

Adoption of artificial intelligence in decision-making processes and effects on organizational performance: a systematic review and a conceptual framework.

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Abstract

Organizational performance increasingly depends on organizations' ability to integrate advanced technologies that support strategic decision-making. In this context, artificial intelligence is emerging as a significant catalyst of transformation, particularly in environments characterized by uncertainty, competitive pressure, and rapid digital development. Although previous work confirms the positive effects of AI on decision-making quality and organizational outcomes, the literature remains fragmented regarding the mechanisms linking its adoption, the reconfiguration of decision-making processes, and performance improvement. In this context, this systematic review synthesizes the results from a selection of articles in order to provide an integrated understanding of AI adoption in an organizational context. On this basis, a conceptual model is developed to explain the mechanisms by which the adoption of AI influences decision-making processes, and show how this transformation translates into organizational performance.

Keywords: Artificial intelligence, adoption, decision-making process, organizational performance, organizational capabilities.

Introduction

The accelerated development of artificial intelligence has become a central force reshaping contemporary organizations. By transforming business models, altering managerial routines, and influencing strategic orientations, AI now constitutes a cornerstone of digital transformation. Beyond its traditional role as an automation instrument, AI increasingly operates as a cognitive mechanism capable of learning, interpreting data, and supporting complex judgments in environments characterized by volatility, informational saturation, and uncertainty (Hanelt et al., 2025; Lichtenthaler, 2020). This structural shift compels organizations to rethink their modes of functioning, as the capacity to integrate AI is progressively emerging as a determinant of competitiveness, adaptive capability, and long-term value creation.

Understanding how organizations adopt AI has therefore become a critical research priority. Recent studies highlight that adoption outcomes are shaped by the interplay of organizational resources, human factors, and strategic orientations, which together condition firms' ability to appropriate intelligent technologies (Yuniawan et al., 2025; Garlatti Costa et al., 2025). Work on digital maturity further demonstrates that organizations progress through successive stages of AI integration—from initial experimentation to fully embedded intelligent systems—each stage being associated with specific learning trajectories, restructuring processes, and governance challenges (Lichtenthaler, 2020; Bencsik, 2021). Consequently, AI adoption must be understood not as a discrete technological decision but as a multilayered organizational process requiring leadership engagement, capability development, and continuous adaptation. Parallel to these transformations, AI is reshaping the foundations of organizational decision-making. Recent contributions show that intelligent systems enhance analytical depth, facilitate the detection of strategic signals, and modify how organizations generate, evaluate, and arbitrate decision alternatives (Eicke et al., 2025; Numbi & Elongha, 2025). The integration of AI into decision routines reflects a broader digital transformation in which firms revisit their processes, business models, and internal and external interactions (Taherizadeh & Beaudry, 2023; Hautamäki & Heikinheimo, 2025).

This conceptual reconfiguration has stimulated growing scholarly interest in the link between AI and organizational performance. Existing studies demonstrate that AI contributes to performance through multiple channels, including improved operational efficiency, enhanced innovation capabilities, and better coordination across activities and resources (Grewal et al., 2023; Filieri et al., 2025; Munjeyi & Schutte, 2025). Moreover, AI plays an increasingly

strategic role in human resource management, notably by optimizing recruitment processes, strengthening talent matching, and supporting skills development, thereby reinforcing its transformative influence within organizational settings (Choudhari et al., 2025).

Despite this conceptual and empirical richness, the literature remains fragmented. Studies on adoption, decision-making processes, and organizational performance have often been conducted separately, without systemic coherence. This dispersion makes it difficult to gain an integrated understanding of how AI spreads, is implemented, and generates value within organizations. A systematic review is therefore needed to identify the convergences and divergences in existing work and come up with a conceptual model that articulates these three dimensions. However, one central question remains insufficiently addressed:

How can organizations adopt artificial intelligence in their decision-making processes, and how does this integration influence their organizational performance?

This study explicitly focuses on the adoption of artificial intelligence in decision making processes and its effect on organizational performance. In light of this, the aim of this article is to examine how organizations adopt artificial intelligence within their decision-making processes and to clarify how this integration translate into organizational performance, through the development of an integrative conceptual framework grounded in a systematic literature review.

To carry out this research, the article is structured as follows: the first part is devoted to the theoretical framework, followed by a detailed presentation of the methodology adopted in accordance with the PRISMA approach. Next, the selected studies are analyzed through a synthesis of the factors favouring the adoption of artificial intelligence in the professional environment and its impact on organizational performance. We then propose a conceptual model that explains the relationships between AI adoption, decision-making, and organizational performance. Finally, we conclude by highlighting the main lessons learned from this analysis and its managerial implications.

1. State of the art: Literature review

In order to rigorously identify the underlying factors driving the adoption of artificial intelligence in organizations, and the influence of decision-making on organizational performance, we must first clarify the fundamental concepts that govern our question. To this end, we began by establishing the conceptual framework for our study, before moving on to a review of the theoretical and empirical literature.

