

Artificial intelligence as a driver of organizational digitalization: Benefits, conditions and challenges.

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Abstract

This theoretical article examines artificial intelligence in organizational digitalization. It distinguishes digitization, digitalization, and digital transformation, then combines sociotechnical theory with the dynamic capabilities perspective to explain how technology interacts with employees, routines, organizational structures and adaptation. The framework proposes that artificial intelligence supports transformation when aligned with strategy, integrated into processes and complemented by employee expertise, data and responsible governance. It highlights tensions involving discretion, bias, accountability and the fit between standardized systems and local practices. The article contributes propositions for empirical research and argues that AI's value depends on integrating technical systems with human capabilities and organizational oversight. AI applications can automate repetitive tasks, analyze large amounts of data, personalize services and support decisions. However, their effects depend on data quality, employee skills, leadership commitment and the organizational context. For this reason, the article moves the focus beyond the simple adoption of AI and highlights the organizational capabilities and governance needed to integrate it responsibly.

Keywords: artificial intelligence; organizational digitalization; digital transformation; dynamic capabilities; sociotechnical systems; AI adoption; responsible AI governance.

1. Introduction

Digital technologies have gradually changed how organizations create value, organize their activities, interact with customers and compete within the market. It has initially involved converting analogue information into digital form and has gradually expanded into a broader transformation that reshapes how organizations operate. Therefore, digital transformation reflects how organizations respond to digital change by reconsidering how they create value and by adapting their strategies, structures and ways of working (Vial, 2019; Verhoef et al., 2021). Verhoef et al. (2021) distinguish digitization which involves converting analogue information into digital form, digitalization which refers to the use of digital technologies to improve existing processes and digital transformation which includes wide changes affecting the organization as a whole. The current spread of digitalization is driven by the increasing availability of data, improvements in computing infrastructure and advanced technologies in machine learning and natural language processing, with generative artificial intelligence emerging more recently as an important development. These developments have been expanding the role of information technologies. Rather than simply supporting administrative tasks and operational efficiency, digital systems are increasingly able to learn from data, generate content, recommend actions, assist decision-making and interact with users with a certain degree of autonomy. As a result, Artificial intelligence is increasingly integrating organizational processes, services and management practices (Berente et al., 2021; Kaplan & Haenlein, 2019). Berente et al. (2021) explain that modern artificial intelligence tools differ from traditional information technologies because they can operate with autonomy, learn from data and may operate in ways that are difficult to fully understand. These characteristics create new challenges for organizations trying to manage AI effectively.

Artificial intelligence is increasingly integrating companies as a compulsory tool used for both daily operations and longer-term strategy. Companies can use it in order to automate repetitive activities, process large amounts of data, support managerial decisions, improve customer services and develop new products or business models. However, having access to AI technology does not automatically create these benefits. Its value also depends on the resources and capabilities available within the organization, particularly technical resources, employee skills, managerial capabilities and the way work is organized (Enholm et al., 2022; Mikalef & Gupta, 2021). Mikalef and Gupta (2021), for example, show that AI creates greater value when technological resources are combined with the skills and organizational processes needed to use them effectively.

These facts highlight an important research problem. Although the adoption of artificial intelligence is often expected as an improvement of organizational performance, introducing the technology does not guarantee better results. Many organizations still struggle to move from small-scale experiments and pilot projects to a wider use of artificial intelligence across their activities. Effective AI depends on several factors including good-quality data, appropriate skills, suitable infrastructure, coordination between teams, management support and clear governance. Artificial intelligence also introduces ethical and social concerns that may be more significant than those associated with traditional information systems (Enholt et al., 2022; Jöhnk et al., 2021; Papagiannidis et al., 2025). Therefore, understanding AI as a driver of organizational digitalization requires considering not only what it can do but also the conditions that enable organizations to effectively use and integrate it.

From an academic perspective, this topic is also important because research on artificial intelligence is spread across different fields including information systems, management, economics, organization studies, computer science and ethics. A purely technical perspective cannot explain why the same technology may produce different results across organizations. At the same time, focusing only on management may ignore the specific features of AI systems that influence how they are used and integrated. This makes a sociotechnical perspective useful since it enhances the interaction between technical systems and the social environment in which they are used (Sarker et al., 2019). The dynamic capabilities perspective helps explain why some organizations are better than others at identifying technological opportunities, using their resources effectively and adapting their structures to the ongoing digital development (Teece et al., 1997; Warner & Wäger, 2019).

These issues are highly relevant in practice since managers working with rapidly changing AI technologies must make decisions that go beyond choosing algorithms or software tools. They need to decide which tasks can be automated, which should remain under human supervision, how employees should interact with AI systems, how data should be used responsibly and how AI-based decisions should be monitored. These decisions can directly affect organizational performance, employees, customer trust and the responsible use of AI within the organization (Berente et al., 2021; Kellogg et al., 2020; Papagiannidis et al., 2025).

