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ORGANIZATIONAL DETERMINANTS FOR ADOPTING AND IMPLEMENTING ARTIFICIAL INTELLIGENCE

DETERMINANTES ORGANIZACIONAIS PARA ADOÇÃO E IMPLEMENTAÇÃO DA INTELIGÊNCIA ARTIFICIAL

DETERMINANTES ORGANIZACIONALES PARA LA ADOPCIÓN E IMPLEMENTACIÓN DE LA INTELIGENCIA ARTIFICIAL

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ABSTRACT

This study is a meta-synthesis of six case studies that aim to examine the organizational determinants of adopting and implementing artificial intelligence (AI). Conducted in light of the theoretical perspectives of the Technology–Organization–Environment (TOE) Framework and the Diffusion of Innovation (DOI), the study integrated empirical evidence from 2021 to 2025 in the Web of Science and Scopus databases. The findings indicate that effective incorporation of AI is not conditioned by isolated factors but by the coordinated interaction between three vertices: Leadership-Strategy, Data Maturity, and Training-Culture. This dynamic highlights a non-linear trajectory, in which experimentation and perception of relative advantage in using AI are fundamental to the acceptance of the technology. Furthermore, the study points to a reconfiguration of AI that moves it from an operational tool to an agent of strategic reconfiguration, reinforcing its relevance for innovation and organizational competitiveness.

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Keywords: Artificial Intelligence. Technology Adoption. TOE Framework. Diffusion of Innovation. Organizational Determinants.

RESUMO
Este estudo consiste em uma metassíntese de seis estudos de caso que visam examinar os determinantes organizacionais da adoção e implementação da inteligência artificial (IA). Realizado à luz das perspectivas teóricas do modelo Tecnologia-Organização-Ambiente (TOE) e da Difusão de Inovações (DOI), o estudo integrou evidências empíricas do período de 2021 a 2025, provenientes das bases de dados Web of Science e Scopus. Os resultados indicam que a incorporação eficaz da IA não é condicionada por fatores isolados, mas pela interação coordenada entre três vértices: Liderança-Estratégia, Maturidade de Dados e Treinamento-Cultura. Essa dinâmica evidencia uma trajetória não linear, na qual a experimentação e a percepção de vantagem relativa no uso da IA são fundamentais para a aceitação da tecnologia. Além disso, o estudo aponta para uma reconfiguração da IA, que transita de ferramenta operacional para agente de reconfiguração estratégica, reforçando sua relevância para a inovação e a competitividade organizacional.

Palavras-chave: Inteligência Artificial. Adoção de Tecnologia. Modelo TOE. Difusão de Inovações. Determinantes Organizacionais.

RESUMEN
Este estudio constituye una metasíntesis de seis estudios de caso cuyo objetivo es examinar los determinantes organizativos de la adopción e implementación de la inteligencia artificial (IA). Realizado a la luz de las perspectivas teóricas del marco Tecnología-Organización-Entorno (TOE) y de la teoría de la Difusión de Innovaciones (DOI), el estudio integró evidencia empírica del periodo 2021-2025 proveniente de las bases de datos Web of Science y Scopus. Los hallazgos indican que la incorporación efectiva de la IA no está condicionada por factores aislados, sino por la interacción coordinada entre tres vértices: liderazgo y estrategia, madurez de datos, y formación y cultura. Esta dinámica pone de relieve una trayectoria no lineal, en la que la experimentación y la percepción de ventaja relativa en el uso de la IA resultan fundamentales para la aceptación de la tecnología. Asimismo, el estudio apunta a una reconfiguración de la IA que la transforma de una herramienta operativa en un agente de reconfiguración estratégica, reforzando así su relevancia para la innovación y la competitividad organizacional.

Palabras clave: Inteligencia Artificial. Adopción de Tecnología. Marco TOE. Difusión de Innovaciones. Determinantes Organizativos.

1 INTRODUCTION

The dynamism of technological transformation driven by artificial intelligence (AI) has been occurring at an accelerated pace, opening up new possibilities for individuals, organizations, and societies (Dwivedi *et al.*, 2021). In organizations, intelligent systems stand out for their ability to automate processes and enhance decision-making, moving from mere operational resources to strategic elements of business models (Nam *et al.,* 2021; Borges *et al.,* 2021). In different sectors, AI has become an essential part, appearing not only as an operational resource but also as a strategic component in business models (Dwivedi *et al.,* 2021).

