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EXPLORING ARTIFICIAL INTELLIGENCE IN THE DECISION-MAKING PROCESS

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TABLE OF CONTENTS LIST

List of Tables

List of Figures

INTRODUCTION

Artificial intelligence (AI) is a branch of computer science that has increasingly attracted the attention of academics and professionals. According to the perspective of Hosseini and Rossi (2024), “Artificial intelligence refers to programs, algorithms, systems, and machines that imitate human intelligence in tasks such as learning, planning, and problem-solving by generating higher-level and independent knowledge.” In recent years, AI systems have played an essential and significant role in organizational decision-making across various domains. These systems have created potential benefits for organizations, including workforce enhancement, cost reduction (Duann et al., 2019), increased human interactions (Makarius et al., 2020), and the creation of desirable job opportunities (Porter & Heppelmann, 2015). Moreover, AI systems include subfields such as machine learning (Jahan & Tripathi, 2021), natural language processing (Taniguchi et al., 2019), computer vision (Algendy & Alragal, 2014; Ikeuchi, 2014), and data learning (Howard, 2013), which are widely used by organizations to integrate AI into their decision-making processes. In AI-driven organizations, these technologies are not merely simple communication tools; rather, they serve as informative and empowering tools for managers and employees during decision-making (Caputo et al., 2019; Dwivedi et al., 2021). For example, such tools provide benefits such as accuracy, timeliness, efficiency (Ali et al., 2023), and improved accountability (Lenner et al., 2022) in decision-making processes. However, studies have identified fundamental challenges in adopting and collaborating with AI. One of these challenges relates to ethical concerns—such as security and privacy issues, transparency, lack of responsibility and accountability in AI systems, and distrust—particularly in AI-based decision-making in organizational financial reporting (Papagiannidis et al., 2023; Booyse & Scheepers, 2024; Roumbanis, 2025). In this context, one appropriate strategy for organizational decision-makers to overcome such challenges is to improve their skills and develop sufficient capacity to better interpret AI explanations. The more managers are aware of the ethical issues surrounding AI, the more effective they will be in dealing with these challenges (Tuncalp, 2025; Barile et al., 2025). With the rapid growth and advancement of technologies, organizations are increasingly using AI systems in the workplace, which has led to greater collaboration between employees, managers, and these systems. This is because the combination of humans and AI can reduce risks, enhance efficiency, and enable more effective decision-making (Candrian & Scherer, 2022). However, conflicting attitudes exist regarding human–AI collaboration in decision-making processes and task execution. Traditionally, we believe that humans are always responsible for controlling and supervising AI. Yet, with the widespread adoption of technologies in organizations, AI systems have reached a level of autonomy that allows them to make important organizational decisions even without human control or intervention (Murray et al., 2021; ServiceNow, 2020). This means that these technologies have been able to limit, complement, or even fully replace human capabilities (Schrage, 2017), indicating that some technological systems have surpassed humans in terms of productivity, efficiency, and safety (Kaasinen et al., 2015). AI has become embedded in organizational processes and in the ways employees and managers interact, and it has been widely accepted and collaborated with across organizations (Chowdhury et al., 2022; Kong et al., 2023). The more positively employees view AI-enabled work environments, the more they perceive such technologies as useful and reliable. Conversely, the more these technologies display human-like features and characteristics, the greater the level of collaboration between humans and AI becomes (Song et al., 2023; Singh & Chandra, 2024). Human–AI collaboration is defined as the interaction between employees and AI to enhance performance in the workplace (Kong et al., 2023; Pereira et al., 2023). One of the critical mechanisms for strengthening this collaboration is delegating responsibility or decision-making authority to AI systems (Freesinger & Schneider, 2024; Spitzer et al., 2025).

This thesis addresses the broader question of how the role and impact of AI in the decision-making process—by integrating both theoretical and empirical analyses— and shape human–AI collaboration. Despite extensive research on AI and its impact, significant gaps remain regarding its influence on organizational decision-making and the ways in which it collaborates with humans. In particular, there are conflicting perspectives on the adoption of AI and on human–AI collaboration in decision-making processes and task execution. To address this gap, this thesis adopts a multi-study approach that progressively examines different dimensions of this phenomenon. The first study was designed to establish a foundational understanding of the current state and recent developments in research on AI and its impact on decision-making processes within organizational activities and strategies. Specifically, it investigates whether and how AI are rapidly growing and evolving within organizations through trends, themes, key concepts, and leading authors, and what role they play in decision-making. This study was conducted using a bibliometric analysis method. This initial step was essential for clarifying the fundamental relationships underlying this phenomenon. However, the first study aimed to provide a comprehensive overview of the diffusion and development of AI and its impacts on decision-making processes, it did not explain the underlying factors through which these effects are generated.

