data governance framework, indicating that they manage data aspects entirely detached from an AI strategy. For the scale of an AI strategy, Operations Stabilizers rely, unlike the other clusters, primarily on *contracting* external service providers to acquire relevant knowledge. Further, they follow a *hybrid* or, unlike the other clusters, even a *buy* approach regarding technology sourcing as they procure ready-to-use AI applications from external vendors. This approach also seems reasonable, as respective organizations often only have limited human and technological resources at their disposal to shape the trajectory of AI. In terms of the speed of an AI strategy, Operations Stabilizers identify AI use cases, unlike the other clusters, either in an *experimental* or alternatively in a *systematical* manner while expanding them predominantly through a *one-to-many* approach. As for the source of an AI strategy, Operations Stabilizers build mostly on *cutting-edge* or, in contrast to the other clusters, only *established* technologies. This reflects the cautious and pragmatic approach of Operations Stabilizers. Correspondingly, organizations of this cluster aim to *complement* their business model while they are the only ones that tolerate only *minimal* risk. This characterization is in line with the practices of respective organizations that focus on reliability and stability in technological advances with a risk-averse attitude towards AI. In doing so, organizations that belong to Operations Stabilizers create value in a mixture of *front- & backstage* value or even only *backstage* value, which, in turn, emphasizes again the aim of respective organizations to focus rather on internal than external value creation. Finally, unlike the other clusters, Operations Stabilizers exhibit *reinforcing* regarding the value recipient effect, which assumes that AI can empower and strengthen the actions and decisions of human beings.

6 Discussion

We are currently observing that organizations across all industries establish AI projects, which leads not only to operational deliberations but also to strategic ones (Keding 2021). Despite mature knowledge of the strategic relevance of AI, the study of the design of an AI strategy has received sparse treatment so far (Collins et al. 2021; Enholm et al. 2022). Although recent contributions to the scientific literature have paved the way to do so, there is yet no shared understanding of what the design space of an AI strategy entails. Against this backdrop, we developed a taxonomy and derived corresponding clusters of AI strategy in line with the organizational systematics approach (Bozeman and McKelvey 1978). In doing so, we built on the chain of argumentation that the facets that distinguish contemporary AI from previous generations of IT give rise to AI-induced market and resource shifts and, thus, to AI-related strategic challenges, which ultimately require a strategic response from organizations in the form of an AI strategy. Therefore, the study of the design of an AI strategy guides not only researchers but also practitioners in the field.

6.1 Intricacies of Artificial Intelligence Strategy

The aim of this study was to understand the design space of an AI strategy by analyzing how organizations currently structure and organize an AI strategy through the taxonomy and by highlighting the predominant design options for developing a new AI strategy or evaluating an existing one through the clusters. In doing so, we found that there are intricacies of an AI strategy compared to established strategy concepts that are reflected in the taxonomy and manifested in the clusters.

The taxonomy consists of 15 dimensions and 45 characteristics that draw on evidence from the review of scientific and professional literature, the conduct of semi-structured interviews, and the analysis of real-world objects. The taxonomy covers the dimensions that are relevant to formulate a strategic response to AI-related strategic challenges and, thus, to AI-induced market and resource shifts that originate from the facets of contemporary AI. The characteristics, in turn, describe potential alternatives to formulate a strategic response in line with firm-specific goals as well as with internal and external constraints. However, when contrasting the taxonomy with established strategy concepts, it becomes evident that not all dimensions and characteristics are entirely new. While the taxonomy allows a seamless integration of the dimensions into the four core themes of a digital strategy (Bharadwaj et al. 2013; Woodard et al. 2013), there are nuances that distinguish an AI strategy from established strategy concepts. First, there are dimensions and characteristics that are known from established strategy concepts but are essential to overcome AI-related strategic challenges. Second, there are dimensions and characteristics that are known from established strategy concepts but encapsulate an altered meaning in the context of AI and, thus, require a new interpretation to overcome AI-related strategic challenges. Third, there are dimensions and characteristics that are not part of established strategy concepts and have just recently gained unprecedented strategic importance to overcome AI-related strategic challenges. These intricacies unfold along the four core themes of the taxonomy.