Despite its high potential, the adoption and implementation of AI remain marked by significant challenges. Issues related to the complexity of the technology, the diversity of organizational contexts, and internal demands often result in outcomes that fall short of expectations or even failures in its integration (Jöhnk *et al.*, 2021; Khanfar *et al.*, 2025). Technological, organizational, and cultural barriers, such as problems with data quality, infrastructure, staff training, trust, and autonomy, hinder this process (Ångström *et al.,* 2023).

Lee *et al.* (2023) emphasize the importance of broadly understanding the entire context surrounding the implementation of artificial intelligence in organizations. Thus, although the most recent literature identifies factors associated with the adoption of intelligent systems, the organizational elements that are decisive for success or failure are not yet clearly defined (Chen *et al.,* 2023; Merhi and Harfouche, 2024; Uren and Edwards, 2023).

Given this context, the central problem is the lack of clarity about which organizational determinants effectively influence the process of adopting and implementing artificial intelligence. This gap limits the ability of organizations to plan more assertive strategies and increases the risk of failed investments.

The objective of this study is to analyze how different organizational factors interact and influence the adoption and implementation of artificial intelligence, with the aim of understanding how these interactions contribute to the success or failure of its integration into organizational processes. To achieve this objective, the following specific objectives were outlined: i) to identify the main technological, organizational, and environmental factors associated with the adoption and implementation of AI; ii) to examine how these factors act in the stages of the innovation diffusion process; and iii) to understand the dynamics of barriers and facilitators in the adoption and application of intelligent systems reported in the studies.

The rationale for this study lies in the practical and academic relevance of the topic. From a practical point of view, understanding organizational barriers and facilitators can help managers maximize benefits and mitigate risks related to AI implementation. From an academic point of view, the meta-synthesis contributes to systematizing fragmented knowledge, broadening the theoretical understanding of organizational determinants, and responding to a topic that is still being consolidated.

The contributions of this research are twofold: (i) in the theoretical field, it offers an integrative synthesis of the available empirical evidence, highlighting the critical organizational factors for the adoption and implementation of AI; and (ii) in the practical field, it provides support for the design of more effective organizational strategies, increasing the chances of success in the incorporation of intelligent systems.

2 THEORETICAL FOUNDATION

This chapter presents the theoretical foundation that underpins this study on AI adoption at the organizational level. First, it contextualizes technological transformation and the disruptive role of artificial intelligence in organizations. Second, it discusses AI adoption and implementation based on the TOE Framework and the Diffusion of Innovation (DOI) Theory. Finally, it examines the main organizational barriers and facilitators that influence this process, providing the conceptual basis for the empirical analysis.

2.1 TECHNOLOGICAL TRANSFORMATION AND AI IN ORGANIZATIONS

In recent decades, developments related to the performance, capacity, and efficiency of information technology (IT) systems have driven the widespread diffusion and popularity of artificial intelligence and machine learning mechanisms (Talib *et al.*, 2021). This movement is part of a broader scenario of technological transformation, in which the rapid development of digital technologies has caused profound changes in the organizational environment, with artificial intelligence playing a fundamental role in this process (Holmström, 2022).

Intelligent algorithms are reconfiguring the dynamics of organizations and expanding the possibilities for strategic value creation. Haenlein and Kaplan (2019) point out that intelligent systems are changing decision-making structures, group dynamics, and the labor market, implying changes in areas such as human resources, marketing, and operations. By offering countless possibilities, such as the optimization of simple, complex, repetitive, and

high-volume tasks, AI surpasses the limitations of human cognitive capacity (Jarrahi *et al.,* 2023).

These characteristics place AI among disruptive technologies, whose reach is already evident in various sectors of society. Păvăloaia and Necula (2023) point out that the areas most impacted by these disruptive technologies are those related to health, business, agriculture, logistics, education, and urban development. Furthermore, these intelligent systems go beyond being mere automation tools; they are integrated into the innovation process and allow for the expansion and improvement of innovation management capabilities (Bahoo *et al.,* 2023; Gama and Magistretti, 2025).

2.2 ADOPTION AND IMPLEMENTATION OF AI IN ORGANIZATIONS

The adoption of AI contributes significantly to organizational growth. Unlike previous technologies, it has a predictive nature, which makes it possible to expand business opportunities based on the potential of big data (Babina *et al.*, 2024). Thus, AI goes beyond process automation, combining automation, value customization, and the use of knowledge, revolutionizing strategic management and expanding the competitive advantages of organizations (Keding, 2021). In this context, considering the business environment as increasingly dynamic and competitive, the adoption of these intelligent systems is a powerful strategic differential in organizations.

