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Artificial intelligence in innovation management: A review of innovation capabilities and a taxonomy of AI applications

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Abstract

Artificial intelligence (AI) is a promising generation of digital technologies. Recent applications and research suggest that AI can not only influence but also accelerate innovation in organizations. However, as the field is rapidly growing, a common understanding of the underlying theoretical capabilities has become increasingly vague and fraught with ambiguity. In view of the centrality of innovation capabilities in making innovation happen, we bring together these scattered perspectives in a systematic and multidisciplinary literature review. The aim of this literature review is to summarize the role of AI in influencing innovation capabilities and provide a taxonomy of AI applications based on empirical studies. Drawing on the technological–organizational–environmental (TOE) framework, our review condenses the research findings of 62 studies. The results of our study are twofold. First, we identify a dichotomous view of innovation capabilities triggered by AI adoption: *enabling* and *enhancing*. The *enabling capabilities* are those that research identifies as enablers of AI adoption, underscoring the competencies and routines needed to implement AI. The *enhancing capabilities* denote the role that AI adoption has in transforming or creating innovation capabilities in organizations. Second, we propose a taxonomy of AI applications that reflects the practical adoption of AI in relation to three underlying reasons: *replace*, *reinforce*, and *reveal*. Our study makes three main contributions. First, we identify the innovation capabilities that are either required for or generated by AI adoption. Second, we propose a taxonomy of AI applications. Third, we use the TOE framework to track trends in the theoretical contributions of recent articles and propose a research agenda.

KEYWORDS

artificial intelligence, generative AI, innovation management, technology adoption, TOE framework

1 | INTRODUCTION

Introduced as a concept in 1955, artificial intelligence (AI) has been defined as the ability of machines to think and perform tasks simulating human behavioral patterns (McCarthy et al., 2006). A growing number of cases demonstrate the influence of AI for innovation activities (Davenport & Ronanki, 2018). For example, IBM introduced AI solutions based on an AI platform called Watson to help physicians quickly diagnose diseases based on image recognition (Magistretti et al., 2019). Netflix uses AI to generate informed, data-driven analyses for content creation (Verganti et al., 2020). Mastercard adopts AI to identify and stop fraudulent transactions without delaying legitimate transactions (Dell, 2021). Airbus combines data on aircraft production with a self-learning algorithm that identifies patterns in production problems (Constantinides et al., 2018). Chat GPT, Open AI's generative AI, is indicated as an outstanding algorithm capable of expanding problem and solution spaces in innovation processes based on design thinking principles (Bouschery et al., 2023). Collectively, these examples suggest that AI adoption can radically alter the nature and structure of new products, services, processes, and business models, spawning novel value creation and appropriation pathways (Verganti et al., 2020) that also require the absorption and implementation of appropriate innovation capabilities (Cooper, 2021; Makarius et al., 2020).

Innovation capabilities are the "skills and knowledge needed to effectively absorb, master and improve existing technologies, and to create new ones" (Romijn & Albaladejo, 2002, p. 1054). In AI adoption, innovation capabilities encompass knowledge and organizational routines and processes related to the collection, aggregation, analytics, and application of data aimed at automating business processes, gaining insights, and collaborating with internal and external organizational members (Kaplan & Haenlein, 2019).

The technological–organizational–environmental (TOE) framework (Tornatzky et al., 1990) is recognized as among the most influential to explain how contextual and firm-level factors influence the *adoption* of technologies in innovation (Asadi et al., 2021; Chatterjee, Rana, et al., 2021; Kinkel et al., 2022; Mitra et al., 2020; Ullah et al., 2021; Uren & Edwards, 2023). Therefore, the TOE framework is an appropriate model to examine the literature on AI and understand the adoption dynamics because it takes into account the contextual factors that influence the adoption of new tech-based solutions (Baker, 2012; Tornatzky et al., 1990), including the technological (e.g., specialized characteristics), organizational (e.g., processes and practices), and environmental (e.g., regulations and industry dynamics) contexts

Practitioner points

- Managers must have a firm grasp of the technological, organizational, and environmental context before and after AI adoption to reap its benefits.
- AI adoption has the potential to replace, reinforce, or reveal innovation management processes and practices.
- AI requires innovation enabling capabilities to be successfully adopted.
- AI adoption influences innovation capabilities (i.e., enabling and enhancing) that enable organizations to innovate better.

(Baker, 2012). While the technological context emphasizes that information technology (IT) capabilities are critical to first adopt and then maintain AI (Enholm et al., 2022), it is unclear how these competencies are modified by AI adoption (Correani et al., 2020; Magistretti et al., 2019). Likewise, in the organizational context, researchers identify practices that firms should adopt to fully benefit from AI (Garbuio & Lin, 2019), but without offering a condensed view of the practices and structures, thereby creating a murky landscape for managerial researchers attempting to advance this emerging field (Kinkel et al., 2022). Finally, while scholars are increasingly examining the influence of environmental elements on AI adoption (Bai & Li, 2020) and the regulatory uncertainty associated with AI-related risks (von Hippel & Kaulartz, 2021), the literature is unclear as to how AI influences other actors and systems in the environment.

The fragmented and multifaceted nature of AI adoption that emerges in the innovation management literature leads us to highlight three main shortcomings. First, the paucity of theory-driven empirical AI research. Even in academic studies, most contributions offer evidence based mainly on a few successful cases, but not explicitly rooted in any theoretical lens (Haenlein & Kaplan, 2019; Verganti et al., 2020). This has led to numerous process- and practice-based depictions of AI adoption that lack coherence about its role in enriching innovation capabilities (Wu et al., 2021). Second, most AI representations are "normative and essentialist" in nature (Yang et al., 2021), mainly conceptualized as a technology that enables innovation within a defined timeframe and context (Iansiti & Lakhani, 2020). This conceptualization only tangentially addresses the competencies that managers and innovators need to possess, learn, and cultivate to drive AI adoption. The innovation capability perspective derives from organizations calling for mastering this emerging technology and capturing the value generated (Wetzels, 2021). Third, some studies propose a sectoral and partial view of different AI applications (Kaplan & Haenlein, 2019), hindering a broader understanding of the AI adoption phenomenon at a more systemic and holistic level in innovation management.

Given the important but fragmented view of AI adoption in innovation management, our systematic literature review aims to understand AI adoption in relation to innovation capabilities and real-world applications by addressing the following research questions: *What is the role of AI in influencing innovation capabilities? How can AI capabilities be conceptualized in line with relevant theories to unveil their relationship in the innovation management literature? What are the main differences in AI applications for innovation management? How might an AI taxonomy of different applications inform the innovation management field?*

To answer these questions, we conducted a systematic literature review (Tranfield et al., 2003) to unveil the innovation capabilities and provide a taxonomy of AI adoption in the innovation field. Our review was also motivated by interviews with innovation managers at two medical technology firms, Essity Healthcare and Getinge, as well as discussions with IBM managers and consultancies involved in implementing AI in products and services, such as Tangity (part of the NTT DATA Design Network) and Deloitte Digital. In the initial screening, our inclusion and exclusion criteria led us to 3566 articles published up to July 2023, which further screening reduced to 127, and after a full reading, a final set of 62 empirical articles. In reviewing the literature, we adopted the TOE framework (Tornatzky et al., 1990), which allowed us to organize the contributions, develop a theoretical framework, delve deeper, and take a holistic view beyond the normative approaches of other studies (Baker, 2012; Oliveira & Martins, 2011; Ullah et al., 2021). Finally, through this framework, we identified relevant future research avenues to help managers and scholars disentangle the multifaceted nature of innovation capabilities and their essence for AI adoption.

The contributions of our study are threefold. First, our review contributes to the innovation management field (Wetzels, 2021) by highlighting how AI adoption influences innovation capabilities (Garbuio & Lin, 2021; Verganti et al., 2020). Our analysis reveals a dual perspective, suggesting that AI adoption requires a set of *enabling capabilities* that act as foundational elements, and once employed, AI promotes *enhancing capabilities* that allow organizations to fully benefit from the algorithms. This advances our understanding of innovation capabilities (Subramaniam & Youndt, 2005) when the focus is on technological innovation, that is, AI applications. The second contribution is offering a theoretical framework that, based on TOE (Tornatzky et al., 1990), proposes a more comprehensive framework that encompasses the different dimensions relevant for dealing with a complex and rapidly growing phenomenon, such as AI (Kaplan & Haenlein, 2019). In particular, the framework advances academic knowledge about the role of AI determined by multiple factors (i.e., technological, organizational, and environmental). Third, we propose a taxonomy of AI applications by systematically analyzing the applications presented in the different studies. A taxonomy is defined as a classification system of a phenomenon, the theory on which the classification system is based, and the methods used to construct it (Chrisman et al., 1988). Drawing on the TOE framework based on diffusion and adoption theory, we construct a taxonomy of AI applications consisting of three different taxa: *replace*, *reinforce*, and *reveal*. These three different means of AI adoption inform innovation scholars and practitioners on how AI can be applied to innovations. Together, these three contributions help us reconcile prior studies with existing knowledge and open up interesting avenues for future research.

2 | THEORETICAL BACKGROUND

In the following, we recall the literature on innovation capabilities and the link with AI adoption. Thereafter, we present the TOE framework (Tornatzky et al., 1990), primarily used in technology adoption studies (Kinkel et al., 2022; Ullah et al., 2021), to systematize the literature in a framework and develop a research agenda.

2.1 | The influence of AI adoption on innovation capabilities

Although AI has been debated in the literature for decades (von Krogh, 2018), in the last 20 years, the discussion has moved toward nontechnological issues (Glikson & Wooley, 2020). Indeed, the increasing adoption of this technology in many fields has shown its potential in unforeseeable contexts (Kaplan & Haenlein, 2019). From manufacturing (Björkdahl, 2020; Kinkel et al., 2022) to healthcare (Gama et al., 2022), AI has been examined as a digital technology that can transform and revolutionize the way we conceive innovation (Magistretti et al., 2019). In the academic literature, AI is recognized as an emerging field with enormous potential (Brem et al., 2021), a technology capable of sensing, interpreting, informing, and evaluating information

(Ferràs-Hernández, 2017), characterized by re-programmability and self-reference (Yoo et al., 2010). Re-programmability implies its use in different fields, naturally adapting to diverse contexts (Haenlein & Kaplan, 2019) and adopted in many industries, hence a general-purpose technology (Yang et al., 2021). These multifaceted interpretations of AI as a digital general-purpose technology (Gambardella & McGahan, 2010; Magistretti et al., 2019) reveal not only its real and potential impact, but also its different roles in the innovation process (Makarius et al., 2020).

The literature also highlights an innovation capability perspective in the adoption of AI solutions (Raj & Seamans, 2019). Innovation capabilities are defined as the "skills and knowledge needed to effectively absorb, master and improve existing technologies, and to create new ones" (Romijn & Albaladejo, 2002, p. 1054). In other words, the capabilities that organizations possess and nurture to innovate (Barczack, 2012; Camisón & Villar-López, 2014). AI is considered a critical technology that influences innovation capabilities, leading to augmentation or automation in the decision-making process (Raisch & Krakowski, 2021), product and service development, and abductive reasoning (Brynjolfsson & Mitchell, 2017; Kellogg et al., 2020). However, the influence of AI is not limited to internal capabilities, also critical in facilitating human-centeredness and real-time interactions (Verganti et al., 2020). As recently reported by Bouschery et al. (2023), the use of AI can augment human innovation in team activities by generating discussion and divergence in design thinking processes.