1.1. Conceptual framework

1.1.1 The adoption of AI in organizations

AI adoption is a multidimensional process through which individuals and organizations assess, accept, and integrate intelligent technologies. Consistent with the stages outlined in Diffusion of Innovations as awareness, persuasion, decision, implementation, and confirmation (Rogers et al., 2019), adoption depends on users' knowledge of AI (Chiu et al., 2021; Li et al., 2019), their evaluation of benefits and risks (Rana et al., 2022; Schiavo et al., 2024), and their self-confidence (Al-Sharafi et al., 2023; Kim et al., 2024). Managerial support further shapes this process by strengthening employees' willingness to use AI (Chen et al., 2021; Li et al., 2019). Ultimately, AI adoption reflects a disruptive innovation capable of transforming organizational systems (Yu & Hang, 2010).

1.1.2 Decision-making and AI Decision-making and AI

In organizations, decision-making consists of cognitive and strategic activities through which leaders orient actions and allocate resources. From a knowledge-management perspective, decision quality depends on the relevance and reliability of available information, which reinforces the value of AI tools capable of processing large data volumes and identifying meaningful patterns (Belas et al., 2015; Belas et al., 2020). AI contributes to this process by enhancing prediction, analysis, and simulation capabilities. It enables managers to better anticipate risks, compare scenarios, and support strategic judgments (Hamilton, 2025; Gümüşay et al., 2022)

1.1.3 Organizational performance

Organizational performance reflects a firm's ability to remain competitive by effectively mobilizing its resources, knowledge, and processes in changing environments. Performance depends on the capacity to combine data, technology, and human expertise, allowing knowledge management systems to enhance adaptability and competitiveness (Sanzogni et al., 2017). Research shows that AI acceptance improves productivity, efficiency, innovation, and process reliability, illustrating its direct contribution to organizational performance (Shabbir & Anwer,

2015). Performance also relies on employees' innovative behavior and digital skills, which help organizations remain resilient and competitive.

1.1.4 Organizational capabilities

The impact of AI adoption on decision-making and performance is strongly conditioned by organizational capabilities. These capabilities reflect the organization's collective ability to mobilize digital skills, learning mechanisms, and adaptive structures to integrate AI effectively. They determine how firms absorb technological knowledge, coordinate human and technological resources, and adjust existing processes in response to AI-driven change. Empirical findings show that limited capabilities—such as insufficient digital skills or weak learning routines—often hinder AI implementation and reduce its benefits (Nene & Hewitt, 2023; Munjeyi & Schutte, 2025). Conversely, organizations with strong capabilities are better able to leverage AI as a strategic and cognitive resource, amplifying its effects on decision-making and performance.

1.1.5 Strategic orientation

Strategic orientation toward AI refers to the degree to which artificial intelligence is integrated into an organization's strategic vision, governance mechanisms, and long-term priorities. Rather than treating AI as an isolated experiment, a strategic orientation positions it as a deliberate driver of transformation. Prior research shows that organizations differ widely in this regard: some deploy AI through fragmented, stand-alone initiatives, while others embed it coherently within innovation policies, investment decisions, and managerial processes (Eicke, Sabel, & Nüesch, 2025). Empirical findings also indicate that a strong strategic orientation enhances the benefits of AI adoption by enabling consistent use of data-driven insights, better alignment between AI applications and organizational goals, and more durable competitive advantages (Padigar et al., 2022; Hanelt et al., 2025).

1.2. Literature review

1.2.1 Theoretical literature review

The adoption and integration of artificial intelligence within organizations are anchored in a multidimensional theoretical landscape. The literature included in the corpus mobilizes several major conceptual approaches that collectively shed light on how AI is appropriated, disseminated, incorporated into decision-making routines, and translated into performance outcomes.

The Diffusion of Innovation Theory remains one of the most prominent lenses for examining AI adoption at the organizational level. Studies drawing on this framework argue that the

diffusion of a technological innovation is strongly shaped by the profile and influence of internal adopters, particularly innovators and early adopters, whose actions contribute to legitimizing and spreading AI tools within the organization (Garlatti Costa et al., 2025). This perspective also emphasizes that adoption trajectories depend on the perceived attributes of the innovation, such as its usefulness, complexity, and compatibility, which affect acceptance across different categories of stakeholders.

The DOI framework therefore explains why organizations with a strong innovation culture or leadership commitment tend to progress more rapidly in AI integration. In parallel, disruptive innovation theory provides complementary insights by portraying AI as a technology capable of fundamentally challenging existing routines. In public and administrative contexts, AI is presented as a disruptive mechanism that can streamline decision systems, reduce human biases, and improve anomaly detection—particularly in monitoring, compliance, and taxation processes (Munjeyi & Schutte, 2025). Its disruptive potential stems from its capacity to reorganize workflows, introduce new modes of operation, and enhance transparency. This perspective underscores the profound transformative effect of AI across both public and private sectors.

Dynamic Capabilities Theory also plays a central role in understanding how organizations integrate AI. The corpus shows that AI adoption is facilitated by three foundational capabilities—sensing, seizing, and reconfiguring—which enable firms to detect opportunities, mobilize adequate resources, and adjust structures in response to technological change (Taherizadeh & Beaudry, 2023). This framework highlights that AI integration is not solely a matter of technical readiness or individual acceptance but requires organizational learning and adaptive capacity.

