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Adoption and integration of AI in organizations: a systematic review of challenges and drivers towards future directions of research

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Abstract

Purpose – This study aims to detail the current enablers and challenges of AI applications in organizations and highlight ways to overcome these challenges to realize the potential of this emerging technology.

Design/methodology/approach – The paper provides a brief history of AI. Then it maps the state of the art, consolidates the heterogeneous corpus of knowledge, investigates the current impacts of AI technology on organizations and provides insights into possible challenges associated with this technology through a systematic review of the literature conducted with the PRISMA method and thematic analysis.

Findings – The research findings offer an overview of the most popular AI techniques within organizations, outlining their value-creation mechanisms. The results shed light on different topics related to enablers and challenges, emphasizing the potential implications of AI within organizations.

Research limitations/implications – The analysis proposes a research agenda to guide future AI research, considering identified trends and challenges.

Originality/value – This study highlights the need for multidisciplinary research, collaboration and ongoing assessment to ensure that AI applications align with organizational values and goals. It provides a meaningful framework for researchers and practitioners to understand and exploit AI as an effective enabler of value creation within organizations.

Keywords Artificial intelligence, Organizational change, Systematic literature review, Organizational challenges, TOE framework

Paper type Research paper

1. Introduction

Artificial Intelligence (AI) is currently a crucial and disruptive technology for organizations, given its potential to radically transform operational methods and competitive models. Various sectors have already experienced these revolutions due to advanced applications that go beyond simple automation (Dwivedi *et al.*, 2021). For instance, by utilizing complex algorithms for computer vision and autonomous decision-making, the autonomous vehicles are redefining the concept of urban mobility and logistics, enhancing transport efficiency and reduce road accidents (Zorman *et al.*, 2023). In the field of medical diagnostics, AI systems integrate data from multiple sources (such as diagnostic images, genomic data and clinical histories) to provide more accurate and timely diagnoses, thereby supporting healthcare professionals in patient care (Dias and Torkamani, 2019). Also, air traffic management benefits from AI through real-time optimization of flight routes and operations, thus

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improving safety and operational efficiency in skies (Tang *et al.*, 2022). Lastly, in the realm of environmental sustainability AI technologies are used to continuously monitor complex environmental data and to identify patterns, trends and effective interventions to reduce the ecological impact of human activities (Saveliev and Zhurenkov, 2021). These rapid advancements were possible both thanks to the increasing availability of data and AI development. These two factors have enabled organizations to explore significant opportunities for improving operational efficiency, enhancing productivity, optimizing decision-making processes and supporting managerial decisions (Shrestha *et al.*, 2021). By leveraging their available data and the AI techniques, organizations had the possibility to generate value and to drive innovation in previously unimaginable ways. For example, through intelligent automation, predictive analytics and recommendation systems, organizations processed data more effectively, thereby improving also the accuracy and timeliness of their decisions (Wellsandt *et al.*, 2022; Lepenioti *et al.*, 2020; Nunes and Jannach, 2017). Accordingly, over time, an evident evolution in the approach of public and private organizations to this technology emerged. Each phase of AI development has introduced new applications and uses, significantly impacting organizational operations and strategies and redefining the organizational landscape like never before (Sinha and Al Huraimel, 2020). In this regard, understanding the enablers and barriers that drive or hinder AI adoption in organizational contexts becomes essential. To address this, several scholars have developed models, offering a valuable theoretical lens to better understand the adoption of AI in organizations, through the consideration of a wide array of psychological, social, technical and structural dimensions. The Technology Acceptance Model (Davis, 1989), for example, focuses on perceived usefulness and ease of use as determinants of technology acceptance. The Theory of Planned Behaviour (Ajzen, 1991), instead, extends the previous view by incorporating factors such as attitudes, subjective norms and perceived behavioural control. The Task-Technology Fit model (Goodhue and Thompson, 1995) highlights the importance of the fit between the technology and the tasks it supports, while the Unified Theory of Acceptance and Use of Technology (Venkatesh *et al.*, 2003), integrating several previous models, adds new dimensions such as social influence and facilitating conditions. Finally, the Technology-Organization-Environment (TOE) framework (Tornatzky and Fleischer, 1990), offers a broader perspective by considering not only technological characteristics but also organizational and environmental factors influencing technology adoption.

Despite these theoretical contributions, existing studies often fail to offer a cohesive framework that connects technological adoption theories with AI's unique characteristics, such as its ability to autonomously learn, adapt and make independent decisions (Keding, 2021). To address this gap, this study proposes a model integrating the TOE framework with the factors enabling and hindering AI adoption, systematising the heterogeneous body of knowledge regarding AI's impact on organizations.

The goal is to stimulate a reflection regarding strategies and approaches to overcome these challenges and maximize the benefits derived from the correct and proper AI adoption.

Therefore, the following research questions are addressed:

RQ1. What are the main challenges and drivers influencing AI adoption within organizations, as identified in the current literature??

RQ2. What are the main research directions suggested by the analysis of the literature on the topic?

To answer these research questions, a Systematic Literature Review (SLR) was performed using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach (Moher *et al.*, 2015). This review contributes to the literature by systematising the scientific knowledge of this phenomenon, problematising key shortcomings and opening new avenues for investigation. Furthermore, the findings of this study can guide practitioners in making informed decisions to innovate organizational processes and effectively integrate AI technologies. The paper is structured as follows. Section 2 briefly describes the historical development of AI use within organizations, while Section 3 shows the methodology used to conduct the systematic literature review. Thereafter, Section 4 reports and discusses the results by identifying the most used AI techniques and their driver and barriers to the adoption. Based on these results, a future research agenda is developed in Section 5. Finally, the theoretical and managerial implications are reviewed in Section 6.

2. Exploring the issue. AI history within organization

In recent decades, AI has radically transformed the way organizations operate, make decisions and create value (Benbya *et al.*, 2020). From basic analytical tools and early automation systems, AI has evolved into an advanced and ubiquitous technology capable of performing complex tasks and adapting to dynamic contexts.

This evolution has been characterized by several phases: initially, the adoption of rule-based tools and simple algorithms to improve operational efficiency; subsequently, the integration of machine learning techniques for predictive analytics and advanced decision support and finally, the emergence of generative AI solutions and autonomous systems that completely redefine processes and business models. As seen, this progression has not only enhanced productivity and accuracy but also enabled new opportunities for innovation, transforming the organizational landscape across both public and private sectors (Dwivedi *et al.*, 2021).