The different uses of AI require a more nuanced understanding of the technology. Iansiti and Lakhani (2020) refer to strong AI as simulating managerial reasoning and decision-making, while weak AI refers to automating basic tasks. Indeed, in the case of weak AI adoption, new technological, organizational, or environmental capabilities are not needed because it is seen as a black box, a tool replacing mechanical and analytical tasks (Huang & Rust, 2018), for instance, image recognition and tagging before uploading photos to an e-commerce catalog (Cao et al., 2021). Strong AI is more profound and promising, supporting the decision-making process (Shrestha et al., 2019) and crafting innovative scenarios and solutions (Garbuio & Lin, 2021). In this case, new capabilities are needed for new interpretations of the information emerging from the AI analysis (Verganti et al., 2020). This is the case of Netflix, where AI supports the plot writer in crafting a more engaging story (Smith & Telang, 2018). AI is also a source of developing innovation capabilities (Correani et al., 2020), as its adoption requires new competencies and supports organizations in fostering these. This latter perspective is less researched, albeit very promising. A strong link between AI technology adoption and the development of new capabilities can strengthen the perceived potential of this technology in many fields (Enholm et al., 2022), thereby significantly increasing its adoption.

Finally, AI has been studied according to different applications (Brock & von Wangenheim, 2019; Lou & Wu, 2021). In innovation studies, many emphasize the role of AI in advancing the performance of solutions (Metcalf et al., 2019), or the technical skills that employees need to integrate AI in products (e.g., algorithm management, machine learning capabilities, and sensor expertise), showing that AI applications outperform human activities. Other studies report that cybersecurity issues and vulnerabilities are important aspects of AI adoption (Hepfer & Powell, 2020), and that AI can support faster service delivery due to autonomous decision-making algorithms (Chatterjee, Rana, Tamilmani, & Sharma, 2021) by substituting human activities. AI adoption in service solutions is recognized as a valuable digital technology to seize emerging opportunities (Correani et al., 2020). Finally, some scholars point out that AI can be considered an intangible asset enabling a disruptive business model (Olabode et al., 2022), opening a new frontier in AI applications.

Overall, the role of AI in innovation capabilities is important for theory and practice due to its impact on innovation and organizational dimensions (von Krogh, 2018). AI can influence the capability lifecycle and act as a selection event in the transformation or creation of new capabilities (Helfat & Peteraf, 2003). Moreover, the literature identifies numerous different practices, routines, and ultimately capabilities as relevant means that influence different AI applications in innovation (Davenport & Ronanki, 2018). Thus, a review of the literature and mapping the emerging AI capabilities and applications can advance the innovation management field by clarifying the role of AI in innovation (Cennamo et al., 2020; Glikson & Wooley, 2020; Haenlein & Kaplan, 2019). In summary, the above theoretical background demonstrates the multifaceted nature of the AI literature and unveils the diverse interpretations and effects of the phenomenon.

2.2 | Interpreting AI adoption through TOE, a theoretical framework

As reported in the previous section, the AI innovation management literature is multifaceted and presents different perspectives (Brock & von Wangenheim, 2019; Glikson & Wooley, 2020), calling for a synthetic view of the role of AI in innovation management. Given the predominance of the technological dimension (e.g., algorithm design and proof-of-concept; Chatterjee, Chaudhuri, et al., 2021), and the technical capabilities required to adopt AI solutions (Iansiti & Lakhani, 2020), aspects of acceptance and ethics should also be considered (Vlačić et al., 2021). Given the inner attributes of radical novelty, prominent impact, and fast growth (Rotolo et al., 2015), AI is seen an emerging and powerful technology supporting innovation at different levels and with varying objectives (Garbuio & Lin, 2021; Verganti et al., 2020). We thus rely on the TOE framework (Tornatzky et al., 1990) to explain how these three firm-level factors influence the adoption and implementation of technological innovations (Baker, 2012) in accordance with technology adoption studies (e.g., Oliveira & Martins, 2011) and the growing use of this framework (Asadi et al., 2021; Kinkel et al., 2022; Mitra et al., 2020; Ullah et al., 2021). Indeed, the TOE framework considers the contextual factors influencing technology adoption (Baker, 2012; Tornatzky et al., 1990), including technological specificity (e.g., unique characteristics), the organizational dimension (e.g., processes and practices), and finally, the environmental dimension (e.g., regulations and industry dynamics). The framework proposes a synthetic view of the contextual aspects that influence the adoption of technology in organizations (Baker, 2012). Numerous studies use the TOE framework to empirically investigate AI adoption (e.g., Chatterjee, Rana, et al., 2021; Chen, 2019; Guan et al., 2020; Kinkel et al., 2022; Kruse et al., 2019; Pillai & Sivathanu, 2020; Ullah et al., 2021; Zerfass et al., 2020), thus appropriate to organize our AI adoption literature review. Moreover, given the shift toward focusing on the role of AI in innovation capabilities (Barczack, 2012; Wetzels, 2021), and not only on the technological aspects of AI, the TOE perspective helps define the technological, organizational, and environmental prerequisites and the changes needed to adopt a technology (Tornatzky et al., 1990).

Therefore, to advance our understanding of AI adoption in innovation, we propose a theoretical framework that leverages the TOE framework dimensions (Tornatzky et al., 1990) to map the AI capabilities and applications. Specifically, we identify different innovation capabilities in the technological, organizational, and environmental dimensions, and construct a taxonomy of AI applications according to the different types of innovation fostered by AI adoption (Davenport et al., 2020).

3 | SYSTEMATIC LITERATURE REVIEW

We followed the systematic literature review process of Tranfield et al. (2003) to investigate the role of AI in innovation capabilities and its applications. The review is organized in three phases: *planning*, *conducting*, and *synthesizing*.

In the *planning phase*, we conducted a scoping review to assess the extent and scope of research on AI adoption, the capabilities, and the shortcomings in the literature. In addition, we undertook the review as a result of the complex nature of AI and the lack, to the best of our knowledge, of a holistic view of AI in the field of innovation management. Our motivation was also influenced by the literature, such as Wetzels (2021), and discussions at conferences with experts in the innovation management field.

In the *conducting phase*, we used the Scopus database to generate a list of research articles related to AI adoption, in line with several literature reviews published in the Journal of Product Innovation Management (e.g., Magistretti et al., 2021; Randhawa et al., 2016). Scopus is one of the largest and most comprehensive databases (e.g., Riahi et al., 2021). The selected subject areas include arts and humanities, business, management and accounting, decision sciences, economics, econometrics and finance, multidisciplinary, psychology, and social sciences. The reason for this comprehensive list of subject areas is the multidisciplinary nature of AI (Haenlein & Kaplan, 2019; von Krogh, 2018).

Thereafter, we selected keywords based on an in-depth analysis of prior AI reviews in the business domain (e.g., Borges et al., 2021; Toorajipour et al., 2021; Vlačić et al., 2021), our experience in the field, interviews with practitioners and scholars in the AI domain, and discussions at conferences where we presented a previous version of this study. We used two subsets of Boolean search terms for data extraction, including the prefix innovat* and AI-related terms. Therefore, the keywords used are artificial intelligence, intelligent system, machine learning, deep learning (OR) with innovat* (AND). Studies were eligible for inclusion if written in English and published in journals. Only scientific empirical studies qualified for inclusion, providing evidence-based results from practical experiences or observations. Conference proceedings, books, abstracts, editorials, and technical reports were excluded (Meier, 2011). The electronic database search was supplemented by snowball sampling of high-ranking quality journals to avoid missing any important and relevant studies (Greenhalgh & Peacock, 2005). This initial search yielded 3566 unique hits. The data range includes articles published up to July 2023. The full search query string is available in Table A1.

In the *synthesizing phase*, we downloaded the information of the 3604 articles into the collaborative software Rayyan (Ouzzani et al., 2016) for evaluation. This phase was essential to avoid including articles not relevant to the role of AI in innovation capabilities in terms of fit and quality. Regarding fit, because AI terms have been misused to increase attention and likelihood of publication, we also restricted the inclusion criteria to account for this aspect, limiting the possibility of including articles outside our scope. We used four exclusion criteria to eliminate unsuitable articles, comprising publication type (e.g., books), perspective (e.g., proof-of-concepts), unit of analysis (e.g., education field), and research quality (e.g., journal rank). For research quality, we excluded all articles published in journals not included in the 2021 Chartered Association of Business Schools (ABS) ranking. In line with other recent reviews on emerging technologies (e.g., Stornelli et al., 2021) and published in the Journal of Product Innovation Management (Gradillas & Thomas, 2023), ABS-ranked journals are more likely to have in place rigorous peer review processes that increase the credibility of the evidence and minimize the inclusion of potentially unreliable or biased research. We independently read and screened the 1030 abstracts and recorded our decision on the Rayyan web platform. The agreement scores for the first articles were substantial (κ score >0.6). After this step, we selected 127 articles as "check full text" for final approval. Table 1 reports the inclusion and exclusion criteria.

After the full-text reading, we retained 62 empirical articles (identified with an asterisk in the references) and created a structured data matrix on the same number of articles in the final stage, as shown in Figure 1. A summary of all included articles, their categorization in the identified context, research method, and journal ABS ranking is reported in Appendix A1.

Following prior reviews, our content analysis was guided by two main aims: conceptualizing the object of analysis and proposing a future research agenda. Regarding the former, we proceeded with searching for capabilities and building the taxonomy. First, we categorized the articles based on the TOE framework using the TOE characteristics and elements of Kinkel et al. (2022) and Sun et al. (2020) for their identification. Second, we identified the predominant capabilities in each article related to the TOE framework. We performed the classification using the MAXQDA software, which accelerated the development of the initial versions of the data structure by quickly providing visual tools to perceive the patterns and gaps in each context. The innovation capabilities in the TOE contexts were not mutually exclusive, as some were classified into multiple contexts in the initial analysis (e.g., partnering agility and multimodal value co-creation). We ensured methodological rigor through constant comparison, reflexive analysis, and peer debriefings. We conducted axial coding upon completion to check for interpretation consistency and to build coding levels resulting in a hierarchical data structure. We then produced a narrative synthesis of the findings of the sample articles, showing the emergence of innovation capabilities that influence AI adoption, and thereby identifying avenues for further research.

TABLE 1 Inclusion and exclusion criteria.

	Inclusion criteria	Reason for inclusion
1	Empirical studies	Quantitative and qualitative studies offer empirical evidence based on direct or indirect observation of the adoption of AI in innovation management.
2	Innovation management outcomes	The findings contribute to innovation management and discuss the necessary or the generated innovation capabilities for AI adoption, implementation, and use in innovation settings.
3	Perspective	Studies that employ AI as the primary tool/perspective/focus offer specific reflections on AI use. We follow Benbya et al.'s (2020, p. 9) definition of AI: "ability of machines to perform human-like cognitive tasks."
	Exclusion criteria	**Reason for exclusion**
1	Publication type	Books, book chapters, conference proceedings, gray literature, theses, and review articles, as they may not have been scrutinized by peers.
2	Perspective	Articles not related to innovation in organizations (e.g., agriculture, education), as unrelated subjects may deflect the discussion toward other audiences.
3	Unit of analysis	Articles that appear as mathematical models based on AI (e.g., pure proof-of-concept) and those not specifically investigating AI capabilities (e.g., industry 4.0, big data, IoT, data analytics).
4	Research quality	Articles published in journals that are not ABS ranked. ABS serves as the reference list for peer review journals in which business and management research are published. Given the focus of the review on innovation capabilities, ABS is a suitable screening level for articles that specifically pertain to the scope of the review.