Protection Motivation Theory complements these insights by examining individual responses to AI through the lens of risk perception and coping strategies. Research drawing on this theory shows that willingness to adopt AI emerges from a balance between perceived threats—such as loss of control, errors, or job substitution—and perceived benefits associated with AI use (Yuniawan et al., 2025). Self-Determination Theory further enriches this perspective by demonstrating that intrinsic motivations, including needs for autonomy, competence, and relatedness, influence engagement with AI tools. Studies from the corpus, particularly in HR and innovation contexts, reveal that when employees feel digitally competent, their motivation to use AI increases, thereby facilitating its incorporation into everyday work practices

(Yuniawan et al., 2025). This theoretical contribution highlights the importance of digital skills development and training initiatives in ensuring successful AI projects.

1.2.2 Empirical literature review

The empirical studies analyzed reveal strong convergences in the ways organizations adopt, implement, and leverage artificial intelligence. The evidence consistently shows that AI adoption is shaped by an interplay of technological, human, structural, and strategic factors, confirming its multidimensional nature.

Work conducted in the financial sector demonstrates that intentions to adopt AI arise from a combination of technological comprehension, perceived trust, and expectations regarding automation benefits. These results reinforce broader findings indicating that prior technological knowledge, perceived usefulness, and digital competence repeatedly emerge as critical drivers of organizational adoption (Chiu et al., 2021; Li et al., 2019). In the manufacturing industry, empirical findings highlight that employees' intention to use AI is conditioned by their sense of self-efficacy, technical expertise, and ability to identify tangible operational advantages. This supports the idea that adoption depends on aligning individual capabilities with the functional requirements of AI systems (Al-Sharafi et al., 2023). Evidence from Italian firms further reveals differentiated adopter profiles that shape the pace and pattern of AI integration. Organizations with a strong nucleus of innovators or technology-oriented actors progress more rapidly in stabilizing AI-enabled processes (Garlatti Costa et al., 2025).

Conversely, research conducted in South African public hospitals and within Botswana's tax administration underscores the influence of structural constraints such as insufficient infrastructure, limited digital skills, and institutional rigidities. These barriers slow down the deployment of AI-based applications, even when their potential utility is widely acknowledged (Nene & Hewitt, 2023; Munjeyi & Schutte, 2025). Other studies conducted in environments exposed to external uncertainties particularly international trade tensions show that AI serves as a stabilizing mechanism by helping suppliers adapt to market volatility, sustain customer engagement, and preserve competitiveness (Filieri et al., 2025).

This set of results aligns with a broader empirical trend indicating that organizations use AI as a strategic mechanism to manage uncertainty and refine decision-making processes. Evidence from Canadian SMEs suggests that AI integration generally unfolds incrementally, often through pilot initiatives aimed at reducing perceived risks and reinforcing internal learning capabilities (Taherizadeh & Beaudry, 2023). Regarding decision-making, empirical research confirms that AI acts as a cognitive enhancer. Studies focusing on large technology firms show

that AI improves decision accuracy, reduces subjective judgments, strengthens the detection of weak signals, and increases the consistency of financial and operational evaluations (Numbi & Elongha, 2025). Similar observations emerge from retail environments, where AI simultaneously boosts employee productivity and elevates customer experience, pointing to its dual operational and service-enhancing role (Grewal et al., 2023).

From a performance standpoint, the empirical corpus converges on the idea that AI improves organizational outcomes across operational, strategic, and decision-making dimensions. Marketing research indicates that financial markets react more favorably to AI-enabled innovations when the marketing function carries substantial internal power, suggesting that strategic effects of AI depend on supportive internal governance (Padigar et al., 2022). In the field of human resources, studies highlight that AI enhances recruitment processes by improving speed, accuracy, and candidate diversity, thereby strengthening human capital performance (Choudhari et al., 2025). Research on AI maturity further shows that organizations fully benefit from AI only after achieving advanced integration stages marked by coherent coordination between human and technological systems (Lichtenthaler, 2020).

Overall, the empirical literature portrays AI as a transformative lever whose adoption, use in decision-making, and effects on performance stem from tightly interdependent individual, organizational, and institutional dynamics.

2. Research methodology

This section outlines the methodology used to select relevant articles dealing with the factors influencing the adoption of artificial intelligence in organizations, and the impact of its integration on their performance. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method was adopted for this systematic literature review.

2.1 Epistemological stance

This work is part of an exploratory approach aimed at understanding and identifying the factors that enable the adoption of artificial intelligence within organizations. The issue involves three closely related but complex dimensions: adoption, decision-making, and organizational performance, whose interactions remain insufficiently understood.

2.2 Presentation of the systematic approach

The systematic method used in this article is PRISMA 2020, an improved version of PRISMA 2009 developed by (Moher et al., 2009) to reflect methodological advances in systematic reviews. This approach aims to ensure clear and reliable conclusions while managing large amounts of data, following four distinct phases: identification, selection, eligibility, and

inclusion (ALLOULI & BOUMESKA, 2023). The choice of this method is justified by its ability to select and identify relevant references to include in qualitative or quantitative analysis. Thus, this method is now widely considered to be the least biased and most rational way to synthesize research results and a powerful tool that provides the best available knowledge on a research topic (Fox, 2005; Zaugg et al., 2014).