This article examines artificial intelligence as a driver of organizational digitalization, focusing on its benefits, the conditions for its effective use and the challenges it raises. It addresses the following research question: Under what organizational conditions does artificial intelligence effectively contribute to organizational digitalization, and what benefits and challenges emerge from its integration? The main objective of the article is to identify the organizational conditions

under which AI creates value in digitalization processes. To do so, the study pursues four specific goals. First, it clarifies the relationship between organizational digitalization and artificial intelligence. Then, it identifies the main mechanisms through which AI can contribute to organizational transformation. Then, it examines the resources and organizational conditions that influence AI adoption and value creation. Finally, it considers the technological, human, organizational and governance challenges associated with the integration of AI.

To develop these objectives, the article adopts a structured literature review related to research in digital transformation, AI management, sociotechnical systems, dynamic capabilities, organizational readiness and responsible artificial intelligence. The main structure of the paper is organized as follows. Section 2 develops the theoretical framework and reviews the relevant literature. Section 3 explains the methodological approach, including the epistemological positioning of the research and the mode of reasoning adopted. Section 4 presents and discusses the main findings, especially the conditions under which AI can move from an isolated technological investment to an organizational capability. Section 5 concludes the article by summarizing the main findings and outlining implications and directions for future research.

2. Theoretical framework and literature review

2.1 Organizational digitalization

The concepts of digitization, digitalization and digital transformation are related but should not be treated as equivalent. Digitization refers to the technical conversion of analogue information into digital formats. Digitalization has a broader sociotechnical meaning and concerns the use of digital technologies in organizational and social contexts. Digital transformation represents a deeper level of change, in which digital technologies contribute to modifications in strategy, organizational structures, processes, capabilities and value-creation mechanisms (Legner et al., 2017; Verhoef et al., 2021). For example, Legner et al. (2017) explicitly distinguish digitization as a technical process from digitalization as a wider process through which digital technologies are included in individual, organizational and societal activities.

Similarly, Verhoef et al. (2021) conceptualize digital transformation as an evolutionary progression from digitization to digitalization. At this stage, companies and firms do not simply digitalize existing activities, they reconsider how value is created, how customers are served, how operations are coordinated and sometimes how the entire business model is designed. Hence, digital transformation involves technological resources but also requires organizational structures and capabilities that enable companies to adapt to changing competitive conditions (Verhoef et al., 2021; Vial, 2019). This perspective is also supported by Vial (2019) who describes digital transformation as a process through which digital technologies disrupt existing

organizational practices, leading firms to reconsider their strategic choices and reshape the ways in which they create value. Digital transformation is shaped by structural changes within the organization and by internal challenges leading to both positive and negative consequences. Therefore, digital transformation is not simply a technological process nor automatically leads to positive outcomes. Its effect largely depends on how organizations respond to new technologies and adapt their structures, processes and practices (Vial, 2019).

The literature shows that organizational digitalization depends on several dimensions that are closely related. Technology provides the infrastructure, systems and applications that make digital transformation possible. However, technology alone is not sufficient because business processes determine where and how these digital tools are used within the organization. Employees also play an important role since their skills and ability to work with new technologies influence whether digital systems are effectively adopted. Organizational culture is another important factor because it can support or limit experimentation, learning, collaboration and openness to change. Finally, changes in the business model determine whether digital technologies are only used to improve existing activities or whether they contribute to creating new ways of delivering value (Hanelt et al., 2021; Legner et al., 2017). Recent research also organizes digital transformation around similar dimensions including technology, processes, people, culture and business models (Al-Moaid & Almarhdi, 2024).

These different dimensions show that digitalization cannot be understood only as a technological process. It also depends on the interaction between technology, people and organizational arrangements. This idea is consistent with the sociotechnical perspective, which considers technical systems and social elements as closely connected. From this perspective, technologies should not be analyzed separately from the employees, structures and work practices in which they are used. Organizational performance depends on how these elements work together. The sociotechnical approach has therefore emphasized the importance of considering technological and human factors at the same time, especially when technologies affect employee autonomy, decision-making, work routines and job design (Bostrom & Heinen, 1977; Sarker et al., 2019). Amanollahnejad et al. (2026) apply this perspective to small and medium-sized enterprises (SMEs). Their study shows that AI adoption in these companies depends on the interaction between technical constraints, organizational routines and external pressures. Leadership engagement, data infrastructure and employees also play an important role in this process.

The dynamic capabilities perspective provides another way to understand digital transformation. Teece et al. (1997) define dynamic capabilities as the ability of an organization

to integrate, develop and reorganize its competencies when the environment changes. In the context of digital transformation, this means that having technological resources is not enough to create long-term value. Organizations also need to continuously adapt their resources, skills and structures as technologies and market conditions evolve. These capabilities are generally described through three main activities: sensing new opportunities and threats, seizing relevant opportunities by committing resources, and transforming or reorganizing existing resources and structures when necessary (Teece et al., 1997; Warner & Wäger, 2019).

Research on digital transformation increasingly supports this idea. Organizations that manage technological change successfully are usually able to identify emerging technologies, evaluate where they can create value, allocate the necessary resources and then adapt their processes and capabilities. Therefore, digital transformation should not be viewed as a one-time technology project. It is rather a continuous process in which organizations need to learn, adjust and reorganize themselves as technologies develop (Warner & Wäger, 2019; Al-Moaid & Almarhdi, 2024).