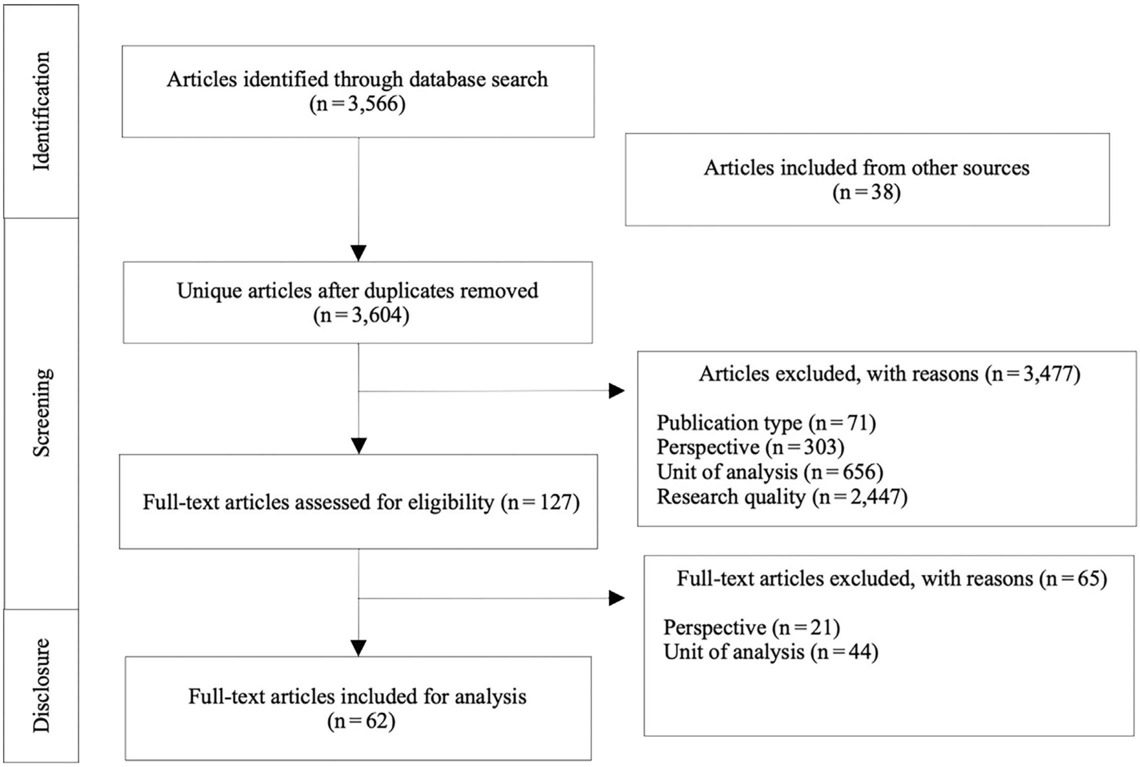


FIGURE 1 Selection of articles.

We also categorized the articles in the collection according to the method used (qualitative or quantitative). We grouped the qualitative empirical articles that report disclosed case histories of AI adoption based on the TOE framework (Tornatzky et al., 1990). We used the TOE characteristics and elements as a theoretical perspective to identify the differences in AI adoption across applications. The analysis of the disclosed qualitative case studies in the selected sample allowed us to identify different AI adoption taxa according to the Chrisman et al. (1988) taxonomy definition. We iteratively verified that the different taxa were mutually exclusive. We concluded the analysis of AI applications by proposing a taxonomy that informs the research agenda for future AI applications.

4 | THE LITERATURE ON INNOVATION CAPABILITIES TRIGGERED BY AI ADOPTION AND AI APPLICATIONS

In this section, we disentangle the influence of AI adoption on innovation capabilities. We identify and group the innovation capabilities discussed in the empirical literature by unveiling how AI adoption influences innovations capabilities in different contexts through the TOE framework (Tornatzky et al., 1990). Thus, in each section below, we report the AI innovation capabilities and applications according to the three contexts of the TOE framework, namely technological, organizational, and environmental. We also pair each identified capability with a real-world example of an AI application, reporting the context of use and its benefits to firm innovativeness (Davenport et al., 2020).

4.1 | Innovation capabilities triggered by AI adoption and AI applications: Technological context

4.1.1 | Functional competence

The analyzed literature indicates that AI adoption requires new capabilities that are both AI-specific (e.g., ability to manage large-scale pretrained language models, such as BERTweet) and generic (e.g., understanding modern programming language, such as Python) (Kinkel et al., 2022). Specific capabilities are directly related to particular domains, tasks, or databases, while general capabilities are applicable across various domains, tasks, or databases (Mayer & Salomon, 2006). In the technological context, internal functional competence is pivotal to develop, implement, and later maintain AI algorithms (Igna &

Venturini, 2023; Khan et al., 2023; Zhang et al., 2021). This competence refers to team proficiency in integrating algorithmic functions in products, services, and processes through data gathering, processing, and transmission within and across devices and platforms (Bessen et al., 2022). The integration of algorithmic functions demands proficiency in modeling and programming (Kinkel et al., 2022), expertise in data collection and transmission, abilities in developing self-calibrated devices (Agarwal et al., 2021), using proprietary training data (Bessen et al., 2022), and ultimately emulating actions in specific innovation activities (Zhang et al., 2021). Notably, proficiency in technical knowledge alone is deemed insufficient for AI adoption, as cognitive and social skills are also required (Karaevli et al., 2020). In addition, the perceived economic value of streamlining complex processes (e.g., the cost-performance trade-off) is a key determinant of successful AI adoption in conservative industries (Khan et al., 2023).

Within functional competencies, examples of AI applications include the use of Edge AI in autonomous machine tools (see Agarwal et al., 2021). In this case, a team of experts successfully developed unmanned garden tools to operate in rough terrain, remote locations, and steep slopes without human intervention. The benefits of Edge AI for innovation rely on real-time decision-making where latency and bandwidth are problematic, providing greater security as the data does not leave the device, and ultimately low maintenance costs (Agarwal et al., 2021).

4.1.2 | Cybersecurity management

Considering the technological contexts, researchers also indicate that most data are network-generated (Brock & von Wangenheim, 2019), which increases the risks of security breaches, pushing organizations to develop cybersecurity management capabilities prior to AI adoption (Rodríguez-Espíndola et al., 2022). Cybersecurity management has become vital to secure data-sharing in real-time, protect access rights, intrusion detection, and data integrity for public and private organizations (Brock & von Wangenheim, 2019; Sjödin et al., 2021). Unlike functional competencies, cybersecurity management refers to the firm's ability to develop, use, and maintain AI-based services protected from internal and external vulnerabilities (Hepfer & Powell, 2020). This is a transdisciplinary field that combines risk assessment and management, aiming to strengthen algorithms for malware classification, intrusion detection, and threatening intelligence sensing (Boyson et al., 2022). When employed, cybersecurity competencies can affect user trust, thereby facilitating the adoption of AI in services (Abou-Foul et al., 2023). Yet, despite its importance, there is little evidence that cybersecurity management is effective in containing all types of breaches (Boyson et al., 2022). The literature emphasizes that this is a new and critical capability that should be mastered to mitigate service security breaches.

Within cybersecurity management, examples of AI applications include practices to safeguard and monitor ship management in real-time operations. The multiple case study of Sjödin et al. (2021) explores a ship control systems firm that adopted AI to advance digital services for fuel optimization, predictive maintenance, and route optimization. The empirical data show the importance of cybersecurity management to identify potential threats to ensure robust connectivity and real-time data flow of multiple equipment performances in offshore operations.

4.1.3 | Ambidextrous competence

The empirical literature indicates that AI adoption fosters the development of *ambidextrous competencies* (Lou & Wu, 2021), referring to the firm's ability to exploit existing IT knowledge for operational efficiency while simultaneously identifying new skills to help innovate and create differentiated customer value (Chatterjee, Rana, Tamilmani, & Sharma, 2021). Exploitative competencies aim to deliver high-quality services at a lower cost (Chatterjee, Rana, Tamilmani, & Sharma, 2021), while exploratory competencies aim to sense and seize opportunities made possible by emerging technologies (Chatterjee, Chaudhuri, et al., 2021).

For example, Dicuonzo et al.'s (2023) qualitative study in healthcare indicates that AI adoption favors collaboration among "tech-savvy" and business experts to innovate. In practical terms, AI adoption encourages IT project members to be proficient in exploitative and explorative modes, thereby learning to operate with dual agendas and conflicting time horizons (Karaevli et al., 2020). Ambidextrous competencies can be observed in the development of the new antibiotic—Halicin—and other drugs (see Lou & Wu, 2021). In this case, the drug development firm combined machine learning with a convolutional neural network with a chemical library to discover new drugs. The study suggests that the main effect of AI adoption is attributed to employees with a combination of AI skills and drug discovery domain expertise, as opposed to employees with only AI skills (Lou & Wu, 2021).

Table 2 summarizes the innovation capabilities influenced by the adoption of AI and real-world examples in the technological contexts.

TABLE 2 Summary of findings of the innovation capabilities triggered by AI adoption and AI applications: technological context.

Technological context			
Innovation capability	**Description**	**Examples of AI application**	**Key references**
Functional competence	AI adoption requires *functional competencies*. This refers to team proficiency in embedding algorithmic functions in products and processes through data gathering, processing, and transmission within and between devices and platforms.	A forest and garden tool firm, empowered by Edge AI, developed unmanned tools to operate in rough terrain, remote locations, and steep slopes with no human intervention (e.g., machinery firm).	Agarwal et al. (2021); Bessen et al. (2022); Khan et al. (2023); Kinkel et al. (2022); Igna and Venturini (2023); Zhang et al. (2021)
Cybersecurity management	AI adoption requires *cybersecurity management*. this refers to the organization's ability to identify, evaluate, and monitor potential risks against internal and external vulnerabilities.	A ship control systems firm uses risk management routines in AI applications to mitigate threats and safeguard real-time dataflow in offshore operations (e.g., marine system firms).	Abou-Foul et al. (2023); Boyson et al. (2022); Brock and von Wangenheim (2019); Rodríguez-Espíndola et al. (2022); Sjödin et al. (2021)
Ambidextrous competence	AI adoption favors *ambidextrous competencies*. This refers to the IT personnel's ability to exploit existing competencies for operational excellence while simultaneously exploring novel AI solutions.	A drug discovery firm benefits from ambidextrous competencies to discover a new antibiotic able to kill many species of antibiotic-resistance bacteria (e.g., Halicin case)	Chatterjee, Chaudhuri, et al. (2021); Chatterjee, Rana, Tamilmani, and Sharma (2021); Dicuonzo et al. (2023); Lou and Wu (2021)

4.2 | Innovation capabilities triggered by AI adoption and AI applications: Organizational context

4.2.1 | Search and recombine knowledge

Empirical studies indicate that top managers have an essential role in searching and recombining knowledge prior to AI adoption (Warner & Wäger, 2019). Top managers provide headroom and R&D resources for exploratory trials, promote sharing AI experiences, feedback, and actively engaging staff in experiencing AI developments in line with the organization's digital technology strategy (Warner & Wäger, 2019). Top managers also allocate significant resources to democratize AI knowledge, with the goal of making AI accessible to the entire organization and demonstrating its potential and risks (Sjödin et al., 2021). The culture of searching and recombining knowledge helps managers foster employees' willingness to experiment with AI solutions in innovation (Bouschery et al., 2023). Incentives facilitate a data-driven culture and expose members to small trial and error experiments (Warner & Wäger, 2019). The objective is to enable members to identify and try AI applications across business units and ultimately create collaborative innovation projects. Support from top managers is also critical to understanding the institutional pressures from suppliers, customers, and governments to improve skills and accelerate AI adoption across different innovations (Bag, Pretorius, et al., 2021). Finally, managerial support assists in searching for novel solutions to implement AI in products, shedding light on (un)intended consequences, and recombining resources for incremental and radical innovations (Chatterjee, Rana, et al., 2021; Yams et al., 2020).

General Motors is an automotive firm that adopted AI in generative design applications to optimize its materials, costs, and manufacturing methods, and make auto parts 40% lighter and 20% stronger. In their study, Füller et al. (2022) underline the importance of searching and recombining capabilities to promote adoption behavior by establishing concrete principles, offering specific incentives and implementation options. Similarly, in mining equipment firms, managers use data visualization artifacts (e.g., dashboard) to promote AI adoption. Leaders compare customer AI practices that help employees understand the value of AI (Sjödin et al., 2021).