Despite early promises regarding the practical utility of AI, during the early stage of its development, 1960s and 1970s, AI did not yield tangible results. This was due to several obstacles, the most important being the lack of computational power necessary for the interested operations (Deng, 2018). Accordingly, during these two decades, AI did not have a significant impact on public and private organizations. Technological limitations, in fact, made the practical application of AI difficult, and the lack of tangible results led to a decrease in interest from businesses and governments. Consequently, this period witnessed a slowdown in research funding and a loss of momentum in the AI field.

In the 1980s and 1990s, interest in AI experienced a resurgence due to significant investments by governments and businesses in research on expert systems (Duan *et al.*, 2019; O'Leary and Turban, 1987). These systems, developed to emulate human expert decision-making in specific domains (e.g. medical diagnosis, financial management and industrial automation), sparked renewed enthusiasm (Edwards *et al.*, 2000) and enabled organizations to optimize operations and enhance efficiency, though their applications remained relatively constrained by today's standards.

In the 2000s, unprecedented computational capacity and increased data volumes gave a strong impetus to the development of AI applications (Tien, 2017). Consequently, public and private organizations began leveraging the potential of machine learning to analyse large volumes of data and derive useful insights, enhancing, in private sector, service personalization and supply chain management (Shah *et al.*, 2023), and in the public sector, public services and operational efficiency.

In the following decade, thanks to advances in computational power, the availability of big data and deep learning algorithms (Raschka *et al.*, 2020) AI reached an advanced level of development. AI applications became increasingly sophisticated and capable of surpassing human performance in specific tasks (Topol, 2019). Private organizations started using AI to enhance automation, personalization, risk management and market trend forecasting (Bharadiya, 2023), while public ones (e.g. law enforcement, public health and administration) have adopted AI solutions to improve security, service efficiency and governance. Emerging technologies such as chatbots, recommendation systems and autonomous vehicles became integral parts of business and operational strategies.

Seems clear that the evolution of AI has transformed organizational operations, decision-making and value creation (Benbya *et al.*, 2020), progressing from rule-based tools to advanced generative AI systems. Anyway, the impact of introducing AI into an organization's processes and activities depends on its ability to maximize AI's benefits while minimizing associated risks, ensuring a smooth integration into business processes and strategies (Allioui and Mourdi, 2023).

3. Methodology

A SLR was conducted between February and June 2024 to collect evidence from previous studies, offer an overview of the current state of knowledge on AI utilization within organizations and outline directions for future research (Linares-Espinós *et al.*, 2018). Explicitly, based on the above-mentioned overarching research questions, the investigation seeks to accomplish the following research objectives:

(1) What are the most recurrent AI techniques within organizations?

(2) What are the main enablers fostering AI adoption, and what challenges can hinder its implementation?

The SLR was carried out using PRISMA, a structured and thorough method to search, filter, select and analyse literature findings based on the study's objective (Moher *et al.*, 2015). Moreover, PRISMA was selected because it ensures comprehensive planning of the review process from beginning to end, ensuring methodological accuracy, replicability and transparency (Tranfield *et al.*, 2003). To conduct the SLR, PRISMA's steps–including identification, screening, eligibility and inclusion (Moher *et al.*, 2009) - were followed as detailed below and shown in Figure 1.

3.1 Identification

The review questions guided the identification of keywords to isolate the relevant literature from Scopus which was chosen for its extensiveness and relevance in the social sciences (Norris and Oppenheim, 2007). The keywords were connected with the "AND" and "OR" Boolean operators. Thus, the following search string was defined:

("artificial intelligence" OR "AI") AND ("organization" OR "enterprise" OR "business" OR "company")

These keywords needed to be contained in the title, abstract or keywords to ensure a comprehensive search. In doing so, 12,894 records were produced.

3.2 Screening and eligibility

Following Cooper's methodology (1988), criteria for inclusion and exclusion were established to select the pertinent literature from the databases. Chapters from books, editorials, conference proceedings and working papers were omitted, whereas articles from international peer-reviewed journals were included in the analysis. Additionally, only documents written in English and related to the specific fields of business management and social sciences were considered. Based on these criteria, 3,393 records were initially selected. Titles and abstracts of these 3,393 records were reviewed to identify those most relevant to the research area and review questions. Consequently, 2,719 records were excluded, and 674 articles were evaluated for eligibility.

3.3 Inclusion

After reading the introductions and some parts of the texts of the 674 remaining articles, 196 publications were included in the review process because they contributed to answering the review questions, as explained below. The final collection of 196 works was examined using both descriptive and thematic analyses. The descriptive analysis followed a deductive approach, classifying the studies by journal, temporal and geographic distribution and