Together, the sociotechnical and dynamic capabilities perspectives provide a useful theoretical foundation for studying AI-driven digitalization. The sociotechnical perspective helps explain why the impact of AI depends on the way technical systems interact with employees, work practices and organizational structures. The dynamic capabilities perspective helps explain how organizations identify opportunities related to AI, mobilize the resources needed to use these technologies and adapt their existing activities as AI continues to evolve (Sarker et al., 2019; Teece et al., 1997; Warner & Wäger, 2019).

2.1 Artificial intelligence

Artificial intelligence refers to a large group of technologies that enable computer systems to perform tasks that are generally associated with human intelligence, such as learning, reasoning, interpreting information, making predictions and solving problems. Kaplan and Haenlein (2019) define AI as the ability of a system to correctly interpret external data, learn from them and use what it has learned to achieve specific objectives. However, AI should not be considered as one single technology because AI systems can differ considerably in their capabilities, level of autonomy and the tasks they are designed to perform (Kaplan & Haenlein, 2019).

Machine learning is one of the most important areas of AI currently used in organizations. Unlike traditional systems that mainly follow predefined rules, machine-learning systems can learn patterns from data and use them to make predictions, classifications or recommendations. Deep learning extends these capabilities by using more complex models that can process large amounts of unstructured data such as images, audio and text. Natural language processing

allows AI systems to understand, analyze and generate human language. These developments have contributed to the growing use of AI in different organizational activities, including customer service, data analysis, knowledge work and decision support (Berente et al., 2021; Davenport & Ronanki, 2018; Dwivedi et al., 2023).

More recently, generative AI has further expanded the use of artificial intelligence within organizations. Unlike AI systems that mainly classify information or make predictions based on existing data, generative AI can produce new content such as text, images and software code. Large language models are an important example because they allow employees and customers to interact with AI systems through natural language. This makes AI more accessible for a wide range of tasks including content creation, information analysis, customer interaction and support for knowledge-intensive work. However, these systems can also produce inaccurate, biased or fabricated information. Their use therefore requires appropriate verification, human supervision, transparency and adequate user skills (Dwivedi et al., 2023). As a result, generative AI can provide important productivity opportunities but also creates new managerial, ethical and governance challenges.

From an organizational perspective, AI can therefore be understood as a group of technologies with different levels of learning, autonomy and interpretability rather than as a single application. Berente et al. (2021) explain that these characteristics distinguish modern AI systems from many traditional information technologies and make their management more complex. As AI systems become increasingly involved in organizational activities and decision-making, managers need to consider more than their technical performance. They also need to understand how these systems interact with employees, influence existing work routines, affect customers and create broader organizational and social consequences (Berente et al., 2021).

2.2 The Relationship between AI and organizational digitalization

One of the main ways AI contributes to digitalization is through the automation of tasks and processes. AI can perform repetitive or information-intensive activities, which can reduce processing time, improve scalability and allow employees to focus on other tasks. However, AI-based automation goes beyond traditional mechanization because it can also support cognitive activities such as classification, prediction, communication and decision-making (Acemoglu & Restrepo, 2019; Raisch & Krakowski, 2021).

However, automation does not always mean replacing human workers. Raisch and Krakowski (2021) distinguish between automation, where machines perform tasks previously carried out by humans, and augmentation, where humans and AI work together. These two approaches are

closely related and can be combined depending on the task and organizational context. Focusing only on complete automation or only on human involvement may create limitations. In many cases, effective AI integration requires a balance between both approaches that can evolve as technologies and work practices change (Raisch & Krakowski, 2021). Johnson et al. (2022) also support this idea. In the case of research and development, they find that companies mainly use AI to increase human activities rather than to automate them.

AI also supports digitalization through data analysis and decision support. Machine-learning systems can analyze large volumes of data, identify patterns that may be difficult for individuals to detect and generate predictions quickly. Shrestha et al. (2019) explain that organizations can organize human-AI decision-making in different ways, from full delegation to AI to different combinations of human and algorithmic judgments. The most appropriate approach depends on several factors including how easy the system is to understand, the number of possible alternatives, the required decision speed and the type of decision being made (Shrestha et al., 2019).

The combination of human and AI capabilities becomes especially important when decisions involve uncertainty, context or ethical judgment. AI can process large amounts of information quickly and consistently, while humans can provide contextual understanding, social awareness, intuition and responsibility. For this reason, Jarrahi (2018) presents human-AI collaboration as a useful model for organizational decision-making, especially in situations where neither fully human nor fully automated decisions are sufficient. This collaboration also depends on the trust that employees place in AI. For example, Gkinko and Elbanna (2023) show that employees' trust in an AI chatbot used within the organization has cognitive, emotional and organizational dimensions.

AI also contributes to digitalization through customer-related activities. Organizations can use algorithms to analyze customer behavior, identify different customer groups, personalize communication, provide recommendations and automate service interactions. Conversational AI and generative AI can further support continuous interaction with customers through natural language and can generate personalized responses more quickly. These applications can improve customer experience when they are accurate, relevant and well-integrated into organizational processes. However, poor use of personalization can also create concerns related to privacy, manipulation, lack of transparency and trust (Dwivedi et al., 2023; Papagiannidis et al., 2025).