4.2.2 | Digital project governance

A debate has emerged in service-oriented firms on whether algorithmic development projects require digital project governance prior to adoption (Mikalef et al., 2021). Given the high exposure to moral and ethical liabilities, the literature indicates the need for specific AI project management procedures and roles prior to adoption (Correani et al., 2020). Procedures include data management (i.e., access, storage, and control), actions to maintain user privacy (Correani et al., 2020; Uren & Edwards, 2023), and data ownership rights and consent (Mikalef et al., 2021). Roles comprise fairness, accountability, and transparency (Tambe et al., 2019). The debate is not limited to project delivery and has recently extended to service maintenance (Correani et al., 2020), including the requirement to mitigate concept drift where AI model accuracy degrades over time, advocating reviewing and periodically retraining the algorithm (Tambe et al., 2019).

In this sense, Vodafone and CNH Industrial adopted AI in their product and service innovations (Correani et al., 2020). Vodafone improved customer service by using autonomous conversational interfaces based on AI that operates across multiple channels (e.g., web, home assistants, apps, chatbots). CNH Industrial developed unmanned agricultural machines endowed with AI that operate through a digital platform (Correani et al., 2020). This research emphasizes the importance of implementing data project governance to ensure the confidentiality of data via internal policies, privacy guidelines, and encryption to protect the data. Similarly, Google created an AI Advisory Council to address the ethical vulnerabilities of its algorithms (Tambe et al., 2019). This research highlights the importance of digital project governance to comply with privacy regulations to protect employee data.

4.2.3 | Augmented decision-making

The literature also shows that AI adoption influences the development of augmented decision-making (Bag, Gupta, et al., 2021; Keding & Meissner, 2021), amplifying team perceptions, accurate assessments, accelerated real-time decisions, streamlining R&D resource allocation, and thereby improving decisions (Chaudhuri et al., 2021; Keding & Meissner, 2021; Metcalf et al., 2019). Although the literature points to numerous benefits of AI adoption in the decision-making process (de Carvalho Botega & da Silva, 2020), researchers warn that accepting AI advice can lead to overreliance, creating the need to systematically review AI outcomes (Keding & Meissner, 2021). In delving deeper into the acceptance of AI advice, an ambiguous perception emerges. On one side, a top manager may champion AI adoption, given the possibility of a more structural process, or be skeptical due to the lack of transparency and ability to explain the outcomes (Chaudhuri et al., 2021). Moreover, ambiguous perceptions of the perceived usefulness of AI in decision-making can lead to conflicting reliance and ultimately AI failure.

Metcalf et al.'s (2019) study provides a real-world example, examining the effectiveness of artificial swarm intelligence as a collaborative technology that can overcome the challenges of group decision-making. Artificial swarm intelligence is shown to enhance the intelligence of human groups, facilitating better business decisions by addressing the limitations commonly associated with traditional group decision-making processes. It also contributes to understanding the use of AI to supplement team collaborative efforts in making business decisions, rather than replacing them altogether.

4.2.4 | Processes optimization

The empirical literature also indicates that AI-enabled firms can accelerate process optimization (Akter et al., 2021). Referred to as processes that enable the organization to capture and analyze data generated by service systems to improve or personalize service encounters, process optimization allows managers to create value for providers and customers (Akter et al., 2021; Cao et al., 2021). Process optimization can generate insights from statistical, contextual, cognitive, and predictive models (Brynjolfsson et al., 2019), allowing managers to foster business agility (Wang et al., 2022). Despite the expected benefits, researchers signal that AI is contingent on task type. For example, mechanical and analytical tasks can use AI, while intuitive and empathetic tasks require caution (Huang & Rust, 2018). Moreover, the process optimization capability suggests that managers should be vigilant about algorithmic biases when using AI (Akter et al., 2022; Choudhury et al., 2020; van Giffen et al., 2022).

A real-world case is an international trading firm that adopted AI to increase its business (Brynjolfsson et al., 2019). eBay successfully implemented machine translation tools to optimize its processes and ultimately increase exports for less experienced buyers and cheaper products. The study predicted that AI would have a positive impact on productivity and trade, further optimizing processes in applications such as medical diagnosis, customer support, hiring decisions, and self-driving vehicles. Similarly, the Australian Tax Office prepopulates information on the tax form to simplify tax filing (Akter et al., 2022), thereby automating taxpayer reporting and reducing involuntary errors.

4.2.5 | Automatic problem-solving

AI adoption allows firms to advance problem-solving-activities. Automated problem solving refers to the firm's ability to rapidly search, refine, and prioritize ideas with the support of algorithms (Christensen et al., 2017; Kakatkar et al., 2020). The literature indicates that AI is often operationalized in cloud-based forums or idea crowdsourcing platforms intended to allow users to discuss unmet needs, unarticulated desires, and propose ideas (Govindan, 2022; Hoornaert et al., 2017). Supervised machine learning has been implemented to evaluate product ideas according to novelty, feasibility, and value based on user-generated content (Christensen et al., 2018). In practice, the insights gained from the AI experience expand the problem search frame and amplify the relevance and plausibility of the hypotheses (Garbuio & Lin, 2021). However, the literature emphasizes the need to diligently evaluate AI to avoid biases during AI operationalization (Lebovitz et al., 2021).

An example includes the development of a proof-of-concept to identify innovative ideas in social media related to the Norwegian brewery, Nøgne Ø. In the experiment, the algorithm identified the need to develop a gluten-free beer (see Christensen et al., 2018). The user content indicated a recipe to add color and taste to beers. Another example is a Danish expansion joint firm that adopted AI to identify novel frugal innovations (see Govindan, 2022). Expansion joints are used in various applications, including chemical and power plants, gas turbines, oil rigs, steel mills, and offshore. The firm integrates AI in its portfolio to observe how customers use and customize products to create sustainable innovations.

Table 3 summarizes the innovation capabilities influenced by the adoption of AI and real-world examples of AI applications in organizational contexts.

4.3 | Innovation capabilities triggered by AI adoption and AI applications: Environmental context

4.3.1 | Screening regulations

The empirical literature suggests that firms should develop routines to screen regulations before adopting AI (von Hippel & Kaulartz, 2021). The evidence indicates that the AI regulatory environment is rapidly evolving, attracting increasing attention from government and political institutions where security lapses can have serious consequences (von Hippel & Kaulartz, 2021). Privacy and consent are concerns that are echoed throughout the literature, imposing strict algorithm development practices (e.g., data anonymization; Martin, 2019; Rammer et al., 2022). However, the importance of such practices does not appear to be a major concern among experts. According to a recent Delphi study, experts do not prioritize AI-related regulations as a top priority for technology adoption, indicating that despite its importance, it is not a necessary capability (Stahl et al., 2023).

In their multiple case study, Trocin et al. (2021) investigate the affordances of AI adoption in recruitment and staffing. The cases highlight the importance of implementing screening routines prior to AI adoption to monitor privacy and security regulations, such as General Data Protection Regulation (GDPR), the California Consumer Privacy Act (CCPA), or the Personal Data Protection Act (PDPA; von Hippel & Kaulartz, 2021).

4.3.2 | Partnering agility

Firms respond to the complex regulatory framework through *partnering agility*. This innovation capability refers to firms' ability to swiftly coordinate and control external partners to operationalize AI development and implementation (Teece et al., 2016; Warner & Wäger, 2019). Partnering agility involves developing AI solutions in global networks of interdependent partners, complementors, providers, and customers for value creation and delivery (Burström et al., 2021). In an ecosystem context, firms can adopt AI to detect future technologies (Mühlroth & Grottke, 2020), create knowledge alliances (Bai & Li, 2020), renew their business models (Åström et al., 2022), and forecast customer operational use (Burström et al., 2021). Partnering agility allows firms to build a network of strategic, extended, or virtual partnerships to exploit and explore AI opportunities with multiple partners.

Burström et al. (2021) examine four real-world cases of AI adoption in global Swedish firms. One of the cases is a mining firm that uses AI to optimize the preparation and maintenance of heavy machinery. The study suggests that firms can use AI to reconfigure the ecosystem strategy in the short term and revitalize it in the long term.

4.3.3 | Multimodal value co-creation

The empirical literature also suggests that adopting AI solutions favors multimodal value co-creation with external partners (Li et al., 2021; Verganti et al., 2020). This is an iterative and collaborative process centered on creating value through meaningful interactions and engagement with actors (Li et al., 2021). Multimodal value co-creation entails the organization's ability to broaden the scope of traditional services in real time with partners (Verganti et al., 2020). The interconnected

TABLE 3 Summary of findings of the innovation capabilities triggered by AI adoption and AI applications: organizational context.

Organizational context			
Innovation capability	**Description**	**Examples of AI application**	**Key references**
Searching and recombining knowledge	AI adoption requires top manager support to *search and recombine knowledge* related to AI. Managers seek solutions, provide headroom and R&D resources, share experiences, provide feedback, and empower staff to experience AI developments.	An automotive firm adopted AI in design applications to reduce the weight of its vehicles. The search and recombination capability are recommended in the form of compliance inducements, such as incentives, best practices, and implementation options (e.g., General Motors).	Bag, Pretorius, et al. (2021); Chatterjee, Rana, et al. (2021); Füller et al. (2022); Yams et al. (2020)
Digital project governance	AI adoption requires specific *digital project governance*. The practices include data management, data ownership and access rights, privacy and consent, code of ethics for AI-related initiatives, and creating an AI Council with representatives from all stakeholders.	A telecommunication firm used AI to improve customer service across multiple channels (e.g., web, home assistants, apps, chatbots). Data project governance included internal policies and privacy guidelines to protect data (e.g., Vodafone).	Correani et al. (2020); Mikalef et al. (2021); Tambe et al. (2019); Uren and Edwards (2023)
Augmented decision-making	AI adoption favors *augmented decision-making*. It positively influences managers' choices and enhances the perception of decision process outcomes.	A software development firm developed algorithmic-based platforms to augment group decision-making for more accurate forecasting, assessments, evaluations, and insights (e.g., Unanimous AI).	de Carvalho Botega and da Silva (2020); Bag, Pretorius, et al. (2021); Chaudhuri et al. (2021); Keding and Meissner (2021); Metcalf et al. (2019)
Processes optimizations	AI adoption favors *process optimization*. This refers to the process of capturing and analyzing data generated by service systems to improve or personalize the service. Algorithmic bias is a concern echoed throughout the literature.	An e-commerce firm implemented machine translation to optimize its processes aimed at less experienced buyers and cheaper products (e.g., eBay).	Akter et al. (2021); Akter et al. (2022); Brynjolfsson et al. (2019); Cao et al. (2021); Wang et al. (2022)
Automatic problem solving	AI adoption favors automatic *problem-solving* activities. This capability refers to the firm's ability to rapidly search for solutions to valuable problems, unmet issues, an unarticulated need in social media platforms.	A craft brewery firm tested AI to identify ideas in online communities. The algorithm allowed screening vast amounts of online information and automatically detect user-contributed ideas (e.g., Nøgne Ø)	Christensen et al. (2017); Christensen et al. (2018); Hoornaert et al. (2017); Kakatkar et al. (2020): Lebovitz et al. (2021); Govindan (2022)

characteristics include real-time data transfer, data-driven innovation, people-centeredness, and co-creation experiences (Buhalis & Sinarta, 2019; Gallego-Gomez & De-Pablos-Heredero, 2020; Kumar et al., 2023). Such partnerships involve multiple partners (e.g., IT organizations, users, and service system suppliers) with different and sometimes contradictory operational incentives and objectives (Li et al., 2021). AI enables collaborative development by streamlining communication and empowering external partners through interpersonal practices. Interpersonal practices are used to build trust, mobilize networks, communicate easily, retain long-term relationships, and facilitate rapid AI adoption (Kumar et al., 2023; Li et al., 2021).

A study conducted with three large payment-processing firms suggests that AI enables promoting new relationships with customers, identifying their needs or experiences, and adapting the service to be more competitive. AI also allows speeding up responses to customer questions and doubts throughout the value chain (Gallego-Gomez & De-Pablos-Heredero, 2020). Similarly, a mixed-methods study conducted in the healthcare sector shows that the development of AI-enabled tools, such as algorithmic prescriptions, image analysis, and speech recognition, is central to establishing and maintaining long-term relationships between patients and healthcare professionals (Kumar et al., 2023).