In the *scope* layer, intricacy one becomes evident, as the dimensions and characteristics are in general known from established strategy concepts. Yet, to govern the ever-evolving landscape of AI applications, it is necessary, for example, to define *strategic ownership* or *organizational anchoring* as part of an AI strategy (Borges et al. 2021; Li et al. 2021). In the *scale* layer, intricacy two becomes apparent, as the dimensions and characteristics are in general known but *technology sourcing*, for example, requires a new interpretation, because any form of sourcing is dependent on data considerations (e.g., ensuring that commercial solutions allow for a seamless training with proprietary data) (Baier et al. 2019; Lins et al. 2021). In the *speed* layer, intricacy three becomes evident, as the dimensions and characteristics have just recently gained an unprecedented strategic importance due to uncertainty as an inevitable factor in the planning and execution of AI use cases. Here, *use case identification* and *use case expansion* gain increasing strategic importance to navigate AI use cases in complex and dynamic environments and ensure that efforts pay off (Vial et al. 2022; van Giffen and Ludwig 2023). In the *source* layer, intricacy three becomes apparent, as some dimensions and characteristics have also just recently gained an unprecedented strategic importance due to the challenges and opportunities arising from data-driven and inscrutable decision-making. Especially, the *value recipient effect* has moved to the center of strategic deliberations owing to the changing role of humans as a result of the influence of AI on human capabilities (Coombs et al. 2020; Krakowski et al. 2023). Further, *risk tolerance* gains an unprecedented strategic importance due to ethical problems, bias, and lack of transparency associated with AI applications (Rowland et al. 2022; Papagiannidis et al. 2023). Besides, in the *source* layer, intricacy two becomes apparent again, as the dimensions and characteristics are in general known but *value creation* and *business models*, for example, require a new interpretation, because AI changes the mechanisms of value creation and value destruction (Sjödin et al. 2021; Shollo et al. 2022). Overall, while most dimensions and characteristics are grounded in established strategy concepts, they require a nuanced perspective in the context of an AI strategy to formulate a strategic response to AI-related strategic challenges.

Building on the sample of 51 real-world objects, we further derived four clusters (i.e., Technology Navigator, Innovation Explorer, Business Enhancer, and Operations Stabilizer) that delineate predominant design options for developing a new AI strategy or evaluating an existing one. The clusters reveal the range of objectives that organizations can pursue with an AI strategy. In other words, the clusters provide insights into typical combinations of characteristics of an AI strategy that co-occur in real-world objects. Hence, the clusters offer insights into the systematization of the current landscape of the design of an AI strategy and demonstrate that organizations can follow a continuum of strategic objectives depending on firm-specific goals as well as internal and external constraints. We can substantiate the presence of the clusters in the real world through four overarching observations.

First, organizations may have different starting positions and entry points regarding the strategic use of AI. For example, software-related organizations, which typically shape the technology landscape, may have a head start in *knowledge acquisition* or *technology sourcing* in contrast to hardware-related organizations (Lins et al. 2021; Weber et al. 2022). Accordingly, we find that organizations that belong to the *Technology Navigator* cluster are primarily software-related organizations (e.g., Microsoft, SAP), whereas organizations that belong to the *Operations Stabilizer* cluster are primarily hardware-related organizations (e.g., Henkel, Nike). Second, organizations may have different expectations and ambitions regarding the business value of AI (Enholm et al. 2022; Keramidis and Shollo 2024). For example, service-oriented organizations may focus on enhancing customer experience (i.e., *frontstage value*) through AI, while product-oriented organizations tend to prioritize the automation of processes and routines (i.e., *backstage value*) (Sjödin et al. 2021; Shollo et al. 2022). As such, *Business Enhancers* rely merely on the improvement of internal operations, while *Innovation Explorers* tend to seek a mixture of internal and external value creation or even only external value creation. Third, organizations may have different perceptions of opportunities and threats regarding the strategic use of AI (Borges et al. 2021; Faraj and Leonardi 2022). For example, organizations with a higher *risk tolerance* or advanced *technology aspiration* may be more forthcoming to the breadth and depth of the use of AI, while risk-averse and technology-anxious organizations may proceed cautiously, focusing on minimizing potential disruptions and safeguarding existing business models (Burström et al. 2021; Weber et al. 2024). As such, *Innovation Explorers* seem to be more open to technological advances and more resistant to take risks and are therefore more likely to extend or even renew their business model than *Business Enhancers*, although they center around the same value proposition (e.g., in the automotive sector BMW as *Innovation Explorer*, Mercedes-Benz Group as *Business Enhancer*). Fourth, organizations may have different structures, processes, and relations regarding the strategic use of AI (Rowland et al. 2022; Papagiannidis et al. 2023). For example, organizations may not be able to replicate good practices or principles that they themselves or other organizations embrace in another division, function, or context despite similar or even equal objectives (Stecher et al. 2020; Laut et al. 2021). Accordingly, we find that organizations follow different clusters although they operate in the same industry (e.g., in the energy sector E.ON as *Innovation Explorer*, Chevron as *Business Enhancer*, RWE as *Operations Stabilizer*). Overall, these observations illustrate the argument that organizations navigate disparate paths regarding the strategic use of AI in line with firm-specific goals as well as with internal and external constraints.