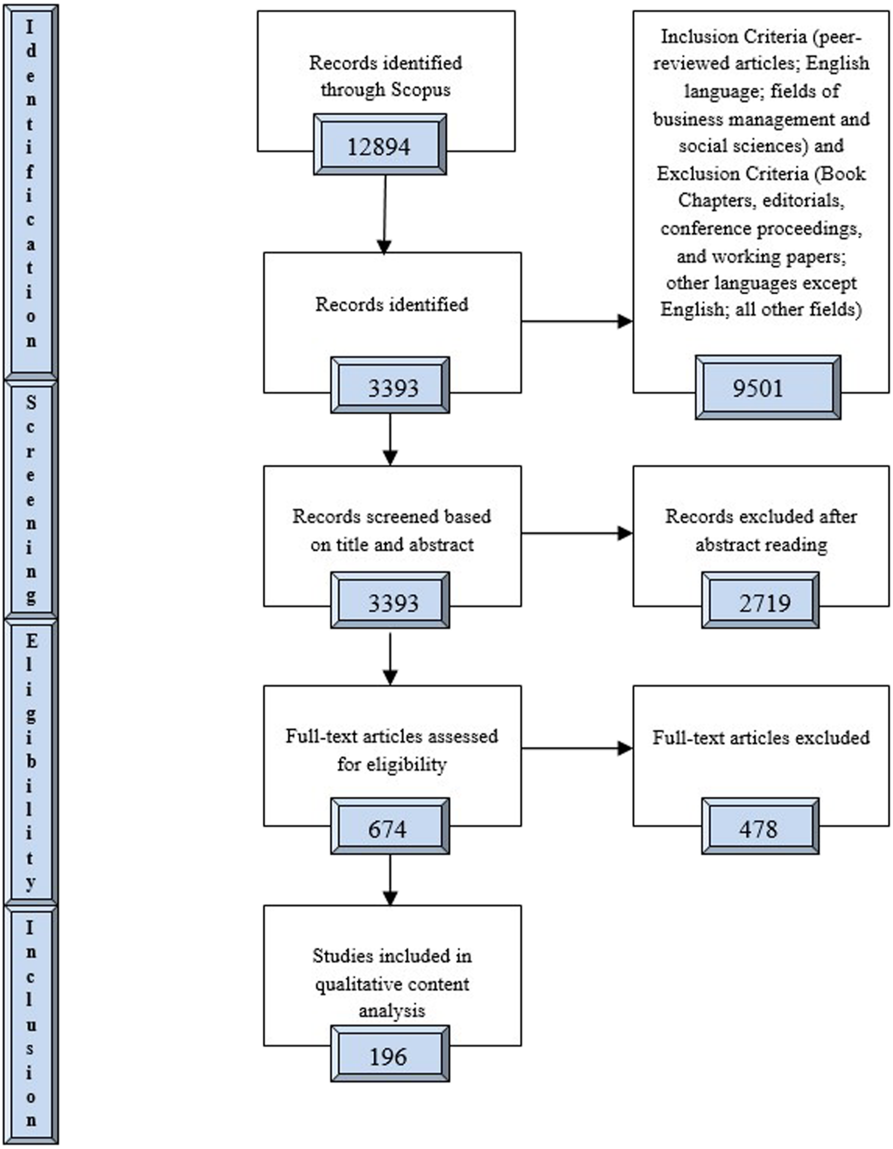

Figure 1. The assessment and selection of contributions. PRISMA flow diagram. Source: Authors' own work

methodological approach. For the thematic analysis, an inductive method was employed (Bales *et al.*, 2009). The two researchers independently coding and categorizing the studies. They then discussed their findings through phone calls or Zoom meetings to ensure the review's quality. The thematic analysis focused on three main themes: (1) the most implemented AI techniques; (2) the drivers behind AI implementation and (3) the challenges arising during AI implementation.

3.4 Descriptive and thematic analyses

The study performed descriptive and thematic analyses to gain a quantitative and qualitative understanding of the literature. In particular, most descriptive analyses (e.g. the frequency distribution of articles by publication year and journal) were carried out using Excel. In addition, VOSviewer (van Eck and Waltman, 2010) and its overlay visualization feature were used to explore the temporal evolution of the keywords within the dataset. This feature assigns colours to the keywords based on their average publication year. This is useful for identifying how specific topics or key terms emerge and evolve over time, providing insight into shifts in AI-related research foci within organizational contexts.

Subsequently, a thematic analysis (Clarke and Braun, 2017) was conducted to categorize the literature regarding AI techniques, enablers and challenges. The two researchers independently coded the relevant textual segments, and any discrepancies were resolved through discussion. This iterative coding process continued until theoretical saturation was reached (Saunders *et al.*, 2018). At that point, no further information was sought within the sample of articles, as additional data did not generate substantially new categories or subthemes. This dual strategy aligns with systematic review guidelines (Tranfield *et al.*, 2003) that encourage quantitative mapping and qualitative synthesis to ensure a robust and multifaceted understanding of the literature.

4. Results

As AI has evolved from theory to practical application, its transformative potential across industries has become increasingly evident, aligning with major projections from the McKinsey Global Institute (MGI) and the World Economic Forum (WEF). MGI has forecasted that AI could add up to $13 trillion to the global economy by 2030, driven largely by enhanced automation, productivitygains and data-driven decision-making processes (Chui *et al.*, 2018). Additionally, the WEF anticipates that AI will fundamentally reshape organizational structures, redefine job roles and generate demand for new skill sets as businesses adopt AI for strategic advantages. These insights underscore the significant impact of AI on organizational landscapes and highlight interest from both academia and industry in understanding the drivers and challenges associated with AI adoption. The literature reviewed in this study reflects this shift, tracing the evolution of AI research within organizational contexts over time and examining how theoretical insights and practical applications have shaped current perspectives.

4.1 Academic research performances of AI impacts on organizations

The time scale of the selected articles can be divided into two temporal segments according to the keywords used through the years (Figure 2). In the first segment, from 1984 to 2017, blue and purple keywords highlight previous-studied topics, whereas from 2018 to 2024, green and yellow keywords indicate topics that have gained more prominence in recent years. Thus, in the first period, keywords such as “artificial intelligence”, “machine learning”, “decision-making”, “automation”, “robotics” and “information management” indicate that research primarily focused on the introduction and application of AI in business processes, with particular emphasis on information management and process automation. “Decision-making” emerged as a central theme, reflecting an interest in understanding how AI could support and enhance decision-making processes (Lawrence, 1991). Keywords like “automation” and “robotics” also suggest attention to the adoption of advanced technologies to improve operational efficiency and reduce costs. In the second period, keywords include “generative AI”, “resilience”, “supply chain management”, “ChatGPT”, “healthcare” and “customer satisfaction”. This shift highlights a movement toward AI applications in specific contexts, such as supply chain management (Dubey *et al.*, 2020) and organizational resilience (Kumar *et al.*, 2024b). The terms “generative AI” and “ChatGPT” reflect an increasing interest in