This limitation motivated Study Second, which focuses on identifying the positive and negative factors of AI in decision-making. Since decision-making is considered one of the most important challenges across various research domains, identifying these challenges is of great significance. Despite extensive studies in this area, contradictory findings still exist regarding the relationship between decision-making processes and AI. On the one hand, the adoption of AI can lead to more accurate and faster decision-making. On the other hand, fundamental challenges in adopting AI may negatively affect decisions. In this study, we employed a meta-synthesis method to evaluate and identify these factors. Based on these findings and the identification of key positive and negative factors linking AI and decision-making and considering that these factors in our model form a circular framework of human-AI collaboration, we were guided to examine how managers can collaborate with AI in organizational decision-making processes. Therefore, the third study extends the research by examining the collaboration between humans and AI, regardless of the type of technological system involved. The aim was to develop a matrix for evaluating the overall collaboration between humans and AI. Based on the analyses conducted of the existing literature, the final model identifies four modes of collaboration between AI and humans, depending on who is responsible for decision-making and who executes the tasks. By identifying these modes, the study enables managers to better understand the role of AI in different business contexts. With a clearer understanding of AI's role, managers can select the most appropriate form of collaboration between humans and AI.

After identifying the different modes of collaboration between humans and AI, and drawing on prior literature and studies, it became necessary to ground the research in empirical investigation and provide stronger justification. Accordingly, we developed and empirically tested a research model proposing that trust beliefs, namely human-like trust and system-like trust, both play a significant role in shaping employees' willingness to delegate tasks to AI and ultimately collaborate with it. We also examined the ambiguous role of delegating authority to AI in shaping perceptions of perceived usefulness (PU), perceived ease of use (PEOU), satisfaction, and collaboration. This investigation was conducted through a questionnaire administered to employees in French, Italian, British, and American companies, and the data were analyzed using PLS software. The findings suggest that organizations can enhance positive attitudes toward AI by providing appropriate training, encouragement, and support for employees and managers. Such efforts can increase employees' willingness to delegate tasks to AI, which in turn can foster greater collaboration with these systems and ultimately improve organizational performance. Overall, these studies follow a coherent and structured progression. The thesis begins by examining trends, themes, and key concepts related to AI in decision-making processes. It then moves toward identifying the fundamental positive and negative factors of AI in decision-making. Finally, building on the theoretical investigation, it explores the key factors of human–AI collaboration—both from a theoretical perspective, through the identification of different modes of collaboration, and from an empirical perspective, through the examination of the factors that may influence such collaboration.

Based on the points discussed above, this dissertation aims to examine the role and impact of artificial intelligence in the decision-making process by integrating both theoretical and empirical analyses. Specifically, this dissertation seeks to address the following research questions:

RQ1: How has academic discourse evolved in response to recent advancements in organizational activities and decision-making processes, and what key themes, concepts, and research gaps have emerged?

RQ2: Which AI factors do managers and organizations use (under certain conditions and circumstances) in their decision-making processes, and how do these factors affect optimal decision-making?" "Under what conditions are Challenges Driven by AI (e.g., human resources, organizational goals, and ethics) likely to have a negative impact on individuals and organizations?"

RQ3: Academic discourse on technological advancements has expanded the collaboration between humans and AI in the workplace. What themes related to modes of conjoined agency and what research gaps have emerged in this context?

RQ4: How do different types of trust contribute to the decision to delegate tasks to AI, and how does this delegation, in turn, shape core technology perceptions and collaboration between employees and AI?

The research begins with an exploratory phase grounded in a comprehensive review of existing literature. The primary chapters address the current state and recent developments in studies related to AI and its impact on decision-making processes in organizational activities and strategies. The initial analysis of our studies was presented in a bibliometrics course, meta-synthesis, and conjoined agency.

The fourth chapter marks the beginning of the second part of the research project, which focuses on empirical research. In this study, a research model is developed and empirically tested that integrates trust beliefs (human-like and system-like), AI delegation, perceived ease of use (PEOU), perceived usefulness (PU), satisfaction, and employee–AI collaboration.

Through this dual structure, the thesis aims to contribute both theoretically and practically to the ongoing discourse on AI and its impact on decision-making processes.