Keding (2021) points out that integrating this technology into strategic management involves continuous learning by managers and organizations, who need to gradually redefine their structures, processes, and culture. Research on generative AI, for example, shows that its adoption is conditioned by important factors such as the degree of complexity, the size of the company, the intensity of competition, compatibility, regulations, and the level of uncertainty in the environment (Prasad Agrawal, 2024). Thus, the adoption and implementation of these systems does not depend solely on an isolated decision; understanding the associated factors is essential.

The literature on AI adoption has structured its analyses based on the TOE Framework (Technology–Organization–Environment) model proposed by Tornatzky and Fleischer (1990), as evidenced in several studies (Prasad Agrawal, 2024; Neumann, 2024; WaelWael AL-khatib, 2023; Chittipaka *et al.,* 2023; Merhi and Harfouche, 2024). Tornatzky and Fleischer (1990) point out three fundamental dimensions for analyzing the adoption and

implementation of technological innovations in organizations, which are: the technological dimension, the organizational dimension, and the environmental dimension.

Regarding the technological context, Tornatzky and Fleischer (1990) indicate that it encompasses both internal and external technologies that influence companies. Thus, it is correlated with the technologies available on the market and how they fit into the company's practices. According to the authors, the organizational context corresponds to how the company's infrastructure, resources, and internal processes impact the adoption and implementation of technology. The environmental context encompasses external business forces, such as competition, suppliers, and regulations, and their effects on technological implementation.

In addition to these contextual determinants of TOE, it is relevant to complement the analysis based on the Diffusion of Innovation Theory (DOI), proposed by Rogers (1983). In this theory, diffusion is conceptualized as “the process by which an innovation is communicated through certain channels over time among the members of a social system” (Rogers, 1983, p.5). Thus, this theory aims to analyze a gradual process that organizations go through when incorporating an innovation. This process is divided into the following sequential stages: i) knowledge, ii) persuasion, iii) decision, iv) implementation, and v) confirmation.

Once the existence and functioning of the innovation are understood, the second phase of persuasion begins, marked by the adoption of an attitude derived from individual perception of the technology. Rogers (2003) attributes five characteristics to this perception of innovation: i) relative advantage, which corresponds to the level of perception of innovation as superior to the previous idea; ii) compatibility, which refers to the perception of how much the innovation is aligned and compatible with the interests and experiences of adopters; iii) complexity, which concerns the perceived difficulty in using and understanding the innovation; iv) trialability, which refers to the level at which the innovation can be tested before actual adoption; v) and observability, which is linked to the visibility of results to others. These characteristics allow for a better understanding of the factors that permeate the process of adopting and implementing artificial intelligence in organizations.

Furthermore, based on the temporal and social aspects of DOI, which explain how and at what speed innovation is implemented, it can be considered that this theory complements and strengthens the TOE framework (Shahadat *et al.*, 2023). While DOI covers, through the characteristics and dynamics of acceptance, how and why new technologies are adopted and

implemented, the TOE framework allows us to identify the contexts that shape this adoption (Oliveira and Martins, 2011). The combination of these theoretical approaches is commonly used in the literature (Al-Okaily *et al.,* 2024; Sun *et al.,* 2020; Pateli *et al.,* 2020; Prasad Agrawal, 2024; Molinillo and Japurá, 2017), reaffirming the explanatory potential of this integration to analyze the determinants in the adoption and implementation of artificial intelligence in organizations.

2.3 ORGANIZATIONAL BARRIERS AND FACILITATORS IN THE ADOPTION OF AI

Among the main barriers to the adoption and implementation of intelligent systems, Kelley (2022) highlights factors such as communication, technological infrastructure, training, management support, technical monitoring, metrics, and organizational structure. Kar *et al.* (2021), in their literature review, identified, in addition to infrastructure and management support, the absence of strategy, trust issues, data availability, the risk of professional replacement due to automation, poorly defined problems, limited knowledge of applications, and a lack of reusable models. These barriers show that the effective adoption of AI goes beyond technical resources and involves a complex network of factors.