At a more strategic level, AI can also contribute to innovation in products, services and business models. Digital technologies are increasingly used not only to improve internal efficiency but

also to change the way organizations create and deliver value. AI-enabled products, intelligent services, predictive tools and data-driven platforms can create new forms of value and may also change how organizations generate revenue. In this way, AI adoption becomes directly connected to broader changes in the business model (Berente et al., 2021; Legner et al., 2017; Verhoef et al., 2021). For example, Sjödin et al. (2021) show that manufacturing firms are able to scale AI when they develop capabilities related to data, algorithm development and the wider use of AI across the organization, while also changing their business models.

The relationship between AI and digitalization is therefore not one-directional. Digitalization provides the data, infrastructure, connected systems and organizational experience needed for AI adoption, while AI can further strengthen digitalization by introducing new forms of automation, decision support, personalization and innovation. For this reason, organizations with fragmented data, poorly organized processes or insufficient digital skills may struggle to benefit from advanced AI technologies even when these technologies are available (Enholm et al., 2022; Jöhnk et al., 2021).

2.3 Benefits and limitations of artificial intelligence

The potential benefits of AI are generally related to efficiency, speed, analytical capacity, innovation and organizational performance. By automating routine activities and providing faster access to information and analysis, artificial intelligence can help reduce some operating costs and improve the responsiveness of organizational processes. At a more strategic level, AI can also support innovation and organizational performance when the technology is combined with appropriate human skills, managerial capabilities and organizational resources (Enholm et al., 2022; Mikalef & Gupta, 2021).

Recent research on generative artificial intelligence also provides evidence of productivity improvements, although these effects can vary depending on the type of task and the employees involved. Brynjolfsson et al. (2025), as an example, studied the use of a generative AI conversational assistant among customer-support agents and found an overall increase in productivity, although the benefits were not the same for all employees. These findings suggest that AI can do more than automate tasks. It can also support employees by giving them access to knowledge and helping them perform their work more effectively (Brynjolfsson et al., 2025). However, the implementation of AI also creates important technological and organizational challenges. AI systems depend strongly on the availability and quality of data. If data are inaccurate, incomplete, outdated or biased, the outputs produced by AI systems may also be unreliable. Poor-quality data can also reproduce or reinforce existing inequalities. For this

reason, organizations need appropriate processes for collecting, cleaning, integrating, securing and monitoring data throughout the AI lifecycle (Jöhnk et al., 2021; Mikalef & Gupta, 2021). Algorithmic bias is one of the most important challenges associated with AI because machine learning models can reproduce patterns that already exist in the data used for training. When these patterns reflect social or organizational biases, artificial intelligence systems may generate unfair outcomes. This can affect activities such as recruitment, credit decisions, customer segmentation and employee evaluation. Bias is also closely related to transparency and accountability because it becomes more difficult to understand and challenge a decision when the AI system operates in a way that is not easily understandable (Jobin et al., 2019; Papagiannidis et al., 2025).

Privacy and cybersecurity create additional concerns. AI systems often depend on large amounts of data, including information related to employees and customers. The increased collection and use of such data may create risks of privacy violations, unauthorized access and security problems. Generative and autonomous AI systems can also create new security risks and increase organizational dependence on external platforms and model providers. For this reason, privacy, security, transparency and human oversight should be considered from the beginning of AI implementation rather than only after problems appear (Berente et al., 2021; Jobin et al., 2019; Papagiannidis et al., 2025).

The impact of AI on employment and work organization is also complex. Automation can replace workers in some tasks, but technological change can also increase productivity and create new tasks and occupations. Acemoglu and Restrepo (2019) describe this through two effects. The first is the displacement effect, where some tasks are transferred from workers to machines. The second is the reinstatement effect, where new tasks are created and generate new forms of labor demand. Therefore, the impact of AI on employment does not depend only on the number of jobs that can theoretically be automated. It also depends on how tasks and roles change within organizations and economies.

AI can also change the way employees are managed and controlled. Kellogg et al. (2020) show that algorithmic systems can be used to direct, evaluate and monitor employees through different mechanisms such as recommendations, restrictions, recording, rating, rewarding and replacement. These systems may improve coordination and measurement, but they can also create concerns related to surveillance, employee autonomy, fairness and resistance. The impact of AI therefore goes beyond productivity and also affects the distribution of authority and the quality of working life (Kellogg et al., 2020).

For this reason, the balance between replacement and complementarity is important in the responsible integration of AI. Organizations that use AI only to replace human labor may ignore the value that can be created when human expertise is combined with AI capabilities. At the same time, assuming that collaboration with AI will automatically protect employee autonomy can also be misleading because automation and augmentation often exist together. Effective and sustainable AI integration therefore requires careful decisions about task allocation, employee participation, reskilling and human oversight (Jarrahi, 2018; Raisch & Krakowski, 2021).

2.4 Factors influencing artificial intelligence adoption

Successful adoption of artificial intelligence depends first on the skills and knowledge available within the organization. Employees need enough understanding of AI tools in order to identify useful applications, interpret outputs, interact with AI systems and recognize their limitations. This does not mean that all employees need to become AI specialists. Instead, organizations need a combination of technical skills, domain knowledge, data literacy and general AI awareness across different functions. Jöhnk et al. (2021) identify AI awareness and employee upskilling as important dimensions of organizational readiness for AI. Employee attitudes are also important. Lichtenthaler (2020) explains that the same employees may reject AI when it replaces human interaction, but accept it when they see a personal benefit in using it.