6.2 Theoretical Contributions

From a theoretical perspective, this study has three main contributions that connect to the body of knowledge on AI strategy in IS and strategic management. Thus, in line with the intended purpose of the taxonomy and the corresponding clusters, the results primarily help researchers in describing the design of an AI strategy or in analyzing the design of an AI strategy across multiple real-world instances.

First, our work better situates extant knowledge of established strategy concepts in the context of AI. The scientific literature already provides valuable reference points for the study of the design of an AI strategy. For example, previous work already investigates the definition of a cognitive strategy (Davenport and Mahidhar 2018), the convergence of AI and corporate strategy (Kitsios and Kamariotou 2021), the integration of AI into organizational strategy (Borges et al. 2021), or the components of a data science strategy (Reddy et al. 2022). Here, the taxonomy complements and advances the recent scientific discourse that emphasizes the necessity for a fundamental understanding of AI strategy. Further, the taxonomy allows the seamless integration of the dimensions of an AI strategy into the four core themes that guide the definition of a digital strategy (Bharadwaj et al. 2013). Although some dimensions are grounded in established strategy concepts, the dominant AI-induced market or resource shift per dimension highlights the need for a nuanced perspective in the context of an AI strategy. In this way, we contribute to a better understanding of how contemporary AI differs from previous generations of IT in the context of strategy. Finally, the taxonomy reflects extant knowledge on the strategic use of AI and situates it in the context of AI strategy. For example, the scientific literature on the antecedents for the conceptualization and operationalization of AI in organizations (Pumplun et al. 2019; Jöhnk et al. 2021; Laut et al. 2021; Duda et al. 2024; Stohr et al. 2024) is contextualized in the scope layer, while the scientific literature on specific capabilities required for AI implementation (Mikalef and Gupta 2021; Sjödin et al. 2021; Weber et al. 2023) is reflected in the scale layer. Further, the scientific literature on how to facilitate AI implementation (Hamm and Klesel 2021; Merhi 2023) is contextualized within the speed layer, while the scientific literature on the business value of AI (Shollo et al. 2022; Grebe et al. 2023; Hansen et al. 2024; Keramidis and Shollo 2024) is reflected in the source layer. Thus, the taxonomy allows the consolidation of isolated bodies of knowledge on the strategic use of AI and thereby is one of the first articles that enables a shared understanding of what the design space of an AI strategy entails.