4.3.4 | Platform ecosystem orchestration

Empowered by AI, firms have better-orchestrated platform ecosystems (Garbuio & Lin, 2019). A platform ecosystem is a digital infrastructure based on modular elements that creates value by facilitating business exchanges between interdependent parties (Constantinides et al., 2018). Organizations involved in AI-driven innovations are heavily investing in creating platform-based ecosystems to streamline goods or service exchanges across the value chain (Garbuio & Lin, 2019). Multiple types of cloud-based digital platforms have been discussed, offering a range of options from standalone to self-managed solutions, and on-premises to cloud solutions (e.g., SaaS, Software as a Service, PaaS, Product as a Service; Kulkov, 2021). To reduce friction in adopting digital platform-based ecosystems, scholars often emphasize aspects of interoperability within existing ecosystems (Russo-Spena et al., 2019; Vartak, 2022).

A real-world case that benefits from AI adoption is IBM Watson (see Russo-Spena et al., 2019). The firm provides a set of open application programming interfaces (APIs) for developers to create, test, and implement their own solutions. This platform brings advanced algorithms to cloud-based services, enabling the creation of a platform-based ecosystem.

4.3.5 | Context-based knowledge sharing

Finally, AI adoption streamlines contextual knowledge-sharing by expanding the ways in which knowledge can be extracted, stored, analyzed, and ultimately distributed among internal and external actors (Arias-Pérez & Huynh, 2023). AI systems can increase the speed and accuracy of knowledge sharing to access and use information (Olan et al., 2021) and maximize commercial co-exploration for outbound activities (Arias-Pérez & Huynh, 2023). Consumer and market experts' knowledge can be integrated in AI systems, accelerate the identification of new information (e.g., search engine algorithms), answer frequently asked-questions faster (e.g., virtual assistants), better analyze customers behavior (e.g., sentiment analysis), automatically categorize content (e.g., text summarization), identify knowledge gaps (e.g., topic modeling), and suggest areas for improvement (La Torre et al., 2021; Kar & Kushwaha, 2021; Wamba-Taguimdje et al., 2020).

A showcase of this capability is OpenAI's Generative Pretrained Transformer (GPT-3) (Bouschery et al., 2023). This technology is a large language model (LLM) and supports the exploration of larger problem and solution spaces and can augment human knowledge exchange. Through the use of LLMs, Kar and Kushwaha (2021) examine a fragrance firm to establish and identify the relationship between ingredients and customer demographics.

Table 4 summarizes the innovation capabilities influenced by AI adoption and real-world examples of AI applications in the environmental context.

5 | DISCUSSION

Through a systematic literature review, this study contributes to the innovation management literature by gathering dispersed perspectives on innovation capabilities and applications resulting from AI adoption. This review aims to summarize the influence of AI adoption on innovation capabilities and outline a taxonomy of AI applications based on empirical studies. While AI is gaining traction and has inspired a growing number of reviews in multiple domains, including information science (Enholm et al., 2022), supply chains (Riahi et al., 2021), and management strategy (von Krogh, 2018), there is still limited understanding of the influence of this technology in innovation management based on real-world examples.

Thus, we provide new insights and a more comprehensive view of the emerging nature of AI grounded in innovation management theories. First, we unveil the influence of AI adoption across innovation capabilities. Our review indicates the presence of two sets of capabilities (*enabling* and *enhancing*). Second, we reviewed the empirical cases to identify real-world AI applications and outline a taxonomy to help scholars and practitioners adopt AI. The taxonomy proposes a theory-driven classification (Chrisman et al., 1988) of the different applications, namely *replace*, *reinforce*, and *reveal*.

5.1 | The influence of AI adoption on innovation capabilities

Based on this analysis, we propose a framework that outlines the influence of AI adoption on innovation

TABLE 4 Summary of findings of the innovation capabilities triggered by AI adoption and AI applications: environmental context.

Environmental context			
Innovation capability	**Description**	**Examples of AI application**	**Key references**
Screening the regulations	AI adoption requires the firm's ability to *screen the regulatory* environment to check whether the AI method applied complies with the latest government regulations. The regulatory environment for AI evolves rapidly in many political entities where security lapses can have catastrophic consequences.	Numerous recruitment and staffing firms adopt AI-powered chatbots to assist with tasks related to screening resumes and answering candidate questions. The regulatory environment is constantly monitored to ensure compliances with current directives.	Liu et al. (2020); von Hippel and Kaulartz (2021); Rammer et al. (2022); Trocin et al. (2021), Stahl et al. (2023).
Partnering agility	AI adoption requires *partnering agility* to quickly coordinate and control actors' initiatives. It allows firms to build a network of strategic, extended, or virtual partnerships to exploit and explore AI opportunities with multiple partners.	A mining firm adopted AI to optimize the preparation and maintenance of equipment. Partnering agility practices were implemented to align the actors' needs, data-sharing practices, and calibrate the project goals prior AI adoption.	Åström et al. (2022); Bai and Li (2020); Burström et al. (2021); Mühlroth and Grottke (2020); Warner and Wäger (2019)
Multimodal value co-creation	AI adoption favors *multimodal value co-creation* with suppliers, customers, users, and AI providers. This is a collaborative and iterative process that focuses on creating value through meaningful interactions and engagement with actors.	A payment-processing firm uses AI to identify and stop fraudulent payment-card transactions. AI algorithms process large data sets nearly instantaneously without disrupting or delaying legitimate transactions, creating value in real-time. (e.g., Mastercard)	Buhalis and Sinarta (2019); Gallego-Gomez and De-Pablos-Heredero (2020); Li et al. (2021); Kumar et al. (2023); Verganti et al. (2020)
Orchestrate platform-ecosystems	AI adoption favors the *orchestration of platform ecosystems* that streamline goods or service exchanges across the value chain (e.g., SaaS or PaaS).	A software firm infuses AI into customer applications to automate decisions, make better predictions, and optimize team planning (e.g., IBM).	Garbuio and Lin (2019); Kulkov (2021); Russo-Spena et al. (2019)
Context-based knowledge sharing	AI adoption favors context-based *knowledge sharing*. Tacit and explicit knowledge can be transferred without altering the original content.	A fragrance firm adopted AI to identify the relationship between ingredients of a perfume and customer demographics (e.g., Symrise).	Arias-Pérez and Huynh (2023); La Torre et al. (2021); Kar and Kushwaha (2021); Olan et al. (2021); Wamba-Taguimdje et al. (2020)

capabilities. While Tables 2–4 summarize the key contributions of the empirical articles, Figure 2 depicts the relationships between the constructs, showing that innovation capabilities (Barczack, 2012) can assume a dichotomous role (Raisch et al., 2009) as a result of AI adoption.

The review shows that *enabling capabilities* are needed to allow the development, deployment, and ultimately the adoption of AI in innovation enterprises (Bessen et al., 2022; Brock & von Wangenheim, 2019), identifying six enabling capabilities influenced by the technological, organizational, and environmental context. In the technological context, functional competence and cybersecurity management emerge as foundational elements to enable robust and safe AI adoption (Agarwal et al., 2021; Boyson et al., 2022). Likewise, the search and recombination of knowledge and the governance of digital projects highlight the importance of experiencing algorithmic solutions while respecting data ownership and access rights, privacy, and consent (Bag, Pretorius, et al., 2021; Correani et al., 2020; Yams et al., 2020). Finally, in the environmental context, search regulations and partner agility underscore the importance of monitoring the regulatory framework while

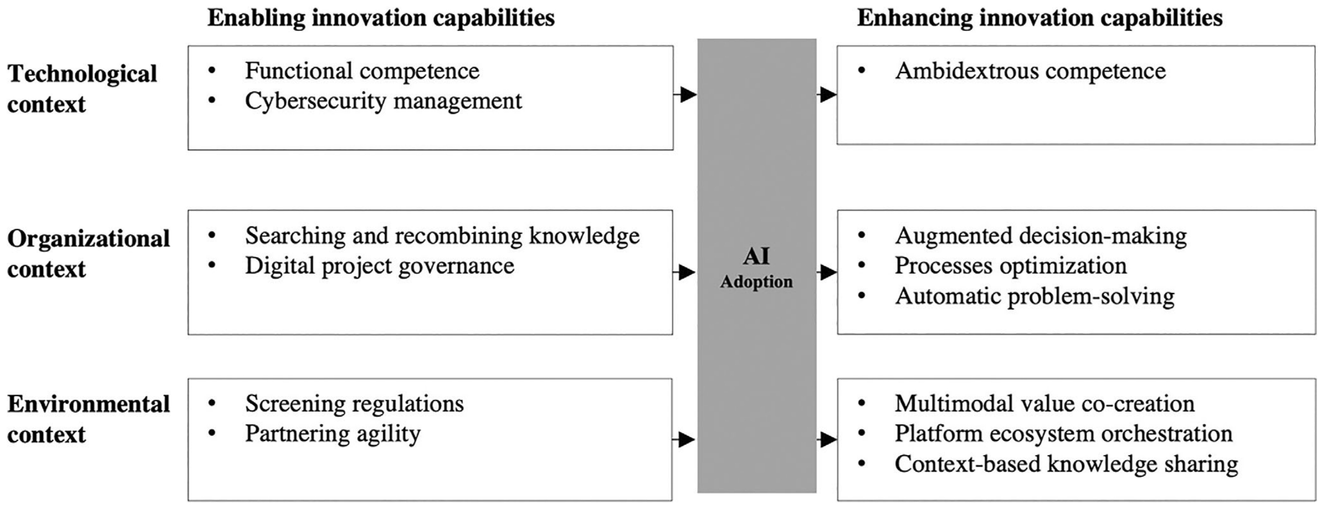


FIGURE 2 The role of AI in innovation capabilities.

building a network of partners to exploit AI opportunities (Liu et al., 2020; Olan et al., 2021).

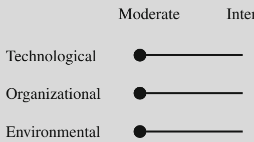
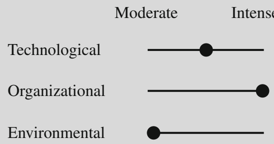
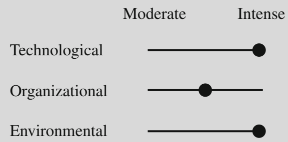
Once AI is adopted and collectively experienced, value is created (Browder et al., 2022), and firms experience innovation *enhancing capabilities* as a result (Garbuio & Lin, 2019; Keding & Meissner, 2021; Mühlroth & Grottke, 2020; Verganti et al., 2020). These new capabilities allow firms to improve their innovation process, fostering, among others, flexibility (Bag, Pretorius, et al., 2021; Gupta et al., 2020; Kinkel et al., 2022) and scalability (Sjödin et al., 2021; Syam & Sharma, 2018). In particular, this literature review suggests seven enhancing capabilities that result from or are enhanced by AI adoption. In the technological context, ambidextrous capabilities highlight that AI adoption stimulates IT members to exploit existing operational competencies while simultaneously exploiting novel solutions (Dicuonzo et al., 2023; Lou & Wu, 2021). In the organizational context, the use of AI assists augmented decision-making, process optimization, and streamlining problem-solving activities (Brynjolfsson et al., 2019; Hoornaert et al., 2017; Keding & Meissner, 2021). Finally, in the environmental context, the deployment of AI advances multimodal value co-creation, streamlines the orchestration of platform-ecosystems, and accelerates context-based knowledge sharing (Garbuio & Lin, 2019; Liu et al., 2020; Verganti et al., 2020).