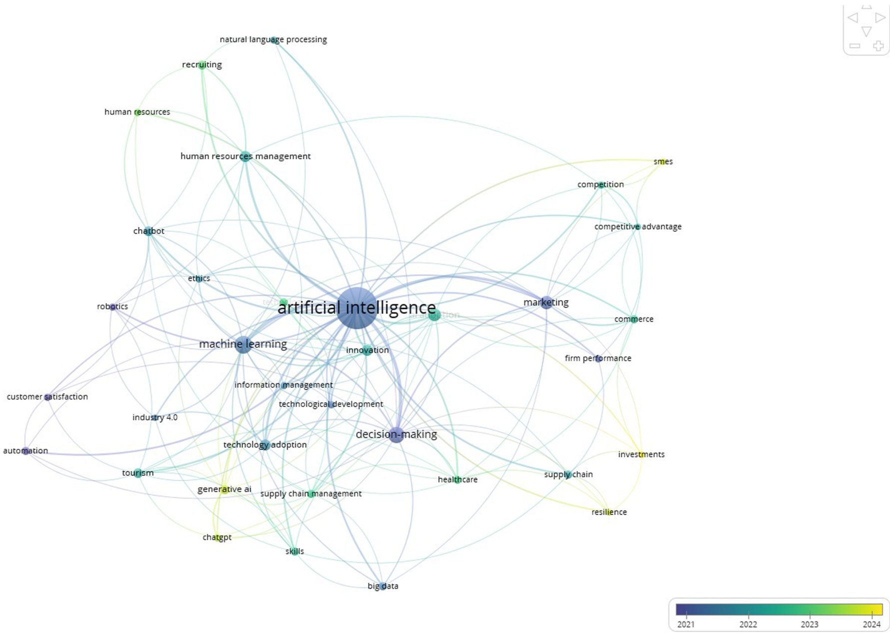

Figure 2. Keywords' overlay representation. Source: VosViewer software

generative AI, revealing a trend towards research focused on conversational capabilities and automated content generation. The focus on "customer satisfaction" implies a shift toward using AI to enhance customer experience and business services. Finally, the keyword "healthcare" suggests a rise in studies on the application of AI to support clinical decision-making and improve patient management (Alami *et al.*, 2021).

Thus, early research primarily explored AI's role in business processes, emphasizing its potential for information management and automation to support decision-making. In contrast, recent studies focus on advanced applications, such as generative AI, and its specific impacts on sectors like healthcare and supply chain management. Furthermore, the presence of keywords such as "resilience" and "customer satisfaction" highlights a more strategic focus on enhancing user experience and risk management. This thematic evolution reflects a shift from the initial stages of AI adoption and technological understanding toward a more mature, strategic use across sectors, which includes leveraging AI to create tangible value and address complex challenges.

The topic under investigation is particularly relevant in Anglophone countries (United States and United Kingdom) and Asian countries (China and India), followed by European countries such as Germany, Italy, France and Spain. Given the geographical distribution of the sample (Figure 3), the review thus includes a diverse range of perspectives and contexts, providing insights into emerging trends and the development of research at a global level.

The articles included in the systematic review are published in 87 different journals. Primarily, a significant portion finds its place in *Technological Forecasting and Social Change* with 22 articles, succeeded by the *Journal of Business Research* with 18 articles. Additionally, contributions are also present in journals such as *International Journal of Information Management*, *IEEE Transactions on Engineering Management* and *Industrial Marketing Management*, each comprising respectively 16, 12 and 9 articles. The Figure 4, in which are reported the first ten journal, suggests a detailed overview of key sources, quality of

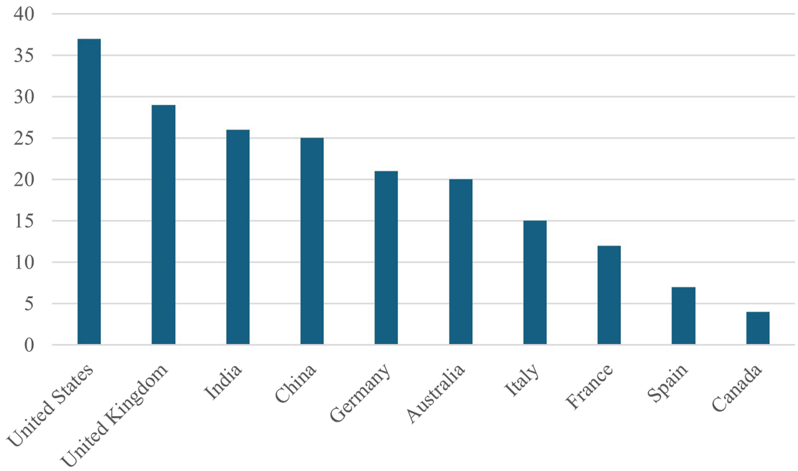

Figure 3. Geographic distribution of the sample. Source: Authors' own work

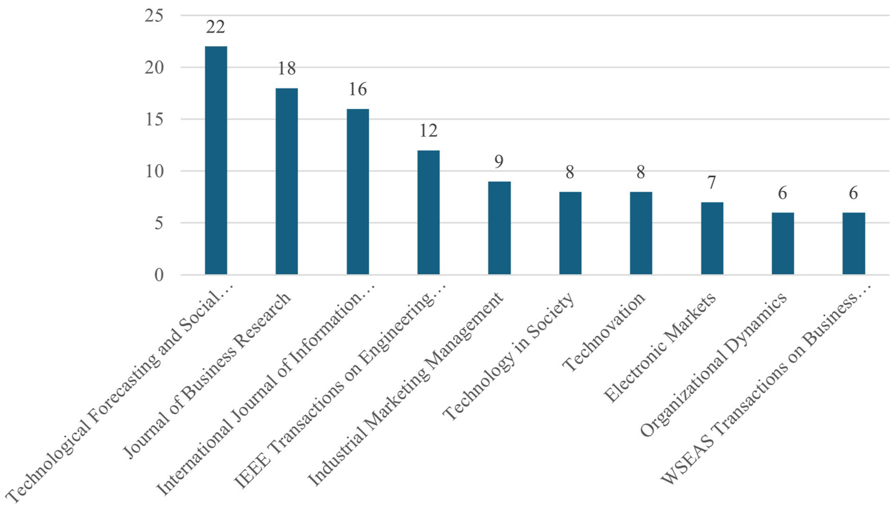

Figure 4. Articles per journals. Source: Authors' own work

publications and research trends in the field of AI. It is possible to highlight a broad acceptance and an interdisciplinary nature of research, transcending various academic domains.

The analysis revealed that the selected sample is composed of 526 unique authors. The large number of authors involved in the research eliminates the risk of a one-sided view on the topic of interest in the study. In any case, among authors who have shown significant interest concerning the use of AI within organizations, Dwivedi stands out as the most prolific, contributing a total of eight articles. Following closely, each with seven article there are Costa, Parida, Gonçalves, Pereira, Chatterjee and Fosso Wamba. Gupta and Dias also contribute substantially, each having authored six articles (Figure 5).