Data availability and quality are also essential. Many AI applications learn from data rather than simply following predefined instructions. As a result, an organization may have access to advanced AI tools but still be unable to obtain useful results if its data are fragmented, inaccessible, poorly labeled or of low quality. Effective AI adoption therefore requires strong data governance and appropriate infrastructures that allow relevant information to be shared securely across the organization (Jöhnk et al., 2021; Mikalef & Gupta, 2021).

Management support is another important factor because AI projects often require investment, experimentation, collaboration across departments and changes to existing work practices. Top management can provide resources, give strategic direction, encourage cooperation between technical and business teams and explain the purpose of AI adoption to employees. Previous research identifies several important conditions for AI readiness including top-management support, strategic alignment, AI-process fit, financial resources, technological infrastructure and qualified personnel (Chatterjee et al., 2021; Jöhnk et al., 2021). In this context, Holmström (2022) proposes an AI readiness framework based on four dimensions, namely technologies, activities, boundaries and goals. Similarly, Tursunbayeva and Chalutz-Ben Gal (2024) highlight

that AI adoption requires organizations to consider technology, organization and people at the same time.

Organizational culture also influences the way AI is adopted and used in practice. A culture that supports collaboration, experimentation, learning and data-informed decision-making can facilitate AI adoption. In contrast, resistance to change, lack of trust, fear and organizational silos can limit the use of AI even when the technology itself works well. Since AI projects often require technical, managerial and domain expertise, collaboration between different functions becomes particularly important (Jöhnk et al., 2021; Mikalef & Gupta, 2021).

These factors can also be understood through the dynamic capabilities perspective. Organizations first need to identify where AI can create real value instead of adopting the technology simply because it is available. They then need to invest in the most relevant opportunities by providing resources, leadership support, skills and infrastructure. Finally, they need to adapt existing processes, roles and organizational structures so that AI can become integrated into everyday activities. Effective AI adoption therefore depends on the organization's ability to adapt over time rather than on technology acquisition alone (Teece et al., 1997; Warner & Wäger, 2019). Recent empirical studies support this view. Taherizadeh and Beaudry (2023) describe AI-driven digital transformation in SMEs as a gradual process that requires the ability to sense, seize and reconfigure. In addition, Peretz-Andersson et al. (2024) show that SMEs combine their AI resources into learning and governance capabilities in order to implement AI.

Governance is another essential condition because AI creates risks that cannot be managed only through technical performance. Jobin et al. (2019) show that many international AI ethics guidelines emphasize similar principles including transparency, fairness, responsibility, privacy and the prevention of harm. However, identifying these principles does not automatically explain how organizations should apply them in practice.

Papagiannidis et al. (2025) address this issue by examining responsible AI governance through structural, procedural and relational practices. Their work shows that organizations need mechanisms that translate general principles such as accountability, transparency, fairness, privacy, human oversight and robustness into concrete practices throughout the AI lifecycle. Responsible governance should therefore be included from the beginning of AI development and implementation rather than introduced only after ethical or legal problems appear (Papagiannidis et al., 2025).

Responsible governance can also influence the way employees and users accept AI systems. Employees may view AI negatively when it reduces their autonomy, increases surveillance or

creates uncertainty about their jobs. Clear communication, employee participation, accountability and attention to human well-being can help reduce these concerns and improve cooperation between employees and AI systems. Governance therefore does not only help organizations meet ethical and legal requirements. It also contributes to trust, legitimacy and better human-AI collaboration (Papagiannidis et al., 2025).

3. Methodology

This study adopts a structured integrative literature review approach. This type of review is useful when a topic is discussed across different research fields and when the objective is to bring together different theoretical perspectives, identify recurring concepts and develop a broader understanding of the subject. Webster and Watson (2002) explain that a literature review should be organized around concepts rather than simply presenting one study after another. Snyder (2019) also distinguishes systematic, semi-systematic and integrative reviews depending on the research question and the nature of the existing literature.

The integrative approach was considered appropriate for this study because the relationship between artificial intelligence and organizational digitalization involves several research areas including information systems, strategic management, organizational theory, economics, digital transformation, technology adoption and AI ethics. Therefore, the review does not focus on only one type of research. It combines theoretical studies, literature reviews, empirical organizational research and more recent studies related to generative AI and responsible AI governance (Snyder, 2019).

3.1 Epistemological stance and reasoning approach

This research is based on an interpretivist epistemological position. The objective is not to measure the effect of artificial intelligence on organizational performance, but to understand how existing studies explain the conditions under which AI contributes to organizational digitalization. Knowledge is therefore built by interpreting and comparing the concepts developed in previous research rather than by testing hypotheses statistically. The study follows an abductive mode of reasoning. The analysis goes back and forth between the two theoretical frameworks used in this article, namely sociotechnical theory and the dynamic capabilities perspective, and the conceptual and empirical findings of the literature. This makes it possible to identify recurring mechanisms and conditions and to propose relationships that can be tested in future empirical research (Dubois & Gadde, 2002). This position is consistent with the integrative review approach, which aims to bring together and reinterpret knowledge from different fields rather than to combine quantitative results (Snyder, 2019; Torraco, 2005).