The recognition of these *enabling* and *enhancing* innovation capabilities, influenced by different contexts, advances the AI innovation literature along three dimensions (Kinkel et al., 2022). First, it reinforces that the adoption of new technologies depends on existent capabilities, but also on the role of new technologies in transforming current innovation capabilities (Helfat & Peteraf, 2003). The transformation of innovation capabilities is not limited to competencies at the technological level (Iansiti, 2000), but is strongly influenced by the organizational and environmental context (Crossan & Apaydin, 2010; Judge & Miller, 1991). Second, it responds to the call for a better understanding of the impact of AI by disentangling the antecedents of the innovation capabilities (von Krogh, 2018). Therefore, our study contributes to advancing scholarly understanding of the influence of external factors on AI adoption in innovation management. Central to this contribution is the discussion on accommodating or leveraging external aspects in AI adoption (Bai & Li, 2020; Burström et al., 2021; Trocin et al., 2021). Finally, the AI innovation capabilities framework and the link with the different context dimensions reveal the need for a more holistic and systemic way of interpreting and studying innovation (Verganti et al., 2020). Indeed, studying only the technological elements could limit the view to innovation outcomes (Zhang et al., 2021). This review also contributes to the ongoing debate on the need for a more holistic and phenomenological understanding of digital technologies (Suddaby, 2006). Indeed, by unveiling the set of capabilities that enable and enhance AI adoption, the complexity of the AI adoption scenario emerges. AI adoption is multifaceted in nature and requires an interpretation that is not limited to single aspects but considers the phenomenon in its entirety.

5.2 | Taxonomy of AI applications

While summarizing the influence of AI (e.g., Enholm et al., 2022; Haenlein & Kaplan, 2019), management research tends to be neither empirically grounded nor comprehensive. Therefore, an important goal of our systematic review is to create a taxonomy of AI applications based on real-world examples. To achieve this, we organized the AI

TABLE 5 Taxonomy of AI applications.

	Replace	**Reinforce**	**Reveal**
Influence of AI adoption on TOE			
Description	AI is adopted as a *tool* to improve existing processes, substitute human beings, and expedite external analyses. The motivation is often economical.	AI is adopted as a *lever* to exploit new technological opportunities, empower existing processes, assist employees in their activities, and expedite external analyses.	AI is adopted as a *sonar* to unveil hidden technological opportunities and unshadow unforeseeable external situations.
	Case examples	**Case examples**	**Case examples**
Technological context	AI replaces tools and tasks previously performed with a different technology in existing processes. • Autonomous tools (Agarwal et al., 2021) • Ship control systems (Sjödin et al., 2021)	AI reinforces existing processes by empowering activities with new features. • Noninvasive medical device (e.g., Beddit; Garbuio & Lin, 2019) • Assisted documentation (e.g., Dragon Medical; Wamba-Taguimdje et al., 2020)	AI reveals new technological opportunities through unconventional exploitation. • Automation capacity (e.g., CNH Industrial; Correani et al., 2020) • Revelation of needs (e.g., Symrise; Kar & Kushwaha, 2021)
Organizational context	AI replaces employees in activities. • Facility optimization (e.g., Humber River Hospital; Dicuonzo et al., 2023) • Product optimization (e.g., General Motors; Füller et al., 2022)	AI reinforces employees' actions by supporting them in new discoveries. • Product evaluation (e.g., Unanimous AI; Metcalf et al., 2019) • Drug discovery (e.g., Halicin; Lou & Wu, 2021)	AI reveals new organizational opportunities to support employees. • Discovery of cross-optimal solutions (e.g., Fujitsu; Liu et al., 2020) • Advanced career development (e.g., IBM; Tambe et al., 2019)
Environmental context	AI replace activities aimed at searching external influential situations. • International trade (e.g., eBay; Brynjolfsson et al., 2019) • Customer care interface (e.g., Vodafone; Correani et al., 2020)	AI reinforce activities aimed at searching and selecting external influential situations. • Identify trends and threats (e.g., AT&T; Mikalef et al., 2021) • Identify fraudulent transaction (e.g., Mastercard; Gallego-Gomez & De-Pablos-Heredero, 2020)	AI reveal new external opportunities by sensing and framing external situations. • Nowness service (e.g., Marriot; Buhalis & Sinarta, 2019)

applications according to the TOE framework (Tornatzky et al., 1990), focusing on representative AI applications that are prevalent in the three contexts, as we believe this will provide the most informative and valuable comparisons. We include the names of the firms or cases to increase practical relevance and better managerial interpretations. Leveraging the TOE theory of technology adoption (Tornatzky et al., 1990), we identified three distinct taxa, namely *replace*, *reinforce*, and *reveal*. The three AI application taxa are summarized in Table 5 and discussed in more detail below.

By leveraging the different AI application examples reported in the studies analyzed and drawing on the TOE framework to classify the different AI adoptions in an informed, theory-driven approach, we created the taxonomy (Chrisman et al., 1988). *Replace* occurs when the main goal of the AI application it is to assist, optimize, control, or accelerate innovation processes (Lou & Wu, 2021). The benefits are often performance-driven, while the replaced tasks are largely mechanical. In contrast to replace, *reinforce* unfolds when the goal is to augment human decisions, accelerate discoveries, and assist humans in analytical tasks, promoting value creation in real time (Garbuio & Lin, 2019). *Reveal* indicates the use of AI to uncover novel solutions that were previously impossible for humans. Autonomous machines and nowness services are examples of this taxonomy (Verganti et al., 2020). Our analysis shows that the configurations differ according to the aims, but also depending on the TOE context. In the case of replace, the examples show that the technological context limits its influence on adoption, as do the organizational and environmental contexts (Zhang et al., 2021). On the contrary, in the case of reinforce, the organizational context highly influences decision-making, as reported in the Halicin case, where AI identified a powerful new drug that can kill numerous antibiotic-resistant bacteria (Lou & Wu, 2021). Finally, in the reveal case, as in the IBM solutions (Tambe et al., 2019), the technological and environmental contexts had a significant influence on AI adoption and the resulting applications, while the organizational dimensions were less influential.

Our taxonomy contributes to academic knowledge about AI (Haenlein & Kaplan, 2019) in two distinct ways. First, it provides a simplified understanding of why and how AI applications differ in their adoption by innovation firms. This enhances scholarly understanding of the multifaceted nature of AI (Brock & von Wangenheim, 2019; Glikson & Wooley, 2020) by deconstructing its underlying elements. Second, informed by the TOE framework (Tornatzky et al., 1990), the taxonomy reports the centrality of understanding and discussing AI adoption by considering different contextual factors. This advances both the relevance of the TOE framework in innovation studies (Kinkel et al., 2022) and the need to study technology and innovation in their contextual embeddedness. Indeed, technologies are not adopted in a vacuum, but as a result of contextual factors that influence firms' decision-making processes and the resulting capabilities.

5.3 | Research agenda on AI applications and the innovation capabilities that enable and are enhanced by AI adoption

The synthesis of the 62 empirical studies identifies several research gaps related to innovation capabilities. Based on the TOE framework (Tornatzky et al., 1990), this section aims to provide a comprehensive framework to guide future innovation management research

TABLE 6 Research agenda on innovation capabilities triggered by AI adoption.

Context	Innovation capabilities	Research questions
Technological	Functional competence	How does the AI lifecycle (development, adoption, and integration) influence functional competence? How does the increased use of AI technologies influence the necessary functional competencies in different types of innovation (e.g., product, service, and process)?
	Cybersecurity management	How to share cybersecurity practices, assess them properly to ensure firms are not vulnerable to breaches? How can cybersecurity management mitigate data poisoning attacks?
Organizational	Searching and recombining knowledge	How does organizational readiness influence the adoption of AI in different industries? How to sustain paradoxical tension before and after AI adoption (e.g., accuracy vs. interpretability)?
	Digital project governance	How can digital project governance simultaneously promote transparency and accountability? How can digital project governance ensure data are reliable and in compliance with current regional and international laws?
	Augmented decision-making	What difficulties will be faced in AI diffusion for decision-making? How can firms transition from human-intensive to AI-centric decision making?
Environmental	Screening the regulations	How can leaders take a proactive stance and use a practical framework (such as the Ethics Guidelines for Trustworthy AI), to create algorithms based on fairness, accountability, and transparency?
	Multimodal value creation	Is there any social dysfunction created or amplified by AI adoption in partner teams? Which practices can motivate multi-actors' engagement and loyalty in the AI context?
	Context-based knowledge sharing	How to transfer tacit knowledge to a search-based AI algorithm? How to deploy formal and informal appropriability mechanisms to protect sensitive data during the knowledge transfer's process?

(Volberda et al., 2013). The goal is to highlight the relevant gaps that emerged from the review that can help scholars and practitioners expand current knowledge of the capabilities and application perspective of AI adoption. Table 6 provides a list of questions that emerged from our systematic review of AI adoption on capabilities, while Table 7 reports the new research avenues that emerged from our AI taxonomy.

Due to the distinctiveness of AI compared to other digital technologies (Wetzels, 2021), future research should assess the boundary conditions, idiosyncratic nature, and deployment of trustworthy principles within the technological, organizational, and environmental context (Kinkel et al., 2022). In the technological context, scholars are encouraged to investigate the consequences of AI adoption throughout the AI lifecycle and the requisite idiosyncrasies in different types of innovation (e.g., product, service, and process; Magistretti et al., 2019). In addition, innovation scholars are encouraged to investigate the sharing of cybersecurity practices among firms to mitigate security breaches (Haenlein & Kaplan, 2019). Cybersecurity is galloping ahead in other domains, such as information systems, but is still in its infancy in innovation science (Yeoh et al., 2022). In the organizational context, knowledge is needed to understand firms' idiosyncratic characteristics to incorporate AI in their innovation processes. A higher level of organizational readiness may be an important element in optimizing AI adoption, but has yet to be examined. In digital data governance, scholars call for sustainable responses to mitigate concerns and balance legitimate but contradictory demands, such as transparency and accountability (Mikalef et al., 2021; Uren & Edwards, 2023). In the decision-making literature, questions related to the transition to AI-centric processes are gaining traction (Keding & Meissner, 2021). In the environmental context, the questions ultimately revolve around leader proactivity in deploying government guidelines for trustworthy AI, the potential social dysfunction in partner teams triggered by AI adoption, and the interplay between tacit and explicit knowledge-sharing (Bessen et al., 2022).

In addition, we propose a research agenda derived from the taxonomy (Chrisman et al., 1988) of AI applications in Table 5 (e.g., Agarwal et al., 2021; Garbuio & Lin, 2019) and our analysis of the empirical cases reported in the selected articles to either delve deeper into the TOE dimensions (Tornatzky et al., 1990) of the different taxa or to understand the influence of the taxa in the innovation management literature. Therefore, Table 7 offers several potential research avenues that emerged from the analysis of the 62 articles in our systematic literature review that can assist scholars in expanding the scope and relevance of this taxonomy. Furthermore, as highlighted in the systematic literature review, the emerging innovation capabilities that enable AI adoption or are enhanced by AI adoption are currently not linked to the taxonomy. This presents an interesting opportunity for a fruitful empirical study to further explore the potential links between different capabilities and the taxonomy.

5.4 | Theoretical, managerial, and ethical implications, limitations, and conclusions

This systematic literature review contributes to the innovation management literature by summarizing the role of AI in influencing innovation capabilities and providing a taxonomy of AI applications. Based on the analysis of 62 empirical studies, the review also proposes a research agenda. The findings illustrate the importance of reflecting on innovation capabilities before and after technology adoption, and gaining an independent perspective on whether and how well other cases deploy AI in real innovation settings. As more and more firms foresee the use of AI, these findings are important, especially in the digital age where innovation activities play a critical role in sustaining competitive advantage (Wetzels, 2021).

5.4.1 | Theoretical implications

Our results contribute to emerging discussions about the impact of digital technologies on innovation management (Nambisan et al., 2017), the need to better understand capabilities in digital contexts (Warner & Wäger, 2019), and the importance of establishing a common language for AI applications across different domains (Davenport et al., 2020). As such, our contribution is twofold.