Second, our work facilitates further theorizing on the emerging phenomenon of AI strategy. The taxonomy and the corresponding clusters provide a fundamental understanding of AI strategy in the form of a theory for analyzing (i.e., Type I) (Gregor 2006). As knowledge of the emerging phenomenon is still in its infancy in the scientific literature (Collins et al. 2021; Enholm et al. 2022), the results serve as a catalytic means for researchers to further theorize on the design of an AI strategy as follows (Gregor 2006). Here, the taxonomy and the corresponding clusters serve immediately as a basis for theories for explaining (i.e., Types II and IV). For example, researchers can use the taxonomy as a framework to describe and analyze why organizations design an AI strategy in a certain way and how firm-specific goals as well as internal and external constraints affect the design. Further, researchers can use the clusters as a means to evaluate the performance of typical combinations of characteristics of an AI strategy that co-occur in real-world objects. Here, it might be particularly interesting what are appropriate metrics to measure the performance of an AI strategy and to determine whether an AI strategy leads to the outcomes intended by the applied rationales. Further, the results also inform the development of theories for predicting (i.e., Types III and IV). Here, we acknowledge possible changes in dimensions or characteristics over time. Researchers can use the results as a basis to develop models that assess whether and how the taxonomy and the corresponding clusters may evolve over time or forecast market success. Finally, the results also inform the development of theories for design and action (i.e., Type V). Here, we see the results as a basis for researchers to contextualize established strategy concepts in the context of AI and to determine how to integrate an AI strategy into established strategy concepts. Developing design principles for AI strategy that provide guidance to keep pace with the ever-evolving frontier of computational advancement may be another fruitful avenue for future research. Overall, the taxonomy and the corresponding clusters contribute to theory-building as a springboard for further sense-making and design-led research on AI strategy (Gregor and Hevner 2013).

Third, our work intensifies the scientific discourse at the nexus of IS and strategic management in the context of AI. While both research streams highlight the mutual relevance to advance the real-world use of AI (Keding 2021), the scientific literature has so far considered them as separate entities, leading to a discrepancy in the understanding of the interplay between the operational implementation of AI and its strategic implications. Here, IS research focuses primarily on how organizations should proceed to turn conceptual use cases into productive applications (van Giffen and Ludwig 2023; Sagodi et al. 2024) but often pays limited attention to the strategic actions organizations should take in response to the emergence of AI, which is a focus of strategic management research (Volberda et al. 2021; Faraj and Leonardi 2022). With the study of the design of an AI strategy, we emphasize a relevant perspective on the interplay of IS and strategic management that transcends the boundaries of both research fields. Specifically, the taxonomy and the corresponding clusters provide an understanding of which dimensions are relevant in strategic planning and which characteristics are possible in operational implementation. In this way, the study of the design of an AI strategy serves as a starting point to portray operational and strategic deliberations as intertwined, and to bring the rich knowledge of strategic management even more into the context of IS (and vice versa) to strengthen one-sided views. For example, researchers can build on the results to develop methods or models that consider both the operational implementation of AI and its strategic implications from an interdisciplinary perspective.

6.3 Practical Implications

From a practical perspective, this study has three main implications that support managers as high- and mid-level decision makers in strategic discussions on the design of an AI strategy (e.g., business development representatives, chief digital officers, and in-house strategy consultants). Thus, in line with the intended purpose of the taxonomy and the corresponding clusters, the results primarily inspire practitioners in developing a new AI strategy or in evaluating an existing one.

First, managers can use the taxonomy to structure and organize the design space of an AI strategy. While the design space of an AI strategy is currently scattered among various manifestations, the taxonomy provides managers with a framework within which organizations can potentially shape a strategic response to AI-related strategic challenges in theory. Building on the well-grounded compilation of dimensions and characteristics, the taxonomy makes it straightforward to classify both a current and a future AI strategy in a consistent and coherent manner. In addition, it allows classifying individual manifestations of an AI strategy and analyzing the similarities and differences among them. In this context, managers can use the taxonomy to comprehend which combination of characteristics constitutes an existing AI strategy. At the same time, the taxonomy serves as a morphological box, meaning that each combination of characteristics leads to a new AI strategy. Accordingly, managers can use the taxonomy not only to understand which design options of an AI strategy are possible but also which are desirable, feasible, and viable in line with firm-specific goals as well as with internal and external constraints. Thus, the taxonomy provides managers with a landmark to design an AI strategy more efficaciously.