2.3 Choice of keywords and databases

Our approach began with an exploration of articles published in the Scopus database. In order to optimize the relevance of the results, we developed a search strategy based on specific keywords used in English. In addition, we used a combination of all keywords with Boolean operators such as “AND” and “OR” to refine our search. We determined a selection of keywords used to identify appropriate studies: “managerial innovation” and “artificial intelligence” or “AI.” As a result, an exhaustive literature search was conducted in the Scopus database, which is considered one of the leading sources of high-quality bibliometric data covering a wide variety of scientific disciplines. These database guarantee scientific rigor and minimize selection bias by providing access to publications validated by peer review processes.

Scopus stands out for its broader representation of journals focused on management sciences and interdisciplinary approaches, which are at the heart of this study. In addition, the use of a single database ensured consistency, traceability, and transparency in the study selection process, in line with the methodological recommendations for systematic reviews. The simultaneous use of several databases, although relevant in exhaustive bibliometric or quantitative approaches, can introduce redundancies and heterogeneities that are not always necessary in a qualitative review aimed at constructing a conceptual framework.

From this perspective, Scopus was considered sufficiently robust and representative to achieve the research objectives, ensuring both the scientific quality of the sources selected and the analytical consistency of the final corpus. This choice does not exclude the value of complementary databases, but is part of a methodological focus adapted to the qualitative and conceptual nature of the study.

2.4 Selection of inclusion and exclusion criteria

The methodological approach used to select articles reflects a rigorous and clear process aimed at ensuring the relevance and consistency of the sources chosen for the research. The structure of our research follows the steps for filtering results described in the PRISMA method. We identified a total of 281 documents during the initial keyword search. Inclusion and exclusion criteria were then applied at each stage of the selection process, as shown in Table n°1, we

selected a publication period ranging from 2015 to 2025. In terms of document type and availability, only open-access scientific articles related to our topic were selected. Finally, we limited the selection to documents published in English, which is the most widely used language in the scientific world. ZOTERO software was used for bibliographic management, classification, and elimination of duplicate references.

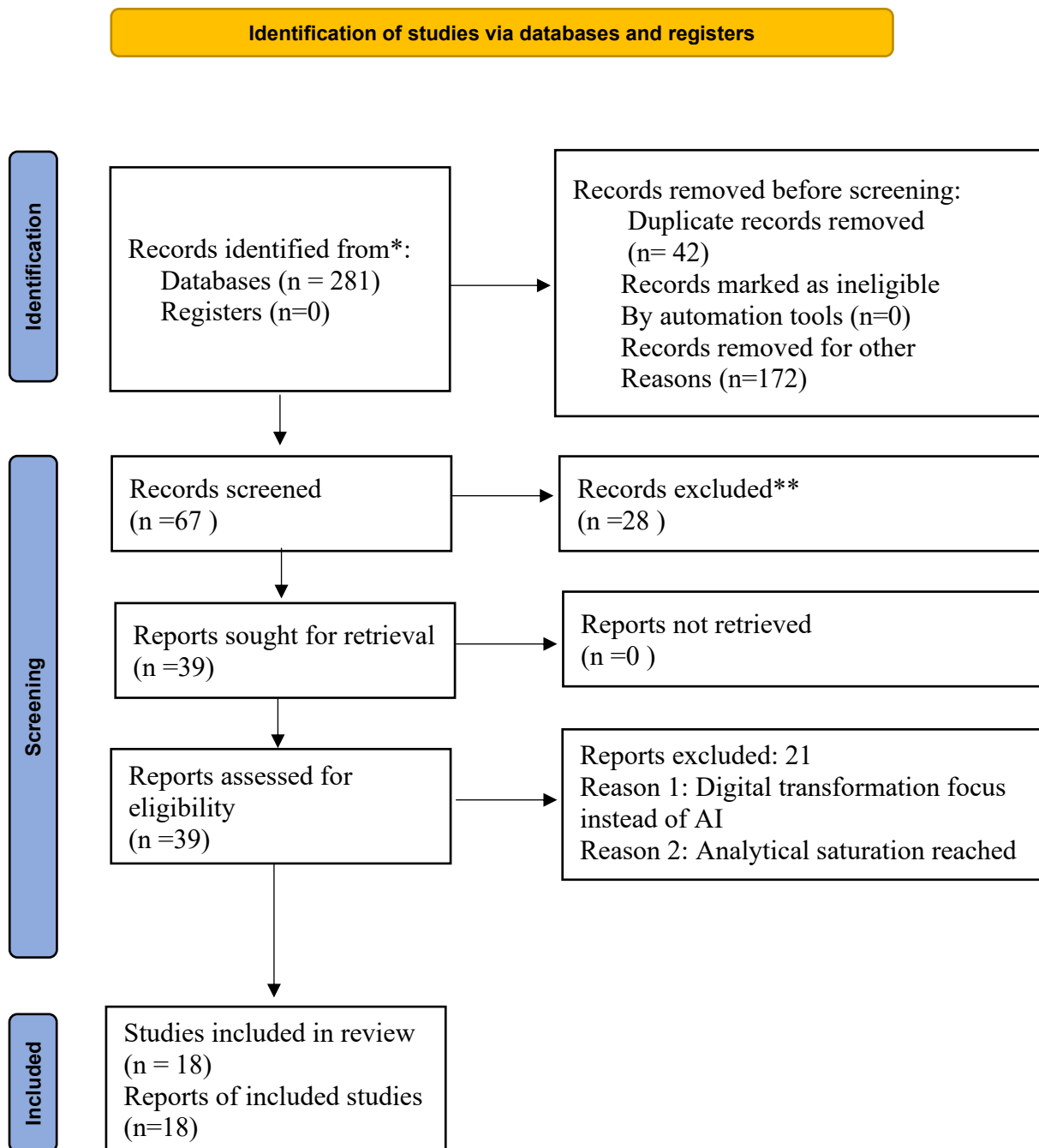
Table N°1: Inclusion and exclusion criteria