First, our review contributes to the capabilities perspective by identifying two distinct sets of innovation capabilities that emerge from AI adoption, namely *enabling* and *enhancing*. While the AI literature is rich in detailing the key activities (Correani et al., 2020), processes (Uren & Edwards, 2023), and competencies (Wu et al., 2021), studies that condense AI-based capabilities provide fragmented insights. A capabilities perspective can therefore offer a more comprehensive understanding of the complex sets of skills and organizational processes that ultimately help firms coordinate activities and make use of their assets to drive digital technology adoption (Crossan & Apaydin, 2010). In particular, the novelty of the enabling and enhancing capabilities perspective

TABLE 7 Research agenda on AI taxonomy.

Context	Taxa	Research questions
Technological	Replace	How can AI adoption impact new product development performance by replacing existing technologies?
		What are the AI requirements from a technological standpoint to introduce in innovation processes?
	Reinforce	How can AI developers influence the discovery of new functionalities and features in AI solutions?
		How can firms develop explainable algorithms (open the black box) of AI and explore new functionalities?
	Reveal	How can firms reveal hidden technological values in AI?
		What are the technological development processes firms can explore to unveil unconventional AI adoptions (e.g., outsourcing)?
Organizational	Replace	What are the human–tech interactions that need to be designed to enable AI adoption in organizations?
		What are the key barriers that organizations face when implementing AI systems, and how can these be overcome?
		How do firm characteristics (e.g., family and nonfamily) influence AI adoption from an organizational point of view?
	Reinforce	How can small and medium-sized enterprises exploit the adoption of AI as a lever and not a tool?
		How and why should organizations invest in AI to empower their employee decision-making? Are there any unintended consequences for employees?
	Reveal	What role can AI play in promoting innovation and creativity within organizations?
		How can innovators discover quiescent meanings in AI to pursue meaningful innovations?
Environmental	Replace	What are the ethical and social implications of using AI in organizations, and how can these be addressed?
		How does the environmental context influence the adoption of AI?
	Reinforce	What are the functionalities of AI adoption that can support the search and selection of relevant external influencing factors?
		How can AI support future-making by interpreting contextual factors?
	Reveal	How and why can AI adoption influence the discovery of new opportunities?
		What are the antecedents of external influence over AI adoption?

arises from the combination and sequencing of routines and processes in discrete capability sets (Felin et al., 2012). The analysis extends the literature by focusing on how AI requires or magnifies innovation capabilities over time by theorizing how the use of such technology affects the routines, practices, and processes at a given point in time. This conceptualization extends the literature on capability sets, specific managerial ways to manage the deployment of AI, and provides novel avenues for future in-depth research.

Second, our review proposes a taxonomy that reflects the practical use of AI in innovation activities along three taxa: *replace*, *reinforce*, and *reveal*. In an effort to further increase the clarity of AI applications (Davenport et al., 2020), the review builds this taxonomy according to the TOE framework (Tornatzky et al., 1990) to guide scholars and practitioners in theorizing about AI. In particular, we group three clearly defined constructs into a taxonomy that synthesizes the current state of knowledge about AI applications in real-world settings (Chrisman et al., 1988). By defining, sorting, and ordering the AI applications (Wu et al., 2021), this taxonomy mitigates ambiguities and creates a common language for the innovation field. As such, this taxonomy can serve as a building block for further investigations of AI applications in innovation research.

5.4.2 | Managerial implication

This study also has several implications for managers. First, our systematic review helps managers understand the diverse nature of AI adoption. By segmenting two important aspects of AI adoption (capabilities and applications), the review disentangles the complexity of the AI adoption phenomenon and highlights the relevance of the contextual dimensions (TOE). Second, by systematizing the different enabling and enhancing capabilities, our review informs managers of the need to assess the impact of different contextual factors (TOE) on the capabilities required for or resulting from AI adoption. By considering the dichotomous views of innovation capabilities on AI adoption, managers can better understand the different actions required to foster these capabilities in the context of future AI adoption. Third, by identifying the three aims of adopting AI, the taxonomy informs managers that AI can be adopted for different purposes, and that not every adoption is the same. It also informs managers of the influence of contextual factors (TOE) on the different taxa. This can improve managers' understanding of the importance of assessing the context before adopting AI, and a clearer sense of the reasons for doing so.

5.4.3 | Ethical implications

Despite the value of AI applications for innovation, the literature acknowledges the existence of potential unintended consequences of AI adoption across ethical, legal, and social aspects (ELSA; Akter et al., 2022). Poorly designed AI can introduce or amplify dysfunctions across technological contexts (e.g., algorithmic bias and privacy invasion), organizational contexts (e.g., organization learning myopia and automation complacency), and environmental contexts (e.g., blurred lines of accountability and unscalable oversight; Benbya et al., 2020; Challen et al., 2019; Garbuio & Lin, 2021). This review highlights the importance of ongoing research on ELSA aspects before, during, and after AI adoption. To minimize the vulnerabilities of AI in innovation activities, a set of actionable methods should be developed and implemented by organizations. These methods include preliminary landscape assessment, error management, multi-stakeholder participation and cross-sector feedback, and tools to support AI adoption, operationalization, and maintenance (Martin, 2019; van Giffen et al., 2022). Future research cannot shy away from the ELSA aspects of AI adoption (Garbuio & Lin, 2021; Tambe et al., 2019).

5.4.4 | Limitations and conclusions

Like all research, our systematic literature review has some limitations. First, as a systematic review, our inclusion and exclusion criteria may have influenced the identification of relevant articles. Although we aimed to be comprehensive, the subject categories considered are limited, and the inclusion of other categories could yield different results. Second, a limitation could be related to the perspective and framework adopted. We made a conscious decision to use the TOE framework to study innovation capabilities in technology adoption because of its recognized value in research. However, a different choice could potentially alter the overall interpretation and limit the generalizability of our innovation capability framework. Finally, it is important to note that the field of AI is currently in a state of high hype, with new research being published all the time. Therefore, innovation capabilities need to be continuously explored and integrated with new findings.

To conclude, while our systematic literature review is an important step forward in understanding the complex relationship between AI, innovation management, and capabilities, there is still much to be explored. We hope that our study will inspire future research that builds on this initial understanding of AI applications and innovation capabilities to expand scholarly and practitioner understanding.

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APPENDIX 1: Search query

(TITLE-ABS-KEY (“artificial intelligence” OR “intelligent system*” OR “machine learning” OR “deep learning”) AND TITLE-ABS-KEY (innovat*)) AND (LIMIT-TO (SRCTYPE, “j”)) AND (LIMIT-TO (DOCTYPE, “ar”)) AND LIMIT-TO (SUBJAREA, “SOCI”) OR LIMIT-TO (SUBJAREA, “BUSI”) OR LIMIT-TO (SUBJAREA, “DECI”) OR LIMIT-TO (SUBJAREA, “ECON”) OR LIMIT-TO (SUBJAREA, “ARTS”) OR LIMIT-TO (SUBJAREA, “PSYC”) OR LIMIT-TO (SUBJAREA, “MULT”) AND (LIMIT-O (LANGUAGE, “English”)).

TABLE A1 Full list of included articles with innovation management relevance ($N = 62$ up to July 2023).

#	Author(s)	Year	Title	Journal	Type of study	ABS rank	Context		
							Technological	Organizational	Environmental
1	Abou-Foul, Mohamad, Jose L. Ruiz-Alba, and Pablo J. López-Tenorio	2023	The impact of artificial intelligence capabilities on servitization: The moderating role of absorptive capacity. A dynamic capabilities perspective	Journal of Business Research	Qualitative and Quantitative	3	Cybersecurity management		
2	Agarwal, Girish Kumar, Mats Magnusson, and Anders Johanson	2021	Edge AI-driven technology advancements paving way toward new capabilities	International Journal of Innovation and Technology Management	Qualitative	1	Functional competence		
3	Akter, Shahriar, Samuel Fosso Wamba, Marcello Mariani, and Umme Hani	2021	How to build an AI climate-driven service analytics capability for innovation and performance in industrial markets?	Industrial Marketing Management	Qualitative and Quantitative	3		Processes optimization	
4	Akter, Shahriar, Yogesh K. Dwivedi, Shahriar Sajib, Kumar Biswas, Ruwan J. Bandara, and Katina Michael	2022	Algorithmic bias in machine learning-based marketing models	Journal of Business Research	Qualitative	3		Processes optimization	
5	Arias-Pérez, José, Thanh Huynh	2023	Flipping the odds of AI-driven open innovation: The effectiveness of partner trustworthiness in	Industrial Marketing Management	Quantitative	3			Context-based knowledge sharing

(Continues)

TABLE A1 (Continued)

#	Author(s)	Year	Title	Journal	Type of study	ABS rank	Context: Technological	Context: Organizational	Context: Environmental
			counteracting interorganizational knowledge hiding						
6	Åström, Josef, Wiebke Reim, and Vinit Parida	2022	Value creation and value capture for AI business model innovation: a three-phase process framework	Review of Managerial Science	Qualitative	2			Partnering agility
7	Bag, Surajit Bag, Shivam Gupta, Ajay Kumar, and Uthayasankar Sivarajah	2021	An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision making for improving firm performance	Industrial Marketing Management	Quantitative	3		Searching and recombining knowledge	
8	Bag, Surajit, Jan Ham Christiaan Pretorius, Shivam Gupta, and Yogesh K. Dwivedi	2021	Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices, and circular economy capabilities	Technological Forecasting & Social Change	Quantitative	3		Augmented decision-making	
9	Bai, XuJing, and JiaJun Li	2020	The best configuration of collaborative knowledge innovation management from the perspective of artificial intelligence	Knowledge Management Research & Practice	Quantitative	1			Partnering agility
10	Bessen, James, Stephen M. Impink, Lydia Reichensperger, and Robert Seamans	2022	The role of data for AI startup growth	Research Policy	Quantitative	4	Functional competence		
11	Botega, L. F. de Carvalho, and Jonny C. da Silva	2020	An artificial intelligence approach to support knowledge management on the selection of creativity and innovation techniques	Journal of Knowledge Management	Qualitative	2		Augmented decision-making	
12	Boyson, Sandor, Thomas M. Corsi, and John-Patrick Paraskevas	2022	Defending digital supply chains: Evidence from a decade-long research program	Technovation	Quantitative	3	Cybersecurity management		

TABLE A1 (Continued)

#	Author(s)	Year	Title	Journal	Type of study	ABS rank	Context		
							Technological	Organizational	Environmental
13	Brock, Jürgen Kai-Uwe, and Florian Von Wangenheim	2019	Demystifying AI: What digital transformation leaders can teach you about realistic artificial intelligence	California Management Review	Qualitative and Quantitative	3	Cybersecurity management		
14	Brynjolfsson, Erik, Xiang Hui, and Meng Liu	2019	Does machine translation affect international trade? Evidence from a large digital platform	Management Science	Quantitative	4		Processes optimization	
15	Buhalis, Dimitrios, and Yeyen Sinarta	2019	Real-time co-creation and nowness service: lessons from tourism and hospitality	Journal of Travel & Tourism Marketing	Qualitative	2			Multimodal value co-creation
16	Burström, Thommie, Vinit Parida, Tom Lahti, and Joakim Wincent	2021	AI-enabled business-model innovation and transformation in industrial ecosystems: A framework, model and outline for further research	Journal of Business Research	Qualitative	3			Partnering agility
17	Cao, Guangming, Yanqing Duan, John S. Edwards, and Yogesh K. Dwivedi	2021	Understanding managers' attitudes and behavioral intentions toward using artificial intelligence for organizational decision-making	Technovation	Quantitative	3		Processes optimization	
18	Chatterjee, Sheshadri, Ranjan Chaudhuri, Demetris Vrontis, Alkis Thrassou and Soumya Kanti Ghosh	2021	Adoption of artificial intelligence-integrated CRM systems in agile organizations in India	Technological Forecasting & Social Change	Quantitative	3		Searching and recombining knowledge	
19	Chatterjee, Sheshadri, Nripendra P. Rana, Yogesh K. Dwivedi, and Abdullah M. Baabdullah	2021	Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model	Technological Forecasting & Social Change	Quantitative	3	Ambidextrous competencies		