Second, managers can use the taxonomy as a framework to guide the design of an AI strategy. The taxonomy provides managers with a framework to formulate a strategic response to AI-related strategic challenges and, thus, to AI-induced market and resource shifts that originate from the facets of contemporary AI. However, as firm-specific goals as well as internal and external constraints vary across organizations, the dimensions may have a varying strategic imperative, and the characteristics may have a varying strategic fit. Here, managers can use the taxonomy to determine which elements of an AI strategy are already established and which ones they still need to define. For example, if robust IT governance mechanisms are already in place, managers could immediately integrate them into an AI strategy. Likewise, managers can use the taxonomy as a framework to shape the design of an AI strategy step by step. Here, we state that managers should first define the goals of an AI strategy, which has a direct impact on the design of the dimensions in the source layer. The goals, in turn, correlate with the scale layer, as the dimensions here determine how managers access the resources to achieve the goals. Building on the source and scale of an AI strategy, managers can focus on the speed layer by considering how to translate the goals and resources into use case identification and use case expansion. With the scope layer, managers can then set a frame for the source, scale, and speed layers by defining the anchoring of responsibility and accountability for an AI strategy, among others.

Third, managers can use the clusters as predominant design options for developing a new AI strategy or evaluating an existing one. The clusters illustrate which typical combinations of characteristics of an AI strategy co-occur in real-world objects. They represent manifestations of how organizations actually shape a strategic response to AI-related strategic challenges in practice. Although the clusters are not necessarily ideal types, managers can use them as inspiration for developing a new AI strategy or as a metric for evaluating an existing one. While organizations often struggle to define an AI strategy, the clusters put managers in a position to compare individual manifestations and select the one that not only meets firm-specific goals but is also in line with internal and external constraints. In this way, the clusters help managers to make more informed decisions on the design of an AI strategy. In this context, we also acknowledge that managers can use the sample of 51 real-world objects as a source of inspiration to draw conclusions on how market- and industry-leading organizations around the globe shape the trajectory of AI. Hence, the sample can support organizations in market research and competitor analysis. In addition, the illustrative examples provide insights into the bandwidth in which organizations listed in indices of the world's four largest economies formulate a strategic response to AI-related strategic challenges. Besides, the illustrative examples can serve as an impetus not only for incumbent firms but also for alternative forms of organizations (e.g., small and medium-sized enterprises) to explore the design space of an AI strategy.

6.4 Future Research Opportunities

Throughout the taxonomy development and cluster analysis, we inferred future research opportunities on the emerging phenomenon of AI strategy that result from the review of scientific and professional literature, the conduct of semi-structured interviews, the hosting of a focus group discussion, and the analysis of real-world objects. The future research opportunities extend the results from the study of the design of an AI strategy and are reflected in the intricacies of an AI strategy as well as the theoretical contributions and practical implications of the present work. In the following, we provide an overview of exemplary research questions on AI strategy along the phases of *AI strategy development*, *AI strategy implementation*, and *AI strategy evaluation* (see Table 5).

In the research area of *AI strategy development (1)*, we outline research questions addressing the development of methods or models that support the design of an AI strategy as well as the understanding of the role of different forms of organizations, firm-specific goals as well as internal and external constraints, and organizational starting points and target ambitions on the design of an AI strategy. Regarding *AI strategy implementation (2)*, we highlight research questions focusing on the study of the interplay of an AI strategy with existing strategic concepts and governance frameworks, the understanding of the role of organizational culture and leadership in the successful implementation of an AI strategy, and the mechanisms for ensuring the long-term adherence to and actualization of an AI strategy. In the research area of *AI strategy evaluation (3)*, we present research questions concerning the identification of metrics and frameworks for assessing the performance and impact of an AI strategy, the understanding of the role of an AI strategy in enhancing the organizational AI readiness and maturity, the mechanisms for adapting an AI strategy in an ever-evolving landscape of AI applications, and the evolution of the design space of an AI strategy over time.

7 Limitations and Extensions

As with any research endeavor, this study has limitations. First, the analysis of the sample of 51 real-world objects is limited to publicly available information. Thus, the classification of real-world objects into the taxonomy is based not only on self-reported information from organizations but also on references from websites (e.g., company websites, industry forums) and industry reports (e.g., annual reports, press releases). The information these sources