3.2 Search strategy and source selection

The literature search was carried out in two stages. In the first stage, an exploratory search was conducted on Google Scholar using the keywords “artificial intelligence as a driver of organizational digitalization”, “AI adoption”, “responsible AI” and “digital transformation”. No restriction was applied to the publication date. Priority was given to highly cited studies published in Q1 and Q2 journals, in order to identify the main theoretical contributions and the most influential reviews in the field. This first stage led to the selection of 25 studies. In the second stage, a complementary search was carried out in Scopus. The search query combined four groups of keywords related to artificial intelligence, digitalization, organizations and AI adoption. It was limited to peer-reviewed articles and reviews published in English between 2017 and 2026 in business, management, decision sciences, social sciences and economics. This search returned 1,763 documents (1,630 articles and 133 reviews). The documents whose title included both a term related to AI and a term related to organizations or digitalization were first kept ($n = 656$). Then, in line with the citation criterion used in the first stage, the documents cited at least ten times ($n = 162$) were screened based on their title and abstract. A study was selected when it examined the adoption, implementation, capabilities, effects or governance of AI at the organizational level and was related to at least one of the five themes of the review. Studies focusing on technical applications in a specific sector or on macro-economic analyses were excluded. Among the relevant studies, priority was given to those that added new insights to the five themes of the review and were not redundant with the studies already identified in the first stage. Four of the studies identified in the first stage also appeared in the Scopus results, which confirms the consistency between the two stages. Finally, eleven new studies were added and the final corpus includes 36 studies. Table 1 summarizes this procedure.

Table 1. Literature search and selection procedure

Stage	Source and date	Search terms / query	Selection criteria	Studies retained
1. Exploratory search	Google Scholar	"artificial intelligence as a driver of organizational digitalization", "AI adoption", "responsible AI", "digital transformation"	No date restriction; highly cited studies; journals ranked Q1–Q2	25
2. Structured search	Scopus, 21 October 2026	TITLE-ABS-KEY: (AI terms) AND (digitali* OR "digital transformation") AND (organization terms) AND (adoption, readiness, capabilities, governance, benefits, challenges); 2017–2026; articles and reviews; English; business, management, decision, social sciences, economics	1,763 records → title filter (AI term + organizational term): 656 → cited ≥ 10 times: 162 → title and abstract screening (organizational level, five themes)	11 additional (4 already identified in stage 1)
Final corpus				36 studies

3.3 Analysis of the literature

The literature was organized around five main themes related to the research question. The first focuses on organizational digitalization and digital transformation. The second examines artificial intelligence and its applications within organizations. The third considers the mechanisms through which AI contributes to digitalization including automation, augmentation, decision support and innovation. The fourth focuses on the main benefits and limitations of organizational AI. Finally, the fifth examines the conditions influencing adoption including organizational readiness, dynamic capabilities, sociotechnical alignment and responsible governance. Priority was given to peer-reviewed studies published in established journals as well as important theoretical contributions that support the theoretical foundation of the study.

Some older studies were also included because they remain important for understanding the theoretical perspectives used in this article, particularly sociotechnical theory and the dynamic capabilities perspective. More recent research was then used to examine how these perspectives can be applied to digital transformation and AI adoption today. This allows the study to connect established organizational theories with recent developments in artificial intelligence (Sarker et al., 2019; Teece et al., 1997).

The selected publications were analyzed according to the main mechanisms, resources, conditions, outcomes and challenges associated with organizational AI. The themes identified across the studies were then compared and interpreted using the sociotechnical and dynamic

capabilities perspectives. This approach follows Webster and Watson (2002), who argue that literature reviews should focus on concepts and the relationships between them rather than simply summarize individual studies.

Therefore, this study should be understood as a structured theoretical synthesis rather than an exhaustive systematic review or meta-analysis. The objective is not to include every publication on artificial intelligence and digitalization. Instead, the review brings together relevant and influential studies in order to understand the organizational conditions under which AI can contribute to digital transformation and to identify relationships that can be further examined through future empirical research (Snyder, 2019; Tranfield et al., 2003).

4. Discussion

The literature reviewed in this study shows that AI does not automatically lead to organizational digitalization. The same technology may improve performance in one organization while remaining limited to experimental projects in another. This difference can be explained by the fact that the value created by AI depends on several factors including technology, data, employees, organizational processes, leadership and governance. This supports the sociotechnical perspective which considers that technology cannot be separated from the social and organizational environment in which it is used (Mikalef & Gupta, 2021; Sarker et al., 2019). Artificial intelligence becomes an important driver of digitalization when it is effectively integrated into organizational processes rather than simply used as a technological tool. Even a highly advanced artificial intelligence system may not be valuable if its outputs are not useful for making decisions, workflows, products or services. On the other side, companies with well-defined processes, appropriate data flows and clear responsibilities are in a better position to transform artificial intelligence capabilities into operational and strategic outcomes (Enholm et al., 2022; Jöhnk et al., 2021).

Data also represent an important organizational resource for artificial intelligence. The performance of AI systems depends on the quality, relevance and accessibility of data. However, these characteristics also depend on the way organizations collect, manage and share information. Therefore, investment in AI should not focus only on algorithms, companies also need appropriate data infrastructure, integration of mechanisms and governance practices (Mikalef & Gupta, 2021).