Selection criteria	Inclusion criteria	Exclusion criteria
Publication period	2015 to 2025	< 2015
Document type	Original articles and Reviews	Any other type of document (theses, book chapters, etc.)
Subject area	Documents containing relevant keywords in the title or abstract	Documents that do not contain the keywords in the title or abstract
Language	English	Publication in any other language
Availability	Full text document accessible	Document without access to full text

Source: Authors

The PRISMA diagram illustrated below provides a graphical representation of the various stages of our research, highlighting the results obtained at each phase of the process.

Figure N° 1: Document search and selection process



Source: Authors

2.5 Coding process

The coding process followed a rigorous approach inspired by the work of Strauss and Corbin (1998) and Braun and Clarke (2006). First, lexical extraction was used to identify the most frequent words in the corpus, a step similar to open coding, which consists of fragmenting the data and assigning initial labels to units of meaning. This initial operation was accompanied by

visualization in the form of a word cloud, a tool that facilitates the identification of dominant terms. In a second step, the construction of a frequency table facilitated a more detailed classification of occurrences, allowing connections to be established between codes. The progressive articulation between these levels of coding ensured an analysis that was both systematic and grounded in the data. This integrated approach reinforces the validity of the final interpretation produced.

3. Results

In order to complete our literature review, we will conduct a two-part analysis of the results from the selected reference sample. First, we will present an analysis of the descriptive statistics for all of the selected references. Second, we will focus on an in-depth qualitative lexical analysis of the articles included in the study.

3.1 Results of the document selection

Using the Scopus database, a total of 281 articles were initially identified. Applying the inclusion and exclusion criteria reduced this number to 109 articles. After manually removing duplicates, 67 articles were selected. A further step, based on a careful review of the abstracts, identified 39 articles that met the relevance criteria defined upstream. After a detailed reading and in-depth methodological evaluation, only 18 articles were selected to form the final sample. The selection phase, based on reading titles, keywords, and abstracts, revealed that a significant number of articles dealt with digital transformation in general, without explicitly focusing on artificial intelligence as a core technology. These studies frequently used digital technologies such as big data, blockchain, and the Internet of Things (IoT). Including these studies would have introduced conceptual heterogeneity that could have diluted the research objective and weakened the analytical coherence of the study. As a result, only articles explicitly addressing artificial intelligence as the main technology were selected for in-depth analysis. Furthermore, as the analysis progressed, analytical saturation was reached when the examination of additional articles no longer produced new conceptual categories or substantial theoretical relationships, but essentially reinforced already identified patterns. The convergence of the results observed confirms that the final corpus of 18 articles is sufficient to support an in-depth qualitative synthesis and to provide a robust foundation for the proposed conceptual model. Table 2 below presents the document selection procedure.

Source	Collected articles	After applying the inclusion and exclusion criteria	After eliminating duplicates	After reading the titles, keywords, and abstracts	Articles downloaded after full reading
Scopus	281	109	67	39	18

3.2. Results of the lexical analysis

Figure n° 2 below shows a word cloud reflecting the most representative terms identified from our selection of articles.

Figure N°2: Themes



Source: Release of Nvivo software.

The word cloud above highlights three categories of keywords. The orange words are those with a higher frequency of repetition, such as « management, innovation, intelligence ». The second category, represented in dark gray, surrounds the orange words and includes words with a lower frequency, such as « adoption, process, strategic, technology ». Finally, the light gray words appear less frequently than the other two categories and include terms such as « managerial impact, performance, and leadership ».

Table N° 3: Word frequency

Word	Frequency
innovation	1021
management	760
research	671
journal	619
intelligence	539
Business	501
Technology	454
Adoption	441
Platform	424
Artificial	423
Knowledge	414
Resources	392
Process	383
Strategic	375
Marketing	358
Digital	353
Technologies	353

Source: Source: Release of Nvivo software.