Merhi and Harfouche (2024) identified twelve facilitators for successful AI adoption and implementation. Among the main ones are elements related to organizational culture, data quality and complexity, infrastructure, security, compatibility, perceived advantages, ethical issues, and strategic issues. Chatterjee *et al.* (2021) emphasize that the perception of usefulness and ease of use are key determinants in the adoption of artificial intelligence, emphasizing the importance of leadership in this context. The interaction of these elements demonstrates that well-defined organizational dynamics and behavioral aspects are indispensable for enabling the strategic use of AI (Dey *et al.,* 2024).

Thus, these barriers and facilitators reflect that the adoption of AI in organizations is a multifaceted phenomenon that requires empirical analysis. From this perspective, Horani *et al.* (2025) emphasize that combining TOE and DOI theories makes it possible to expand the capacity to obtain new insights into the influences of adopting intelligent systems at the organizational level. Therefore, this theoretical articulation allows for a more comprehensive understanding to analyze empirical studies that address the implementation of AI at the organizational level.

3 METHODOLOGY

This study adopts the qualitative meta-synthesis approach to case studies, as proposed by Hoon (2013). Unlike a traditional systematic review, which seeks to summarize evidence, meta-synthesis aims to analyze and interpret qualitative data from primary studies to construct theoretical models or develop concepts of a higher level of abstraction. Given the complexity and contextual nature of organizational determinants for AI adoption, this approach is particularly appropriate, as it allows for the integration of rich and dispersed empirical evidence from multiple contexts, culminating in a more holistic and theoretically grounded understanding of the phenomenon.

The meta-synthesis process was structured and conducted through the eight systematic steps proposed by Hoon (2013): i) definition of the research question, ii) location of relevant research, iii) inclusion/exclusion criteria, iv) data extraction and coding, v) case-specific analysis, vi) cross-sectional synthesis, vii) theoretical construction, and finally, viii) discussion.

The first step was to formulate the guiding research question: “How do different organizational factors interact and influence the process of adopting and implementing Artificial Intelligence in organizations?” In the second step, focused on identifying relevant primary studies, a systematic search was conducted in the Scopus and Web of Science databases using search strings to capture studies at the intersection of the central concepts.

Initially, the terms “adoption,” “implementation,” and “organizat*” were used in the title, abstract, and keyword fields of the articles, combined with the requirement that the title must include the terms “artificial intelligence” and “AI.” This set of descriptors resulted in 3,061 results, where we sought to ensure a focus on the adoption and implementation of artificial intelligence in organizational contexts. Next, we sought to narrow the scope to studies whose titles included the term “case study,” which reduced the results to 65.

Moving on to the third stage, the eligibility criteria were strictly applied. Empirical studies that adopt the “case study” methodology, focusing on the adoption or implementation of AI in organizations, published in English, open access, covering the period from 2021 to 2025 (available online by October 2025) to ensure the contemporaneity of the findings, were included. Review articles, theoretical essays, or studies without interpretable qualitative data were excluded. The selection process followed the PRISMA protocol, adapted for qualitative reviews, involving the consolidation of results, removal of duplicates, screening of titles and abstracts, and analysis of the full text. At the end of this process, six case studies were

selected to compose the analysis corpus, in line with Hoon's (2013) recommendation that a smaller, more manageable sample is preferable to allow for in-depth and interpretive analysis, which is the essence of meta-synthesis.

In the fourth stage, relevant data such as citations, descriptions of barriers and facilitators, and researchers' observations were extracted and coded, guided by the theoretical lenses of the Technology-Organization-Environment Framework (TOE) and the Diffusion of Innovation Theory (DOI). This process involves a thorough and detailed reading of the articles for in-depth familiarization and to ensure the interpretive rigor of the content. Two researchers independently coded the data using Microsoft Excel software, and discrepancies were discussed until consensus was reached to ensure coding reliability and minimize subjective bias. These initial codings were subsequently grouped into common themes that capture organizational determinants, with a focus on identifying their interrelationships and dynamics.

Next, the fifth stage, referring to the specific case analysis, aims to identify the patterns, relationships, and mechanisms observed in each case in particular, emphasizing the “reciprocal translation” of concepts between studies for theoretical construction. Thus, this analysis made it possible to examine which variables have the greatest impact on the process of adopting and implementing AI in each organizational context, in order to preserve the theoretical particularities of each case.