Human performances represent another important condition. Although AI can automate several activities, organizational transformation also requires employees who can understand the outputs, interpret them correctly and identify their limitations. Employees also need to recognize situations where human judgment remains important. Therefore, companies need

continuous training, collaboration between departments and interaction between technical experts, managers and employees. This supports the idea that artificial intelligence enhances human performance rather than simply replace it (Jarrahi, 2018; Raisch & Krakowski, 2021). Management also has an important role in connecting technological opportunities with organizational objectives. Managers need to identify which artificial intelligence applications are relevant to the organization, decide where resources should be allocated and determine the appropriate level of automation and human supervision. They also need to manage the organizational changes associated with AI adoption. Without clear strategic direction, AI initiatives may remain limited to small-scale projects and fail to become integrated across the organization. At the same time, implementation that does not involve employees may create resistance and reduce their engagement (Jöhnk et al., 2021; Teece et al., 1997).

The dynamic capabilities perspective helps explain this process. Organizations first need to identify where AI can provide useful solutions or create new opportunities, which corresponds to sensing. They then need to select the most relevant opportunities and mobilize the required resources including data, skills, infrastructure, financial investment and management support, which corresponds to seizing. Finally, organizations may need to adapt their processes, roles, structures and governance mechanisms as AI becomes increasingly integrated into their activities. This corresponds to transforming. Therefore, AI-driven digitalization should be understood as a continuous process of organizational adaptation rather than a one-time implementation project (Teece et al., 1997; Warner & Wäger, 2019).

This also explains why access to advanced AI technologies does not necessarily mean that an organization is ready to use them effectively. AI tools are becoming increasingly accessible, but organizations still need other resources that are more difficult to develop. These include employee expertise, collaboration between departments, data culture, managerial capabilities and organizational learning. Mikalef and Gupta (2021) therefore distinguish between simply possessing AI resources and developing the organizational capability required to use them effectively.

Responsible governance is also important for successful AI integration. Problems related to bias, privacy, lack of transparency, unreliable outputs and unclear responsibility can reduce trust in AI systems and limit their potential benefits. Organizations therefore need clear responsibilities, human supervision, monitoring of data and AI systems and mechanisms that allow important decisions to be reviewed or questioned. Responsible governance should not only be considered as a limitation on innovation. It can also contribute to the sustainable and trustworthy use of AI (Jobin et al., 2019; Papagiannidis et al., 2025).

The impact of AI on employees also depends partly on organizational choices. AI can replace some tasks, but it can also support employees and create new activities or roles. Acemoglu and Restrepo (2019) explain that technological change can both replace existing tasks and create new ones. Raisch and Krakowski (2021) similarly show that automation and augmentation are closely connected. Managers therefore influence the effects of AI on employees through decisions related to task allocation, training, participation and organizational control.

Another important issue concerns the relationship between efficiency and employee autonomy. Algorithmic systems can improve monitoring and standardize some activities, but these same characteristics may also increase employee perceptions of surveillance and reduce autonomy. Kellogg et al. (2020) show that algorithmic management can change workplace relationships and may create new forms of employee resistance. Therefore, the impact of AI should not be evaluated only through productivity or cost reduction. Organizations should also consider job quality, autonomy, fairness and trust (Kellogg et al., 2020; Sarker et al., 2019).

Overall, the findings suggest that AI contributes more effectively to organizational digitalization when several conditions are present at the same time. These include appropriate AI technologies, high-quality data, well-defined organizational processes, employee expertise, strategic management, the ability to adapt and responsible governance. A weakness in one of these areas may limit the value created by AI because these different factors are closely connected (Enholm et al., 2022; Jöhnk et al., 2021; Mikalef & Gupta, 2021; Papagiannidis et al., 2025).

Based on these findings, the article formulates six research propositions that can be tested in future empirical studies. Each proposition links an explanatory variable identified in the literature to the contribution of AI to organizational digitalization. Table 2 illustrates these propositions, the variables they involve, possible indicators for measuring them and the main studies from which they are derived. These propositions are not tested in this article. They are rather intended to guide future research, for example through questionnaire surveys or case studies in different types of organizations.