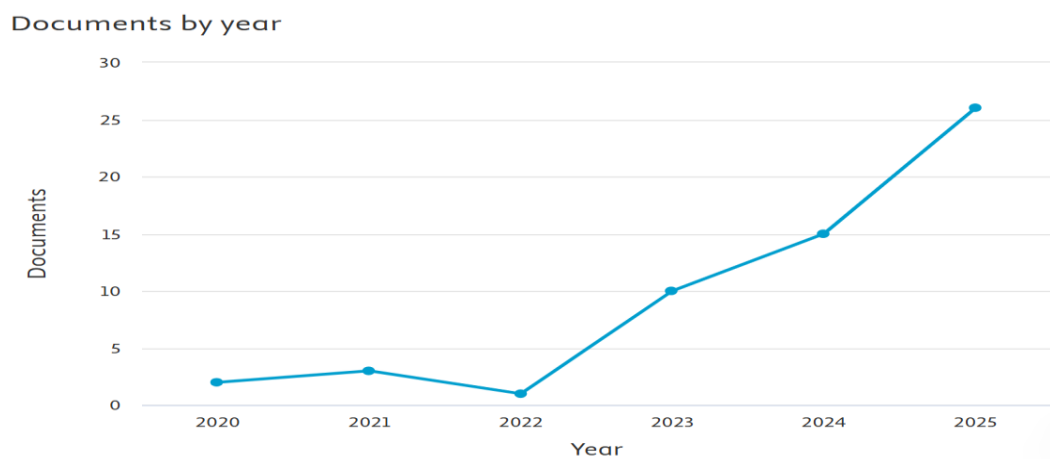
The word frequency table above highlights several major trends. Examination of lexical frequencies shows that the most recurrent terms structure three major dimensions: innovation, management, and artificial intelligence. The predominance of the word innovation confirms that AI is conceptualized primarily as a driver of organizational, technological, and strategic innovation. This orientation is consistent with empirical findings showing that the adoption of AI has a direct impact on the innovative performance of companies, particularly when the organization has an explicit strategic orientation in favor of artificial intelligence (Eicke et al., 2025).

3.3. Distribution of selected studies by geographic area and year of publication

In order to analyze trends in publications on the adoption of artificial intelligence in organizational decision-making processes and its impact on performance, it is essential to focus

on the trend in references published by year of publication and by geographical area. The graph below shows the distribution of studies according to their year of publication:

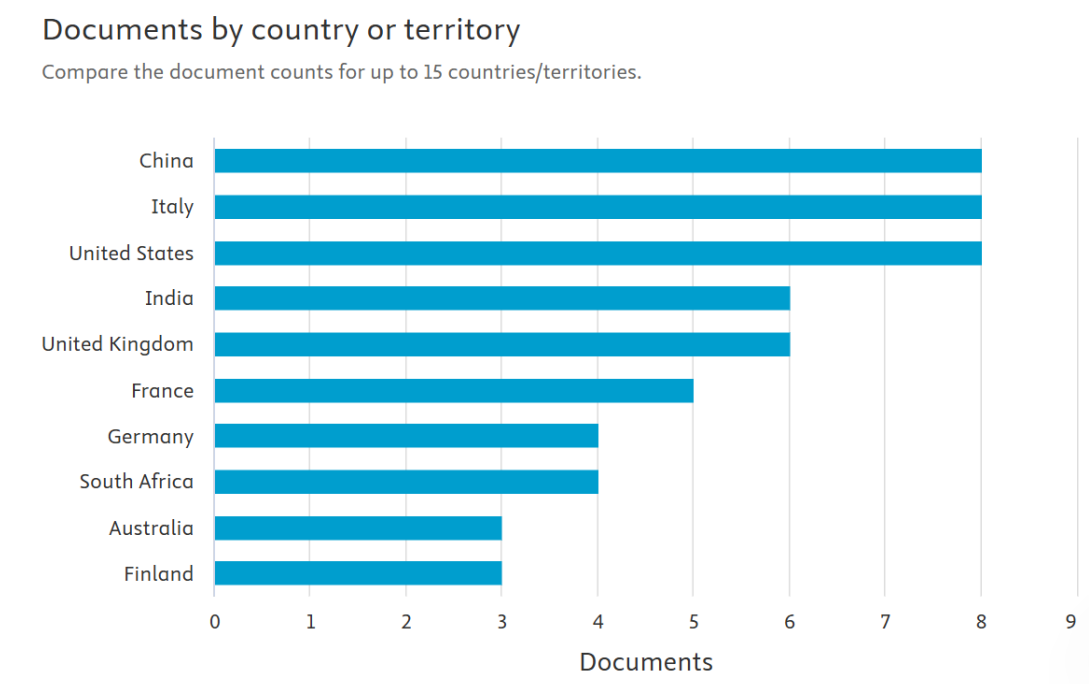
Figure N ° 3: Distribution of studies selected by year of publication



Source: Release of Scopus

The temporal distribution of articles shows a clear and continuous growth in scientific output on the adoption of artificial intelligence in organizations. After a relatively stable initial phase between 2020 and 2022, the literature experiences a marked acceleration from 2023 onwards, corresponding to a proliferation of empirical and conceptual work on the integration of AI into organizational processes. This momentum intensified in 2024 and peaked in 2025, reflecting the academic community's growing interest in the impacts of AI on decision-making transformation, operational performance, and organizational innovation.

Figure N ° 4: Distribution of studies by geographic area



Source: Release of Scopus

The geographical distribution of the corpus shows a high concentration of work in China, Italy, and the United States, which appear to be the most prolific centers. India and the United Kingdom also occupy a significant place. European contributions, such as those from France and Germany, highlight a growing interest in the subject of artificial intelligence and its adoption in organizational management practices. Finally, we note that no research has been conducted in Morocco. This observation leads us to conclude that studies conducted in the African context, particularly in Morocco, are rare, which constitutes a research gap to be exploited in order to investigate the subject in the Moroccan context.