In the sixth stage, a synthesis was carried out at the cross-study level, in which the themes and concepts of the individual studies were compared, contrasted, and integrated into a coherent whole. The objective of this process was to develop an explanatory framework that articulates how the various organizational determinants interact to influence the success or failure of AI adoption and implementation, thus answering the research question and contributing to theoretical construction in the field.

In the next stage, we sought to construct a theory based on the systematization of studies using the dimensions of the Technology–Organization–Environment Framework (TOE) and the Diffusion of Innovation Theory (DOI). The TOE dimensions were used to categorize contextual determinants (technological, organizational, environmental), while DOI stages guided the analysis of the adoption process over time. The integration of both theories allowed for a dual-level interpretation—contextual and processual—of AI adoption. Finally, in the last stage, we discuss the results, articulating the evidence with the theoretical framework and presenting possible limitations.

Having detailed the methodological approach, the following section will be devoted to the presentation and discussion of the results of this meta-synthesis. First, the profiles of the case studies that make up the analysis corpus will be presented, followed by a thematic analysis that culminated in the identification of the central organizational determinants and their interaction dynamics in the process of adopting and implementing artificial intelligence. Through this discussion, we will seek to build an integrated and in-depth understanding of the phenomenon under study.

4 RESULTS AND DISCUSSIONS

This section presents the results of the qualitative meta-synthesis of the six case studies, guided by the research question: “How do different organizational factors interact and influence the process of adopting and implementing artificial intelligence in organizations?” Initially, the profile of the studies that make up the analysis corpus is summarized. Next, an interpretive analysis and reciprocal translation of the data were performed, which allowed the identification of crucial interactional dynamics between organizational determinants, as presented in Table I below.

Regarding the profile of the analysis corpus, the selected case studies cover a variety of sectors, including healthcare (Roppelt *et al.*, 2025), manufacturing (Cannas *et al.*, 2024), auditing (Yang *et al.*, 2024), services (Oliveira *et al.*, 2025), and the public sector (Neumann *et al.,* 2024), involving organizations of various sizes. The AI solutions implemented range from image recognition and demand forecasting systems to chatbots and generative tools. The cross-sectional analysis of these cases, through the lens of the TOE framework and the Theory of Diffusion of Innovations (DOI), revealed a complex and interconnected set of organizational factors, the dynamics of which are detailed below.

The dynamics of organizational determinants were revealed in the meta-synthesis, in which the success or failure of AI adoption is not determined by isolated factors, but by the systemic interaction between them. Three central dynamics emerged from the analysis: (1) the interdependence between leadership, data quality, and human training; (2) the nonlinear journey of adoption, marked by overcoming resistance; and (3) the transition of AI from an operational tool to an agent of strategic reconfiguration.

Another important aspect concerns effective implementation, organized around three central aspects: leadership, data, and people. The analysis identified that these aspects are interconnected and necessary for effective implementation, where leadership and strategy,

data maturity and training, as well as the culture linked to people and the human aspect, reinforce each other.

Leadership acts as a catalyst, not only providing resources but also creating a clear strategy and a culture of innovation. In Neumann *et al.* (2024), the entrepreneurial mindset of leaders was crucial in driving change. However, this leadership only materializes when it directs investments to the technical base. Technological and data maturity proved to be an unavoidable foundation. In multiple cases (e.g., Cannas *et al.,* 2024), the “complexity of data collection” and the inconsistency of databases were critical barriers, while in Cannas *et al.* (2024), data quality made it possible to dramatically increase the reliability and speed of processes.

Finally, the human vertex of this triangle proved to be decisive. Staff training (Oliveira *et al.*, 2025; Yang *et al.*, 2024) and proactive management of organizational culture to mitigate resistance to change (Kemell *et al*., 2025; Neumann *et al.*, 2024) were frequently cited. The interaction is clear: visionary leadership allocates resources to data infrastructure and upskilling programs, which in turn build trust and reduce resistance, creating a virtuous cycle for adoption.

Regarding the methodological aspect proposed in the meta-synthesis, the DOI lens allowed us to map a non-linear journey, where the Persuasion stage is particularly critical. The cases reveal that the relative advantage of AI often becomes apparent in a contingent manner, when conventional technologies prove insufficient (Neumann *et al.*, 2024). The experimentation phase (Kemell *et al.,* 2025; Oliveira *et al.,* 2025) emerged as a key mechanism for building this persuasion, allowing users to test the technology and overcome initial mistrust.