Table 2. Research propositions, variables and sources

Proposition	Explanatory variable	Possible indicators	Main sources
P1. The availability and quality of organizational data positively influence the contribution of AI to organizational digitalization.	Data quality and data governance	Data quality, data integration, data accessibility, data infrastructure	Jöhnk et al. (2021); Mikalef and Gupta (2021); Sjödin et al. (2021)
P2. Employee skills and AI awareness positively influence the integration of AI into organizational processes.	Employee skills and attitudes towards AI	Technical skills, business skills, AI awareness, acceptance of AI	Jöhnk et al. (2021); Lichtenthaler (2020); Mikalef and Gupta (2021); Barodi and Lalaoui (2025)
P3. Top-management support and strategic alignment positively influence the move from pilot AI projects to the wider use of AI across the organization.	Management support and strategic alignment	Top-management support, alignment between AI and strategy, allocated resources	Chatterjee et al. (2021); Jöhnk et al. (2021); Holmström (2022); Tursunbayeva and Chalutz-Ben Gal (2024)
P4. Dynamic capabilities mediate the relationship between AI resources and organizational digitalization.	Dynamic capabilities (sensing, seizing, transforming)	Sensing, seizing and transforming capabilities	Teece et al. (1997); Warner and Wäger (2019); Taherizadeh and Beaudry (2023); Al-Moaid and Almarhdi (2024); Peretz-Andersson et al. (2024)
P5. A balanced combination of automation and augmentation positively influences employee acceptance and the value created by AI.	Human-AI complementarity	Task allocation between humans and AI, human supervision, trust in AI	Jarrahi (2018); Raisch and Krakowski (2021); Johnson et al. (2022); Gkinko and Elbanna (2023)
P6. Responsible AI governance strengthens the positive relationship between AI adoption and organizational outcomes by increasing trust and legitimacy.	Responsible AI governance (moderating variable)	Transparency, accountability, fairness, privacy, human oversight practices	Jobin et al. (2019); Kellogg et al. (2020); Papagiannidis et al. (2025)

These findings also provide several practical implications for organizations. First, managers should start by identifying organizational needs and strategic objectives instead of adopting AI simply because the technology is available. Second, investment in AI should be accompanied by investment in employee skills, data infrastructure, process redesign and change management. Organizations should also identify which activities are suitable for automation and which require collaboration between humans and AI. Responsible governance should be considered from the beginning of AI implementation. Finally, organizations need to recognize that their AI capabilities should continue to develop because technologies, regulations,

employee expectations and user needs are constantly changing (Berente et al., 2021; Jöhnk et al., 2021; Papagiannidis et al., 2025).

On the other side, this study also has some limitations. As an integrative literature review, it focuses on bringing together theoretical and empirical findings rather than including every publication related to AI and organizational digitalization. It also does not measure the overall effect of AI on organizational performance through a meta-analysis. In addition, existing research is not equally distributed across industries, countries and types of organizations. Many studies focus on large organizations and technologically advanced economies, which means that some findings may not apply in the same way to SMEs or organizations in emerging economies. Finally, generative AI is developing rapidly and organizational practices may change faster than academic research can examine them (Dwivedi et al., 2023; Snyder, 2019).

5. Conclusion

This article set out to identify the conditions under which artificial intelligence can contribute to organizational digitalization. According to the literature, AI can support automation, data analysis, decision-making, personalized services, innovation and the creation of new products and business models. However, adopting it does not guarantee a successful digital transformation. What artificial intelligence is worth to an organization depends on how it is combined with organization's resources, processes and capabilities (Enholm et al., 2022; Mikalef & Gupta, 2021).

Our answer to the research question is that AI contributes most effectively to organizational digitalization when it is aligned with organizational goals, included in the relevant processes and backed by sufficient data, adequate employee skills and managerial capabilities. Governance mechanisms dealing with accountability, fairness, transparency, privacy and human oversight are also needed. AI-driven digitalization is better understood as an organizational and sociotechnical transformation (Jöhnk et al., 2021; Papagiannidis et al., 2025; Sarker et al., 2019).

The two theoretical perspectives used in this study help explain this conclusion from complementary viewpoints. The sociotechnical perspective draws attention to the interplay between technology, people, processes and work practices, which shapes what AI ends up achieving. The dynamic capabilities perspective, for its part, explains how organizations detect AI opportunities, mobilize the resources needed and reshape their structures and activities as the technology moves on. Combined, they suggest that the key issue is not simply whether an organization has access to AI, but whether it has built the capabilities to use it well and responsibly (Sarker et al., 2019; Teece et al., 1997; Warner & Wäger, 2019).

For practitioners, this suggests that AI should not be approached as an isolated IT initiative. Clear use cases should be defined, readiness assessed before deployment, data governance strengthened and employees trained. Staff and other stakeholders concerned should take part when processes and roles are redesigned, and suitable governance arrangements should be in place before AI is extended across the organization. Human involvement remains particularly important wherever the work requires contextual understanding, ethical judgment, creativity and interpersonal skills (Jarrahi, 2018; Jöhnk et al., 2021; Raisch & Krakowski, 2021).

The long-term effects of generative AI on employees and on organizational knowledge are also important for investigation. The question of who is responsible when humans and AI systems make decisions together remains largely open as well. Further studies could also look at how

responsible AI governance affects employee trust, well-being, innovation and organizational performance over time (Dwivedi et al., 2023; Kellogg et al., 2020; Papagiannidis et al., 2025). Finally, organizations in emerging economies deserve more attention than they have received so far. Access to data, qualified staff, funding, cloud infrastructure and AI expertise varies widely from one country and institutional environment to another. These differences are likely to influence both AI adoption and the value that organizations are able to derive from it. Research in such contexts would help establish whether frameworks built mostly on evidence from advanced economies can also account for AI-driven digitalization under different economic and organizational conditions. Some studies already move in this direction. In Morocco, Barodi and Lalaoui (2025) show that the lack of digital skills is a major barrier to AI adoption among civil servants and highlight the importance of change management. Muhammad et al. (2025) also warn that AI adoption may increase the digital divide among SMEs when technological, organizational and environmental conditions are not favourable.

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