In terms of citations, the most cited articles have all been published in the last 5 years, that is Dwivedi *et al.* (2021) with 2,164 citations, followed by Warner and Wäger (2019) with 2,304

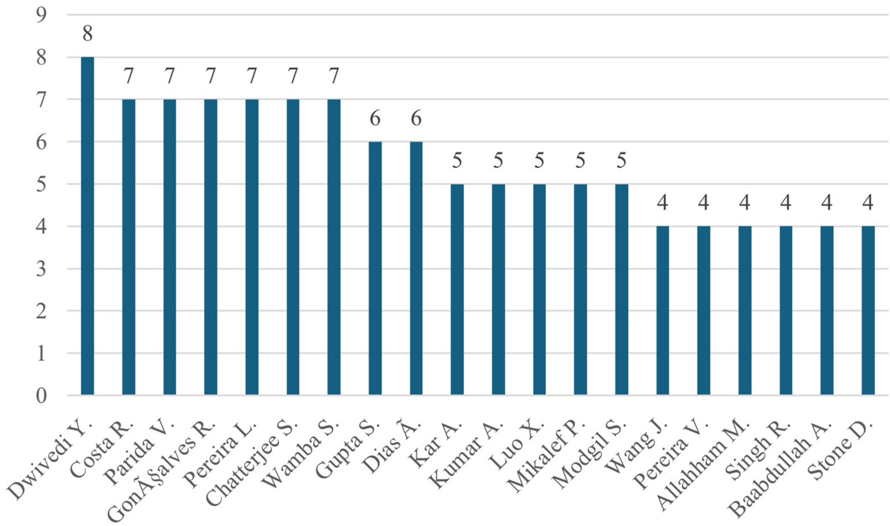

Figure 5. Recurring authors. Source: Authors' own work

citations, Raisch and Krakowski (2021) with 1,072 citations and Luo *et al.* (2019) with 931. The following Table 1 shows the ten most cited articles of the sample. The most cited article (Dwivedi *et al.*, 2021) traces technological innovation from the industrial revolution, emphasizing its role in overcoming human physical limitations. It argues that AI now offers

Table 1. Articles most cited

Authors	Article	No. of citations
Dwivedi *et al.* (2021)	Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities and agenda for research, practice and policy	2,164
Warner and Wäger (2019)	Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal	2,304
Raisch and Krakowski (2021)	Artificial intelligence and management: The automation–augmentation paradox	1,072
Luo *et al.* (2019)	Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases	931
Di Vaio *et al.* (2020)	Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review	772
Vrontis *et al.* (2023)	Artificial intelligence, robotics, advanced technologies and human resource management: a systematic review	729
Mikalef and Gupta (2021)	Artificial intelligence capability: Conceptualization, measurement calibration and empirical study on its impact on organizational creativity and firm performance	692
Wamba-Taguimdje *et al.* (2020)	Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects	661
Haefner *et al.* (2021)	Artificial intelligence and innovation management: A review, framework and research agenda	566
Dubey *et al.* (2020)	Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations	562

Source(s): Authors' own work

similar transformative potential, enhancing or replacing human activities across industrial, intellectual and social domains. The qualitative study of Warner and Wäger (2019) examines how traditional industries develop dynamic capabilities for using new technologies like AI, identifying factors that promote or hinder dynamic capability development for digital transformation. Lastly, Raisch and Krakowski (2021) argue that combining augmentation and automation can yield synergistic benefits, urging scholars to advance AI research in organizations to create robust theories and practical guidance aligned with organizational needs.

The topic under investigation is addressed mainly through empirical methods both qualitative and quantitative (Table 2). Particularly, most of the qualitative articles are based on case studies and interviews to understand the experiences and perceptions of AI users, as in the study by Cao *et al.* (2021), where a qualitative approach is used to understand managers' attitudes towards AI. Similarly, numerous articles use statistical analyses and quantitative models to measure the impact of AI. For example, Mikalef and Gupta (2021) use a quantitative analysis to examine that AI capability results in increased organizational creativity and performance. Few articles combine qualitative and quantitative approaches to obtain a more comprehensive view. Sharabati *et al.* (2024) employ a mixed-methods approach to highlight AI's role in enhancing supply chain agility, transparency and responsiveness. The study of Ivanova *et al.* (2022) analyses, instead, which digital skills are more and less developed in Bulgarian tourism and highlights the lack of digital training in many companies. Solaimani *et al.* (2024) used mixed methods, combining a literature review, a survey and expert interviews to identify critical success factors for AI adoption. Similarly, El Hajj and Hammoud (2023) applied a mixed methods approach to examine AI and Machine Learning (ML) adoption in financial markets. Theoretical studies are present but less frequent compared to quantitative and qualitative studies. For example, Pan *et al.* (2023) use a theoretical approach to examine the adoption of AI in employment decisions.

The Figure 6 illustrates the primary sectors where AI is applied within organizations. Human Resources leads with 38% of implementations, focused on recruitment, performance management and talent development (Vrontis *et al.*, 2023; Nawaz *et al.*, 2024). Marketing follows at 29%, using AI for customer data analysis and campaign personalization (Kumar *et al.*, 2024a). Operations (18%) leverages AI for supply chain optimization (Shah *et al.*, 2023; Sharabati *et al.*, 2024) and process automation (Zebec and Indihar Štemberger, 2024), while

Table 2. Paper types and methodological approaches

Paper type		Method	No. of works
Theoretical		Literature review	19
		Concept development	17
		Modelling and computer simulation	19
		Total	*55*
Empirical	Qualitative	Case study	63
		Interviews	10
	Quantitative	Correlation	2
		Regression	13
		Model based analysis	44
		Social Network analysis	2
		Cluster Analysis	3
	Mixed method		4
		Total	*139*