Table 5 Future research opportunities on artificial intelligence strategy

ID	Research area	Exemplary research questions
1	AI strategy development	• How can organizations proceed to design an AI strategy in line with firm-specific goals as well as with internal and external constraints? • How does the design of an AI strategy differ between incumbent firms and alternative forms of organizations (e.g., start-ups and new ventures)? • How do firm-specific goals as well as internal and external constraints inform the design of an AI strategy? • How do organizational starting points and target ambitions inform the design of an AI strategy?
2	AI strategy implementation	• What structures, processes, and relations are necessary to integrate an AI strategy into existing governance frameworks? • How does the presence of an AI strategy in organizations influence existing strategic concepts and vice versa? • What role do organizational culture and leadership play in the successful implementation of an AI strategy? • How can organizations ensure the long-term adherence to and actualization of an AI strategy?
3	AI strategy evaluation	• What metrics and frameworks can organizations use to measure the performance and evaluate the impact of an AI strategy? • How does the presence of an AI strategy accelerate organizational AI readiness and maturity? • How does the composition of the dimensions and characteristics and, thus, the formation of the clusters of an AI strategy change over time? • How can organizations set up a dynamic AI strategy adaptation process that accounts for the ever-evolving landscape of AI applications?

contain on the dimensions and characteristics of an AI strategy is often only implicitly described and not explicitly stated. Consequently, the classification of real-world objects into the taxonomy draws on logical reasoning and contextual recombination of information and is, thus, to a certain degree subject to bias or at least interpretation of the co-authors. To address this issue, one could enrich the dataset with first-hand insights from the sample of 51 real-world objects (e.g., through semi-structured interviews) to clarify ambiguous assertions and amplify imperfect statements on the design of an AI strategy reported in publicly available information. However, we applied mechanisms, for example, by performing an independent classification by two co-authors and consulting a third co-author in the case of extreme and ambiguous statements to minimize biases and ensure meaningful results.

Second, although the sample of 51 real-world objects already represents a significant number, it is not fully exhaustive in its current form. To address this issue, one could expand the dataset by integrating a larger number of real-world objects to validate or even update the taxonomy and the corresponding clusters. In this context, we also acknowledge the potential to use indices beyond economies and industries emphases, which may provide further insights into the design of an AI strategy and cause possible changes in the results. However, the study considers real-world objects from organizations listed in indices of the world's four largest economies to obtain a comparable dataset. Hence, we consider the sample of 51 real-world objects sufficient to draw valid conclusions on the design space of an AI strategy in the context of incumbent firms in line with the meta-characteristic.

Third, the results focus merely on an overview of the status quo of the design of an AI strategy. Nonetheless, as the ever-evolving frontier of computational advancement, AI represents a moving frontier that enables increasingly sophisticated use cases, which, in turn, may lead to changes in the design of an AI strategy. To address this issue, one could conduct a longitudinal study to investigate whether and how the evolution of the methods and techniques at the core of AI, such as recently the rise of generative AI in general and the release of Large Language Models in particular, stimulates possible changes to the taxonomy and the corresponding clusters. For the taxonomy, this means reflecting on whether there is a need to adapt existing dimensions and characteristics or to add new ones. For the clusters, this entails reviewing whether existing predominant design options evolve or even new ones emerge. However, we regard the taxonomy and the corresponding clusters as a reliable framework that researchers and practitioners can build on in the future to design an AI strategy, even if technological advances cause changes.

Fourth, the study builds on semi-structured interviews with subject matter experts and a focus group discussion with fellow researchers to assess the applicability and usefulness of the taxonomy. Although the external evaluation confirms that the taxonomy accounts for comprehensibility, completeness, robustness, and real-world fidelity in relation to the intended purpose for the respective target user group, a stronger evaluation where the taxonomy is actively used to develop a new AI strategy or to refine an existing one would allow for advanced insights into the design of an AI strategy. To address this issue, one could conduct a practitioner intervention (e.g., through a case study) to evaluate not only the applicability and usefulness of the taxonomy in more detail but also to gather further insights into the design of an AI strategy in general. However, we attribute the quantity and quality of information from the semi-structured interviews and the focus group discussion considerably to ensure applicability and usefulness in the first step.

In conclusion, the above limitations notwithstanding, we are confident that the taxonomy and the corresponding clusters provide researchers and practitioners with a shared understanding of what the design space of an AI strategy entails. We expect the results to serve as both a foundation and a stimulation for fellow researchers to continue the scientific discussion on the design of an AI strategy in future work.

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