(Continues)

TABLE A1 (Continued)

#	Author(s)	Year	Title	Journal	Type of study	ABS rank	Context		
							Technological	Organizational	Environmental
20	Chatterjee, Sheshadri, Nripendra P. Rana, Kuttimani Tamilmani, and Anuj Sharma	2021	The effect of AI-based CRM on organization performance and competitive advantage: An empirical analysis in the B2B context	Industrial Marketing Management	Quantitative	3	Ambidextrous competencies		
21	Chaudhuri, Ranjan, Sheshadri Chatterjee, Demetris Vrontis, and Alkis Thrassou	2021	Adoption of robust business analytics for product innovation and organizational performance: the mediating role of organizational data-driven culture	Annals of Operations Research	Quantitative	3		Augmented decision-making	
22	Christensen, Kasper, Joachim Scholderer, Stine A. Hersleth, Tormod Næs, Knut Kvaal, Torulf Mollestad, Nina Veflen and Einar Risvik	2018	How good are ideas identified by an automatic idea detection system?	Creativity and Innovation Management	Quantitative	2		Automatic problem-solving	
23	Christensen, Kasper, Sladjana Nørskov, Lars Frederiksen and Joachim Scholderer	2017	In search of new product ideas: Identifying ideas in online communities by machine learning and text mining	Creativity and Innovation Management	Quantitative	2		Automatic problem-solving	
24	Correani, Alessia, Alfredo De Massis, Federico Frattini, Antonio M. Petruzzelli, and Angelo Natalicchio	2020	Implementing a digital strategy: learning from the experience of three digital transformation projects	California Management Review	Qualitative	3		Data project governance	

TABLE A1 (Continued)

#	Author(s)	Year	Title	Journal	Type of study	ABS rank	Context		
							Technological	Organizational	Environmental
25	Dicuonzo, Grazia, Francesca Donofrio, Antonio Fusco, and Matilda Shini	2023	Healthcare system: Moving forward with artificial intelligence	Technovation	Qualitative	3	Ambidextrous competence		
26	Füller, Johann, Katja Hutter, Julian Wahl, Volker Bilgram, and Zeljko Tekic	2022	How AI revolutionizes innovation management—Perceptions and implementation preferences of AI-based innovators	Technological Forecasting & Social Change	Quantitative	3		Searching and recombining knowledge	
27	Gallego-Gomez, Cristina, and Carmen De-Pablos-Heredero	2020	Artificial Intelligence as an enabling tool for the development of dynamic capabilities in the banking industry	International Journal of Enterprise Information Systems	Qualitative	1			Multimodal value co-creation
28	Garbuio, Massimo, and Nidthida Lin	2019	Artificial intelligence as a growth engine for health care startups: emerging business models	California Management Review	Qualitative	3			Orchestration of platform-based ecosystem
29	Govindan, Kannan	2022	How artificial intelligence drives sustainable frugal innovation: A multitheoretical perspective	IEEE Transactions on Engineering Management	Qualitative and Quantitative	3		Automatic problem-solving	
30	Hoornaert, Steven, Michel Ballings, Edward C. Malthouse, and Dirk Van den Poel	2017	Identifying new product ideas: waiting for the wisdom of the crowd or screening ideas in real time	Journal of Product Innovation Management	Quantitative	4		Automatic problem-solving	
31	Igna, Ioana, and Francesco Venturini	2023	The determinants of AI innovations across European firms	Research Policy	Quantitative	4	Functional competence		
32	Kakatkar, Chinmay, Volker Bilgram, and Johann Füller	2020	Innovation analytics: Leveraging artificial intelligence in the innovation process	Business Horizons	Qualitative	2		Automatic problem-solving	

(Continues)

TABLE A1 (Continued)

#	Author(s)	Year	Title	Journal	Type of study	ABS rank	Context		
							Technological	Organizational	Environmental
33	Kar, Arpan Kumar, and Amit Kumar Kushwaha	2021	Facilitators and barriers of artificial intelligence adoption in business—Insights from opinions using big data analytics	Information Systems Frontiers	Quantitative	3			Context-based knowledge sharing
34	Keding, Christoph, and Philip Meissner	2021	Managerial overreliance on AI-augmented decision-making processes: How the use of AI-based advisory systems shapes choice behavior in R&D investment decisions	Technological Forecasting & Social Change	Quantitative	3		Augmented decision-making	
35	Khan, Ali Nawaz, Fauzia Jabeen, Khalid Mehmood, Mohsin Ali Soomro, and Stefano Bresciani	2023	Paving the way for technological innovation through adoption of artificial intelligence in conservative industries	Journal of Business Research	Quantitative	3	Functional competence		
36	Kinkel, Steffen, Marco Baumgartner, and Enrica Cherubini	2022	Prerequisites for the adoption of AI technologies in manufacturing—Evidence from a worldwide sample of manufacturing companies	Technovation	Quantitative	3	Functional competence		
37	Kulkov, Ignat	2021	Next-generation business models for artificial intelligence start-ups in the healthcare industry	International Journal of Entrepreneurial Behavior & Research	Qualitative	3			Orchestration of platform-based ecosystem
38	Kumar, Pradeep, Sujeet Kumar Sharma, and Vincent Dutot	2023	Artificial intelligence (AI)-enabled CRM capability in healthcare: The impact on service innovation	International Journal of Information Management	Qualitative and Quantitative	2			Multimodal value co-creation
39	La Torre, Davide, Cinzia Colapinto, Ilaria Durosini, and Stefano Triberti	2021	Team formation for human-artificial intelligence collaboration in the workplace: A goal programming model to foster organizational change	IEEE Transactions on Engineering Management	Quantitative	3			Context-based knowledge sharing

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TABLE A1 (Continued)

#	Author(s)	Year	Title	Journal	Type of study	ABS rank	Context: Technological	Context: Organizational	Context: Environmental
40	Lebovitz, Sarah, Natalia Levina, and Hila Lifshitz-Assaf	2021	Is AI ground truth really true? The dangers of training and evaluating AI tools based on experts´ know-what	MIS Quarterly	Qualitative	4		Automatic problem-solving	
41	Li, Shuyang, Guochao Peng, Fei Xing, Jun Zhang, and Bingqian Zhang	2021	Value co-creation in industrial AI: The interactive role of B2B supplier, customer and technology provider	Industrial Marketing Management	Qualitative	3			Multimodal value co-creation
42	Liu, Jun, Huihong Chang, Jeffrey Y. Forrest, and Baohua Yang	2020	Influence of artificial intelligence on technological innovation: Evidence from the panel data of China's manufacturing sectors	Technological Forecasting & Social Change	Quantitative	3			Screening the regulations
43	Lou, Bowen, and Lynn Wu	2021	AI on drugs: can artificial intelligence accelerate drug development? Evidence from a large-scale examination of bio-pharma firms. Evidence from a large-scale examination of bio-pharma firms	MIS Quarterly	Quantitative	4	Ambidextrous competence		
44	Metcalf, Lynn, David A. Askay, and Louis B. Rosenberg	2019	Keeping humans in the loop: pooling knowledge through artificial swarm intelligence to improve business decision making	California Management Review	Quantitative	3		Augmented decision-making	
45	Mikalef, Patrick, Kieran Conboy, and John Krogstie	2021	Artificial intelligence as an enabler of B2B marketing: A dynamic capabilities micro-foundations approach	Industrial Marketing Management	Qualitative	3		Data project governance	
46	Mühlroth, Christian, and Michael Grottke	2020	Artificial intelligence in innovation: How to spot emerging trends and technologies	IEEE Transactions on Engineering Management	Quantitative	3			Partnering agility
47	Olan, Femi, Jana Suklan, Emmanuel Ogiemwonyi Arakpogun, and Andrew Robson	2021	Advancing consumer behavior: The role of artificial intelligence technologies and knowledge sharing	IEEE Transactions on Engineering Management	Quantitative	3			Context-based knowledge sharing

(Continues)

TABLE A1 (Continued)

#	Author(s)	Year	Title	Journal	Type of study	ABS rank	Context: Technological	Context: Organizational	Context: Environmental
48	Rammer, Christian, Gastón P. Fernández, and Dirk Czarnitzki	2022	Artificial intelligence and industrial innovation: Evidence from German firm-level data	Research Policy	Quantitative	4			Screening the regulations
49	Rodríguez-Espíndola, Oscar, Soumyadeb Chowdhury, Prasanta Kumar Dey, Pavel Albores, and Ali Emrouznejad	2022	Analysis of the adoption of emergent technologies for risk management in the era of digital manufacturing	Technological Forecasting & Social Change	Quantitative	3	Cybersecurity management		
50	Russo-Spena, Tiziana, Cristina Mele, and Marialuisa Marzullo	2019	Practising value innovation through artificial intelligence: The IBM Watson case	Journal of Creating Value	Qualitative	1			Orchestration platform-based ecosystem
51	Stahl, Bernd Carsten, Laurence Brooks, Tally Hatzakis, Nicole Santiago, and David Wright	2023	Exploring ethics and human rights in artificial intelligence—A Delphi study.	Technological Forecasting and Social Change	Qualitative and Quantitative	3			Screening regulations
52	Sjödin, David, Vinit Parida, Maximilian Palmié, and Joakim Wincent	2021	How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops	Journal of Business Research	Qualitative	3	Cybersecurity management		
53	Tambe, Prasanna, Peter Cappelli, and Valery Yakubovich	2019	Artificial Intelligence in human resources management: challenges and a path forward	California Management Review	Qualitative	3		Data project governance	

TABLE A1 (Continued)

#	Author(s)	Year	Title	Journal	Type of study	ABS rank	Context: Technological	Context: Organizational	Context: Environmental
54	Trocin, Cristina, Ingrid Våge Hovland, Patrick Mikalef, and Christian Dremel	2021	How artificial intelligence affords digital innovation: A cross-case analysis of Scandinavian companies	Technological Forecasting & Social Change	Qualitative	3			Screening the regulations
55	Uren, Victoria, and John S. Edwards	2023	Technology readiness and the organizational journey toward AI adoption: An empirical study	International Journal of Information Management	Qualitative	2		Data project governance	
56	Verganti, Roberto, Luca Vendraminelli, and Marco Iansiti	2020	Innovation and design in the age of artificial intelligence	Journal of Product Innovation Management	Qualitative	4			Multimodal value co-creation
57	von Hippel, Erik, and Sandro Kaulartz	2021	Next-generation consumer innovation search: Identifying early-stage need-solution pairs on the web	Research Policy	Quantitative	4			Screening the regulations
58	Wamba-Taguimdje, Serge-Lopez, Samuel F. Wamba, Jean R. K. Kamdjoug, and Chris E. T. Wanko	2020	Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects	Business Process Management Journal	Qualitative	2			Context-based knowledge sharing
59	Wang, Xuequn, Xiaolin Lin, and Bin Shao	2022	How does artificial intelligence create business agility? Evidence from chatbots	International Journal of Information Management	Quantitative	2		Processes optimization	
60	Warner, Karl S. R., and Maximilian Wäger	2019	Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal	Long Range Planning	Qualitative	3			Partnering agility
61	Yams, Nina B., Valerie Richardson, Galina Esther Shubina, Sandor	2020	Integrated AI and innovation management: The beginning of a beautiful friendship	Technology Innovation Management Review	Qualitative	1		Searching and recombining knowledge	

(Continues)

TABLE A1 (Continued)

#	Author(s)	Year	Title	Journal	Type of study	ABS rank	Context		
							Technological	Organizational	Environmental
	Albrecht and Daniel Gillblad								
62	Zhang, Haili, Xiaotang Zhang, and Michael Song	2021	Deploying AI for new product development success	Research-Technology Management	Quantitative	2	Functional competence		