Source(s): Authors' own work

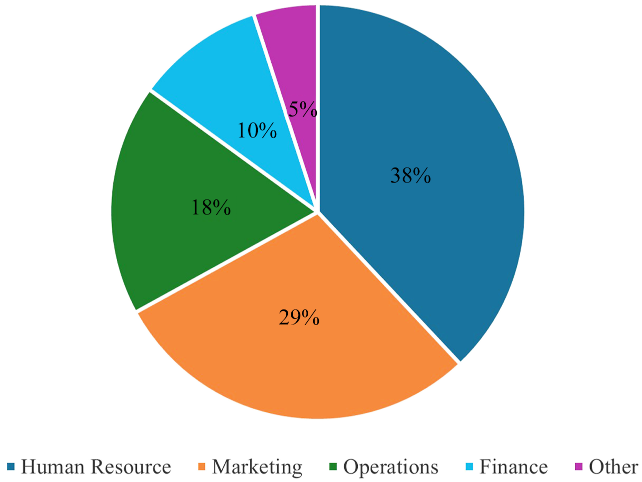

Figure 6. Distribution of AI implementation by sector. Source: Authors' own work

Finance (10%) applies AI in risk management and financial analysis (El Hajj and Hammoud, 2023). The "Other" category (5%) represents sectors with less frequent AI adoption.

4.2 Thematic analysis

4.2.1 Most recurrent AI techniques implemented within organizations. Thematic analysis allowed the classification of the three main AI techniques used in the sample selected for the review. ML emerged prominently, appearing in approximately 56% of the articles reviewed in the sample. ML focuses on developing algorithms and statistical models that enable computers to learn and make data-driven predictions or decisions. In organizational contexts, ML is employed to analyse large volumes of complex data (Jabeur *et al.*, 2023), identify patterns, improve prediction accuracy, optimize decision-making processes (Chowdhury *et al.*, 2023) and innovate business models. For instance, Nafizah *et al.* (2024) argue that a strategic approach to ML can enhance profit margins, reduce supply chain costs, optimize processes and improve customer service. Similarly, from a strategic point of view, Rana and Daultani (2023) highlight the need for a comprehensive application framework to effectively guide AI and ML adoption. Moreover, results show that the implementation of ML spans several sectors with significant outcomes. In the finance sector, El Hajj and Hammoud (2023) highlight ML applications in algorithmic trading, risk management, fraud detection, credit scoring and customer service. Following, Volkmar *et al.* (2022) offer insights into how AI and ML are shaping the marketing management field, exploring the drivers, barriers and future developments. Then, Chowdhury *et al.* (2023), conceptualizing a transparent AI implementation framework for HR managers that enhance the explainability of AI-based ML models in predicting employee turnover, mitigating trust issues in data-driven decision-making.

Natural Language Processing (NLP) appears in about 29% of the articles reviewed in the sample. NLP, merging linguistics, computer science and AI, enables computers to process and generate human language, analysing textual data from sources like social media, reviews, surveys and organizational documents. This analysis helps in extracting meaningful insights, identifying trends and automating processes (Gethe, 2022) through sentiment analysis, topic modelling and information retrieval. For example, in HR departments NLP tools helps recruiters to screen the resume of candidates; to analyse speech patterns of candidates; to conduct some advanced competency tests and neuroscience games in order to demonstrate a candidate's emotional and cognitive ability. Moreover, by leveraging NLP, organizations can enhance communication strategies, improve customer service, streamline operations and support data-driven decision-making processes (Gupta *et al.*, 2024). NLP has been shown to enhance the accuracy and speed of risk assessments. Kalogiannidis *et al.* (2024) highlighted its role in predictive risk assessment and organizational continuity, with AI integration significantly reducing disruptions and improving recovery efforts.

Lastly, Deep Learning (DL) appears in just 15% of the articles reviewed in the sample. As known, DL is a subset of ML that employs neural networks with many layers to model and understand complex patterns in large datasets. DL techniques are utilized to analyse intricate and high-dimensional data, facilitating advanced predictive analytics, natural language processing, image and speech recognition and decision-making processes (Selmy *et al.*, 2023). DL models can capture subtle and abstract relationships within data, enabling the development of sophisticated tools and applications that enhance organizational performance, optimize resource allocation, improve customer interactions and support evidence-based policy-making (Singh and Goyal, 2023). In fact, it has been demonstrated the utility of DL algorithms in managing risk, qualifying them as a promising tool for enhancing organizations resilience.

4.2.2 The main enablers fostering AI adoption, and the challenges that hinder its implementation (RQ1). The analysis of the articles in the sample revealed that the main drivers concerning the implementation of artificial intelligence within organizations are:

(1) Crucial Role of Leadership and Organizational Support: Leadership and organizational support are fundamental for the adoption of AI (Radhakrishnan *et al.*, 2022), as leaders influence the vision, strategy and organizational culture necessary to integrate new technologies (Nawaz *et al.*, 2024). The sample highlights that active involvement of leaders, and their support are critical to overcoming internal resistance and promoting an environment conducive to innovation (Chen *et al.*, 2023; Islam *et al.*, 2023), through the introduction of tech-sensitive innovation culture and AI risk tolerance (Black *et al.*, 2024). Moreover, a proactive leadership approach that fosters cross-functional collaboration and promotes transparency in AI decision-making processes has been shown to facilitate smoother technology adoption (Yin *et al.*, 2024).

(2) AI skilled workforce, Training and Skills Development: AI skilled workforce composed of individuals who possess the knowledge and technical skills necessary to develop, implement, manage and improve AI systems, is necessary for the effective implementation and optimization of operations (Radhakrishnan *et al.*, 2022; Sharma *et al.*, 2022). Key competencies include programming, machine learning, data analysis, AI project management (Issa *et al.*, 2022) and understanding ethical and practical AI applications. Accordingly, continuous training and skill development are vital for effective AI adoption and use. For example, Kumar and Mittal (2024) underscore that employee learning has significant positive impact on the relationship between AI trust, knowledge sharing and AI skills and AI-employee collaboration. Thus, investing in personnel training enhances the capacity of organizations to integrate AI into their operational and strategic processes (Mikalef *et al.*, 2023).

(3) Availability of Financial and Technological Resources: The availability of financial resources (Horani *et al.*, 2023) and technological infrastructure is a critical enabling factor for the effective adoption of AI (Petrescu *et al.*, 2022; Chen *et al.*, 2024). Indeed, scholars emphasize that the successful implementation of AI is heavily dependent on an organization's existing technological infrastructure and its alignment with current and future business objectives (Sharabati *et al.*, 2024). Beyond financial capital, the presence of scalable cloud computing solutions and robust cybersecurity measures is essential to ensure seamless AI integration and minimize risks associated with data processing and storage (Raschka *et al.*, 2020).