The transition to the implementation and confirmation phases is marked by the need for ongoing support and the materialization of benefits. Operational efficiency — such as the dramatic time savings reported by Roppelt *et al.* (2025) — is the most immediate and tangible benefit that leads to confirmation. However, resistance persists as a shadow, often linked to the fear of professional displacement (Oliveira *et al.,* 2025). Overcoming this barrier depends directly on interaction with the other vertices of the triangle: clear communication from leadership, adequate training, and practical demonstration of value (observability).

As for a new strategic configuration, the synthesis showed that more mature AI organizations experience a fundamental transition: technology ceases to be a mere process

optimizer and becomes an element of strategic reconfiguration. Initially, the benefits are centered on operational efficiency and reliability (Cannas *et al.,* 2024; Yang *et al.,* 2024).

However, in advanced stages of confirmation, AI begins to generate value creation in new ways. In Cannas *et al.* (2024), AI guides investment decisions and working capital management. In Yang *et al.* (2024), it becomes a tool for marketing and competitive differentiation, changing the pricing model. This reconfiguration is signaled when AI impacts not only “how” things are done, but “what” is offered and “how” the organization competes in the market.

Overall, the results show that the adoption and implementation of AI in organizational contexts is a dynamic process driven by technological, organizational, and environmental factors that reinforce each other. Based on the TOE and DOI theoretical perspectives, it was possible to understand the systemic interaction between strategic leadership, data maturity, and human empowerment. Furthermore, the studies demonstrate a transition of AI from an operational tool to strategic reconfiguration, especially in organizations that are more mature in cultural and technological terms.

Despite the methodological rigor applied, this meta-synthesis has some limitations. First, the inclusion of case studies published between 2021 and 2025 may have restricted relevant evidence published in other periods. In addition, the qualitative inferences made are dependent on the interpretive nature of the original studies, which may introduce possible biases in the theoretical structure produced. Finally, the results presented reveal theoretical relationships within the specific limits observed and cannot, therefore, be generalized to all organizations.

The implications arising from this meta-synthesis cover both theoretical and practical fields. In the theoretical sphere, the combination of TOE and DOI theoretical perspectives deepens the understanding that the adoption of artificial intelligence transcends a merely technological process, constituting a socially integrated phenomenon influenced by leadership, data infrastructure, and human action. This systemic approach enriches the current debate on digital transformation, positioning AI as a key agent in organizational reconfiguration and strategy. From a practical perspective, there is a clear need for organizations to focus on strengthening leadership, effective data governance, and training programs to ensure trust and mitigate resistance. In addition, managers and policymakers can use these findings to develop interventions that promote technological maturity, ensuring that the adoption of AI generates organizational value.

5 CONCLUSION

In response to the research question, this meta-synthesis demonstrates that organizational factors influence the adoption and implementation of AI through a system of dynamic interdependencies. The process is sustained by the interactive triangle between Leadership-Strategy, Data Maturity, and Training-Culture. This dynamic is traversed by an adoption journey (DOI) where persuasion, facilitated by experimentation and demonstration of relative advantage, is crucial to reaching confirmation, a stage where AI can transcend its operational role and become an engine of strategic reconfiguration. Success, therefore, does not lie in optimizing isolated factors, but in actively managing these interactions to build a sustainable and evolutionary path for artificial intelligence in the organization.

The study contributes theoretically by proposing an integrative TOE–DOI model that emphasizes the triadic interaction between leadership strategy, data maturity, and training culture as key organizational determinants for AI adoption. This integrative model refines the understanding of how contextual (TOE) and processual (DOI) factors intertwine to shape successful AI implementation.

Although these findings offer valuable theoretical insights, they should be interpreted with caution, given the limited number of cases included in the meta-synthesis. As Hoon (2013) emphasizes, qualitative meta-syntheses aim for depth and interpretive richness rather than statistical generalization. Therefore, the results presented here constitute exploratory theoretical propositions that illuminate emerging patterns, rather than universally applicable conclusions about organizational behavior.

In addition to the important contributions made in this study, possibilities for future research are also identified. Expansion to other organizational contexts and different types of AI applications, such as decision support systems, operational task automation, and predictive analysis of organizational performance, is recommended. Such approaches may reveal new dynamics in different contexts applied to the use of AI. In addition, future investigations may integrate other theoretical perspectives to improve understanding of the transformations brought about by AI in organizational structures, processes, and practices.

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