3.4. Results of the exploratory qualitative analysis

The analysis conducted on the 18 articles retained through the PRISMA protocol identifies a set of recurrent determinants shaping the adoption of artificial intelligence within organizations. A deeper examination of these studies reveals points of convergence as well as notable differences in the conditions under which AI is implemented. Overall, the results indicate that AI adoption is strongly conditioned by internal organizational capacities, particularly the availability of digital skills, the level of technological maturity, and the presence of supportive managerial leadership. Perceptions of usefulness, ease of use, and trust in technology also emerge as critical predictors of employees' intentions to adopt AI (Yuniawan et al., 2025).

Conversely, deficiencies in infrastructure, limited digital competencies, and cultural resistance significantly impede the adoption process (Nene & Hewitt, 2023).

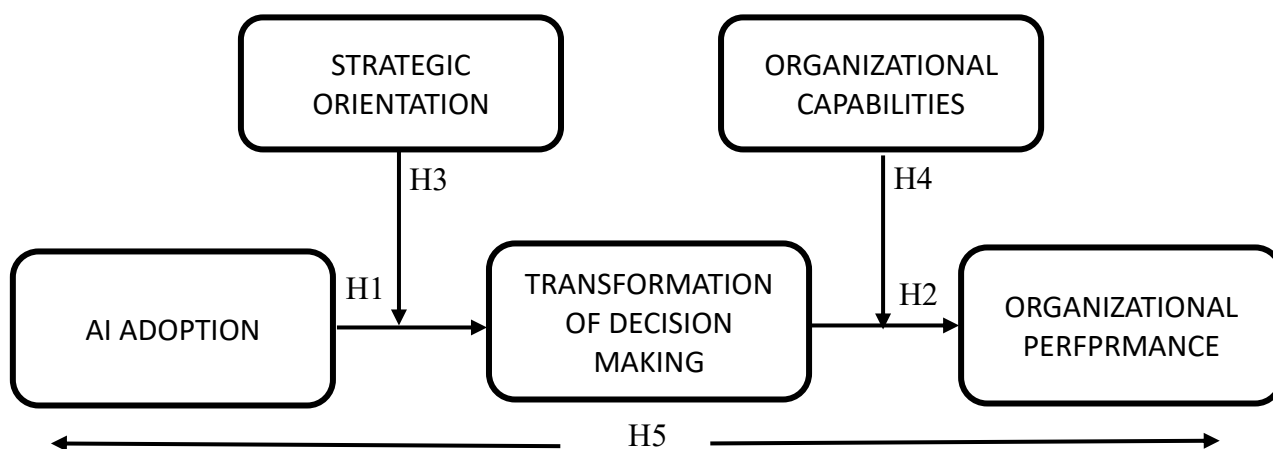
Empirical contributions further demonstrate that AI enhances the quality, speed, and reliability of organizational decisions. In managerial settings, AI supports advanced analytics and facilitates the detection of weak signals, thereby reinforcing strategic foresight and planning (Numbi & Elongha, 2025). From an operational standpoint, AI enables cost reduction, automation of routine activities, and improved internal coordination across industries. Its influence also extends to commercial and strategic performance, with AI-driven innovations stimulating value creation and competitive differentiation. In the field of human resources, AI accelerates applicant screening, improves matching accuracy, and promotes diversity in recruitment pipelines (Choudhari et al., 2025). In contexts where employees possess strong digital literacy, AI tends to stimulate innovative behaviors, contributing directly to organizational performance (Santoso et al., 2019). Moreover, in volatile environments marked by external pressures or market uncertainty, strategic AI integration helps sustain customer engagement and stabilize organizational performance (Filieri et al., 2025). These elements collectively reaffirm the central position of AI as a driver of contemporary organizational transformation.

Beyond these empirical observations, the synthesis of the reviewed studies provides substantial validation for the conceptual model proposed in this work. The findings clearly indicate that AI adoption serves as the initial catalyst that reconfigures decision-making processes, thereby supporting the mediating role attributed to decision-making transformation in the model. The literature also highlights that the extent to which AI adoption generates meaningful shifts in decision routines depends heavily on the degree of strategic orientation toward AI, confirming its role as a moderating construct. Likewise, the translation of improved decision-making into enhanced performance is shown to be contingent on the robustness of organizational capabilities, which reinforces their moderating influence. Overall, the empirical patterns identified across the 18 studies substantiate the causal reasoning underlying the model, demonstrating how AI adoption affects organizational performance through transformed decision-making processes, under the conditioning effects of strategic orientation and organizational capabilities.