(4) Favourable Policies and Regulations: Policies and regulations that incentivize the development and adoption of AI technologies facilitate an environment that supports technological innovation (Virmani *et al.*,2024; Chen *et al.*, 2023; Pan *et al.*, 2023; Sharma *et al.*, 2022). In particular, regulatory frameworks providing clear compliance guidelines and ethical safeguards can enhance AI adoption by reducing legal uncertainties and fostering stakeholder trust.

The examination of the selected articles indicated that the primary challenges concerning the implementation of artificial intelligence within organizations are:

(1) Resistance to Change: Resistance to change, considered one of the primary barriers to the adoption of AI (Dwivedi *et al.*, 2021; Klumpp, 2018), refers to the tendency of individuals and organizations to oppose or avoid modifications to existing processes and practices. This phenomenon is often driven by fears related to loss of control, uncertainty about outcomes and concerns about replacement of human workforces (Moradi and Dass, 2022). In particular, the recurrent drawbacks regard the employees' concern about algorithm biases, and the need for human empathy in sensitive issues. About this La Torre *et al.* (2021) propose an index assessing attitudes toward AI tools in organizations to reduce resistance to machine-based decisions, focusing on technology acceptance, self-efficacy and source credibility.

(2) Lack of Skills: The lack of skills refers to the shortage of specific knowledge and abilities necessary to develop, implement and manage AI solutions. According to Menzies *et al.* (2024) AI has necessitated changes in workplace configurations and the need for organizational and employee adjustments in response to this technology. This has included the emerging need for competencies in programming, data science, machine learning and change management (Dwivedi *et al.*, 2021). Kalogiannidis *et al.* (2024) and Kumar and Mittal (2024) emphasize the importance of AI training and skill development, advocating for upskilling initiatives, AI-based projects and knowledge-sharing environments to enhance AI adoption and employee collaboration.

(3) Issues Related to Data Quantity, Quality and Privacy: Data quantity, quality and privacy are critical for effective AI solutions, with concerns cantered on data collection, management and use (Gurjar *et al.*, 2024). Data quality, for example, directly impacts the performance and reliability of AI, while data privacy involves the protection of sensitive information and compliance with data protection regulations (Moradi and Dass, 2022; El Hajj and Hammoud, 2023). In addition, scholars (Dwivedi *et al.*, 2021; Radhakrishnan *et al.*, 2022) highlighted also the ethical challenges related to the unethical use of data. Accordingly, strong data protection rules and open communication can help to handle privacy and data security concerns (Rukadikar and Khandelwal, 2024). In the end, emerged also that both biases from poor data quality and coding processes can compromise automated decisions (Srouji and Bellè, 2022), making crucial their correction to ensure fair and accurate AI outcomes.

5. Discussion and research agenda (RQ2)

The SLR, regarding the understanding of AI impacts within organizations, revealed that the topic under investigation has got considerable attention in the past and is highly discussed in recent years. Moreover, it emerged that the adoption of artificial intelligence is widespread across various sectors (i.e. Humane Resource, Marketing and Operation), with common techniques such as ML, DL and NLP, playing crucial roles. Among these, ML has garnered the most scholarly attention, reflecting interest in predictive AI applications, such as demand forecasting, logistics planning, marketing automation, customization and enhancing cybersecurity by detecting risks, fraud and data theft. Regarding the main facilitators for AI adoption, from the analysis emerged that favourable regulation, skill development and organizational support are the most discussed. In particular, favourable regulatory frameworks can play a pivotal role by providing clarity on compliance standards, ethical guidelines and data protection protocols, which are essential to building trust and reducing the risks associated with AI deployment. Regulations that encourage innovation, alongside frameworks that protect user data and prevent misuse, create an environment in which organizations are more likely to invest in AI. Skill development is equally critical. As emerged from the results, adopting AI technologies often requires a workforce capable of understanding, implementing and managing these advanced systems. Therefore, organizations must prioritize both upskilling existing employees and attracting new talent with expertise in machine learning, data science and AI ethics. Skill development initiatives, such as specialized training programs and partnerships with academic institutions (Reuben, 2023), can enable organizations to build and sustain a knowledgeable workforce capable of leveraging AI effectively. Furthermore, organizational support, encompassing leadership commitment and an adaptable corporate culture, is essential for the successful integration of AI. Implementing AI often means rethinking traditional workflows, decision-making processes and even organizational structures to accommodate AI-driven insights and automation. Organizations can facilitate these changes by establishing a clear vision and roadmap that align AI initiatives with the organization's broader strategic goals. This approach fosters a culture that values innovation and embraces technological experimentation. In sum, integrating AI into existing systems requires, in fact, significant technological and organizational adaptation, as well as the availability of technologies, funding and appropriate resources. The primary challenges involve the lack of expertise, data security and data quality for training AI models and the resistance to change. To overcome these barriers and ensure successful AI implementation, companies should involve all stakeholders, focus on data quality and management and ensure the AI solution integrates with existing processes and workflows. Additionally, companies should avoid common mistakes when implementing AI, such as neglecting the importance of explainability and transparency in AI decision-making, underestimating the necessity of stakeholder involvement and rushing into large-scale implementation without conducting small-scale pilot projects (Hangl *et al.*, 2023). Thus, both the descriptive analysis and the thematic one led to the identification of some gaps and future research directions (RQ2).

5.1 Research direction 1: insights into ethical implications

Ethical issues related to the implementation of AI systems require further investigation because they can profoundly impact individual rights, perpetuate biases and discrimination and have significant economic implications. Transparency, accountability and the inclusion of ethical considerations in design are essential to ensure the fair and just use of AI (Golbin and Axente, 2021). Scientific studies highlight that the lack of these measures can lead to unfair automated decisions and negative consequences (De Falco and Romeo, 2024).

5.2 Research direction 2: increase in mixed methods and longitudinal studies

From a methodological standpoint, research on AI would benefit from an increase in mixed methods and longitudinal studies. Mixed methods, by combining in-depth qualitative perspectives and broad quantitative insights, offer a comprehensive understanding of AI dynamics. This approach is particularly effective in addressing complex and multifaceted issues, such as the adoption of AI within organizations (e.g. understanding human-machine interaction dynamics, analysing adoption and resistance to AI, comprehending the organizational and cultural impact and so forth), which encompass technological, human, organizational and ethical dimensions. Longitudinal studies, on the other hand, allow for the observation of the evolution and long-term effects of AI implementation, highlighting changes and trends that short-term research would not capture. These approaches would enhance the robustness and depth of the research regarding the AI impacts on organizations.

5.3 Research direction 3: addressing emerging countries

Literature on AI impact on organizations comes mainly from advanced economies, reflecting the view that technological innovations are opportunities able to generate new value in mature settings (Chui *et al.*, 2018) Research on AI would benefit from studies focused on emerging countries because these contexts present unique challenges and opportunities that may reveal new applications and impacts of AI. Investigating AI in such countries could contribute to a more equitable and inclusive development of AI technologies, highlighting potential risks and benefits specific to these settings. Additionally, it could provide valuable insights into how to tailor AI solutions to diverse socio-economic and infrastructural realities.

6. Conclusion

6.1 Theoretical and practical implications

Considering the study's findings, this research extends the application of the TOE framework (Tornatzky and Fleischer, 1990) to the context of AI adoption, proposing a composite perspective that integrates AI-specific attributes. By structuring AI adoption within this framework, the work emphasizes how technological, organizational and environmental factors interact dynamically to shape AI implementation strategies (Figure 7). Accordingly, from a technological point of view, AI adoption is influenced by factors such as data availability, quality and security (Gurjar *et al.*, 2024), as well as the need for explainability and interpretability in AI models to build trust in automated decision-making (Srouji and Bellè, 2022). Organizationally, leadership support and an AI-skilled workforce are crucial enablers (Mikalef *et al.*, 2023; Radhakrishnan *et al.*, 2022), whereas resistance to change and the lack of employee training present major challenges (Dwivedi *et al.*, 2021; Menzies *et al.*, 2024). Lastly, for the environment dimension, external regulatory frameworks, ethical considerations and industry-specific policies play a significant role in AI adoption (Chen *et al.*, 2023; Virmani *et al.*, 2024). Thus, favourable AI governance structures can mitigate risks associated with algorithmic bias and enhance responsible AI integration within organizations (Mikalef *et al.*, 2022).

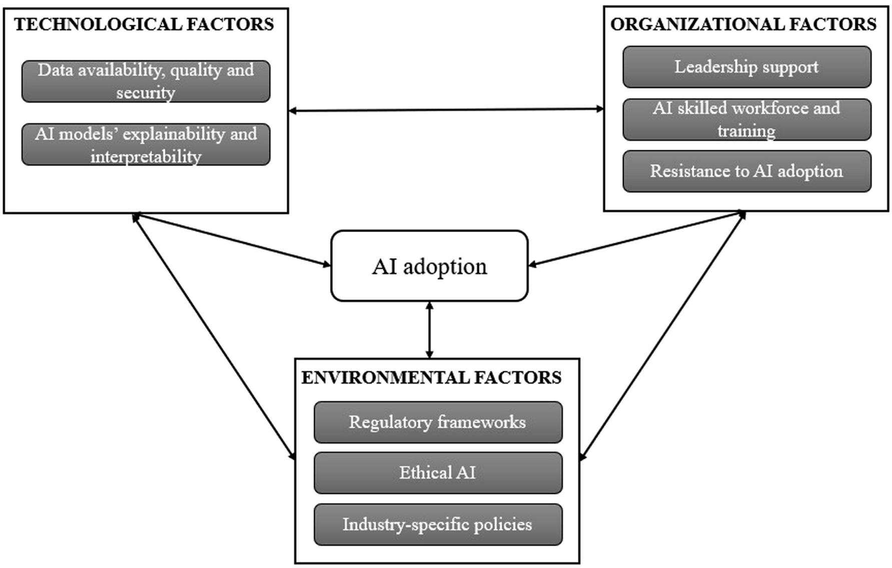

Figure 7. AI adoption according to TOE framework. Source: Authors' own work

From a theoretical perspective, this study, integrating insights from a systematic literature review, presents a comprehensive framework that provides an overview of the key enablers and challenges of AI adoption within organizations (Figure 7), highlighting that AI adoption is not merely a technological challenge but a multidimensional process requiring strategic alignment across technological, organizational and environmental factors. Moreover, by combining descriptive, bibliometric and thematic analyses, it highlights research contributions regarding the time, geographical and publication aspects, the methodological approaches employed and the most used techniques. Lastly, this systematization lays the groundwork for identifying and discussing research gaps, guiding future studies in advancing this field.

From a managerial point of view, this study, underscoring a structured approach grounded in the TOE framework, can facilitate organizational transformation while mitigating AI's risks and ethical concerns. Professionals can use these insights to evaluate and leverage existing strengths within their organizations while addressing and improving the currently lacking factors, thus optimizing the AI implementation process (Sharma *et al.*, 2022). In particular, highlighting both technical (i.e. data quality) and human limitations (i.e. cultural resistance), this study calls for distinct strategies. For example, integrating robust data management policies to address concerns regarding data quality and security (Moradi and Dass, 2022) should be considered. Moreover, managers should actively support AI initiatives by fostering a culture of innovation and addressing employees' concerns about it (Islam *et al.*, 2023). In addition, resistance to change can be mitigated through transparent communication about AI's role and benefits (La Torre *et al.*, 2021).

6.2 Limitations and further research

Despite the value of the findings presented, the paper has some limitations. First, although it is evident that both private and public organizations face similar challenges in AI implementation, the study does not delve deeply into how differences in their operational structures, goals and regulatory constraints may significantly influence their approaches to addressing and overcoming these challenges. Second, the study does not undertake a thorough analysis of the phenomenon of bias, which can lead to significant mistrust in the use of these technologies. Third, the findings of the systematic review are influenced by the authors' educational backgrounds. Therefore, future research should involve interdisciplinary teams to deepen ethical considerations, investigate organizational phenomena and consider specific contexts, such as emerging economies. In summary, this paper represents an exploratory step that lays the foundation for subsequent empirical studies (e.g. qualitative, quantitative, mixed methods) based on the evidence presented.

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