4. Discussion

This section highlights the diversity of methodological approaches, geographical contexts, and results of the selected research studies. However, to better understand the background of the adoption of artificial intelligence in organizations and its influence on organizational performance, an in-depth review of the scientific literature was conducted. Of the 281 articles identified in our search, 18 publications covering different countries were considered relevant. Analysis of the 18 selected articles points to the idea that the adoption of artificial intelligence (AI) is a multidimensional process based on internal resources and strategic orientation. Organizations with a solid technological foundation, innovation-oriented leadership, and a developed digital culture demonstrate a smoother and faster adoption of AI (Hanelt et al., 2025; Eicke et al., 2025). Conversely, when infrastructure is limited, digital skills are insufficient, or organizational routines are resistant, adoption develops hesitantly or in a fragmented manner, as observed in South African public hospitals (Nene & Hewitt, 2023) or in Botswana's tax administrations (Munjeyi & Schutte, 2025). Beyond technological adoption, the corpus highlights that AI acts as a cognitive amplifier for decision-making processes. In organizations where it is fully integrated, AI improves the accuracy of analyses, reduces human bias, and accelerates the detection of weak signals, particularly in strategic, financial, and operational decisions (Numbi & Elongha, 2025). Furthermore, the strategic focus on AI itself appears to be a determining factor in decision-making quality. Organizations with an explicit AI strategy have a greater ability to capture, process, and interpret data, which supports creativity, stimulates innovation, and strengthens decision-making exploration capabilities (Eicke et al., 2025). In-depth analysis consistently shows that AI generates measurable improvements in organizational performance. Overall, the conceptual model represents an achievement that constitutes a foundational driver of organization transformation, primarily through its capacity to reshape decision-making processes. This transformation emerges as the central pathway through which AI contributes to improved performance outcomes. In addition, the literature reveals that the effectiveness of this pathway is conditioned by two dimensions. A strong strategic orientation toward AI enhances the extent to which adoption leads to substantive changes in decision-making routines, while robust organizational capabilities facilitate the translation of these transformed processes into tangible performance gains. Taken together, these insights provide a theoretically grounded basis for integrating AI adoption, decision-making transformation, organizational capabilities, strategic orientation, and performance within unified conceptual framework that reflect the dynamics observed across organizational contexts.

Figure N ° 5: CONCEPTUAL MODEL



Source: Authors

The proposed conceptual model is grounded in the theoretical perspectives and empirical insights emerging from the reviewed literature. Across the analyzed studies, artificial intelligence adoption is not conceptualized as a purely technological decision but rather as an organizational process shaped by strategic intent and internal capabilities. The transformation of decision-making processes therefore constitutes the central mechanism through which AI adoption is expected to influence organizational performance. The reviewed studies consistently highlight that AI-enabled decision-making enhances analytical depth, reduces uncertainty, and improves the quality and timeliness of decisions. Organizational performance is thus conceptualized as an outcome of improved decision processes rather than a direct consequence of technology adoption alone.

Furthermore, the literature reviewed underscores the contingent nature of AI-driven outcomes, thereby justifying the inclusion of organizational capabilities and strategic orientation toward AI as moderating conditions in the model. Several studies emphasize that without adequate organizational capabilities the potential benefits of AI-enabled decision-making remain underexploited. These findings resonate with capability-based arguments recurrent in the corpus, which stress that organizations differ in their ability to translate technological insights into effective action.

Similarly, strategic orientation toward AI emerges as a critical factor shaping the depth and scope of decision-making transformation. The reviewed articles indicate that AI adoption produces more substantial organizational change when it is embedded within a clear strategic

vision and aligned with long-term organizational objectives. In the absence of such orientation, AI initiatives tend to remain fragmented and operational rather than transformative.

In the proposed conceptual framework, AI adoption is conceptualized as the antecedent construct that is expected to positively influence the transformation of decision-making processes (H1). The transformation of these processes operates as the central mediating mechanism through which AI adoption affects organizational outcomes, and is therefore hypothesized to positively influence organizational performance (H2). To account for contextual variations highlighted in the reviewed literature, two moderating variables are incorporated. Strategic orientation toward AI is expected to strengthen the effect of AI adoption on the transformation of decision-making processes, implying that this relationship becomes more pronounced when organizations articulate a clear strategic intent regarding AI (H3). Similarly, organizational capabilities are expected to reinforce the link between transformed decision-making processes and organizational performance (H4). Together, these relationships support the mediating role of decision-making transformation, whereby AI adoption influences performance indirectly through its impact on decision processes (H5).

5. Limitations

This research has several limitations. On the one hand, it is based on a corpus of 18 articles, which, although sufficient for an in-depth qualitative analysis, limits the generalizability of the results. Second, the contexts studied remain heterogeneous, which may influence the comparability of adoption mechanisms, decision-making dynamics, and performance outcomes across sectors and regions. Another significant limitation is the underrepresentation of developing countries, and in particular the absence of studies on the Moroccan context, which reduces the scope of the conclusions for environments where levels of digital maturity, infrastructure, and institutional constraints differ significantly. Finally, certain key dimensions, such as organizational culture, AI ethics, and change management, have only been partially addressed in the articles, suggesting the need for further studies to refine our understanding of these mechanisms. At the end, the proposed conceptual model, while theoretically grounded in the literature, requires empirical testing to validate the hypothesized relationships and explore boundary conditions in diverse organizational settings.

6. Conclusion

This systematic review shows that artificial intelligence has become a key driver of organizational transformation. The findings indicate that AI adoption improves performance primarily when it leads to a substantive transformation of decision-making processes, confirming the central role of these processes in converting technological potential into organizational value. The conceptual model developed in this study integrates these insights by linking AI adoption, decision-making transformation, and performance, while acknowledging the conditioning influence of internal capabilities and strategic orientation. Overall, this review provides a coherent theoretical framework for understanding how AI generates performance outcomes and highlights the importance of organizational readiness and strategic intent for its effective and sustainable integration. This research thus provides a solid theoretical basis for understanding the mechanisms through which AI influences performance and proposes a structured framework to guide future research perspectives. Ultimately, AI is an essential driver of competitiveness and innovation, but its effectiveness depends heavily on the ability of organizations to structure the right conditions for its sustainable integration.

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