This dissertation is part of a research project that began in January 2023 and concluded in January 2025. It was jointly developed by my supervisor and me over the course of three years, with each chapter dedicated to one of the articles produced during the project. Each chapter distinctly reflects its corresponding article. The following paragraphs provide an overview of the progression of these articles.

Chapter I: A Bibliometric Analysis of Artificial Intelligence and Decision-making

The first chapter examines the current state and recent developments in studies related to AI and its impact on decision-making processes within organizational activities and strategies. Our preliminary analysis was presented in the *Bibliometrics* course. Subsequently, after completing the final data analysis, the full study was presented at the 5th International Conference on Decision Economics[1] in July 2023. This research employs a bibliometric method using the Scopus database to provide a comprehensive overview of AI adoption and its vital role in organizational strategy and decision-making. Specifically, we analyzed articles published in journals listed in the AJG by conducting descriptive (performance) and conceptual (scientific mapping) analyses. This approach enables us to examine trends, identify key topics and concepts, analyze leading authors, and uncover research gaps, ultimately offering a holistic understanding of the role of AI in decision-making. The study highlights that AI systems are rapidly growing and evolving within organizations, offering solutions for achieving various organizational and managerial objectives. Our

[1] Javidan, A & Za, S. (2023). A bibliometric analysis of Artificial Intelligence and decision-making. 5th International Conference on Decision Economics, https://www.decision-economics.net. Portugal.

findings indicate that the body of literature related to AI has experienced significant growth over the past five decades. This upward trend in publications reflects the increasing importance of AI in enhancing decision-making. For example, organizational data analysis during the adoption and implementation of these systems may help explain this notable rise in publications. Furthermore, our study reveals that the impacts of AI on decision-making processes can be categorized into controlling factors (deep learning, sentiment analysis), facilitating factors (big data, forecasting), and supporting factors (trust and predictive orientation). In addition, AI is not only essential for improving efficiency and effectiveness from an organizational perspective, but it also offers precise diagnostic tools and faster data analysis in medical care. From an educational standpoint, AI is considered an important tool that supports students by enabling more accurate learning, reducing workload, and enhancing their skills. In summary, this study aims to provide a comprehensive picture of the diffusion and development of AI and its effects on decision-making processes. Our research contributes to enriching the existing literature and encourages further investigations into the various dimensions of the relationship between AI and decision-making. It also highlights the need for future studies in areas such as the impact of these technologies on human resource management and the examination of organizational strategies. This work has been published in Impresa Progetto – Electronic Journal of Management (IPEJM)[2]**.**

[2] Javidan, A., Smacchia, M., Cipriano, M., & Za, S. (2024). A bibliometric analysis of Artificial Intelligence and decision-making. *Impresa Progetto. Electronic Journal of Management*, *2*, 1-26.

Chapter II: Artificial Intelligence and Decision-Making Process: Meta-synthesis Literature

Building on the findings of the initial research on AI and the decision-making process, the second chapter focuses on the discourse surrounding both the negative and positive factors of AI in decision-making. Decision-making is one of the most important challenges in various fields, including finance and technology. Therefore, identifying these challenges, whether positive or negative, has become increasingly important. On the other hand, AI systems have been widely used in organizational decision-making over the years, leading to improvements in organizational decision quality, accuracy, and efficiency. Thus, the greater the collaboration between humans and AI, the more organizational decision-making can be improved. Despite extensive studies in this area, there are still conflicting results regarding the relationship between the decision-making process and AI. On the one hand, the adoption of AI can lead to more accurate and faster decision-making; however, fundamental challenges in accepting AI may negatively affect decisions. For example, ethical concerns (such as security and privacy issues, transparency, lack of accountability and responsibility in AI systems, and trust deficits) have become major challenges in AI-based decision-making in organizational financial reporting. In addition, other challenges—such as job security risks, lack of trust in AI, and the loss of control and power—may also have adverse effects on organizational decision-making. Given the contradictory findings of previous studies on the relationship between AI and the decision-making process—findings that organizations, managers, and employees are not yet familiar with these new technologies- we decided to conduct a study to identify and explain these related factors. In this study, we collected our extracted data using the search engines Scopus, Google Scholar, and Web of Science, focusing on past articles from 1987 to 2025 and relying on the AJG list. After data extraction, we used the Critical Appraisal Skills Programme (CASP, 2018; Yan et al., 2024) to assess the quality of the articles. Finally, after removing irrelevant articles due to mismatched abstracts, titles, content, or research methods, 15 articles were selected for review. The extracted data were thoroughly analyzed using MAXQDA software to derive codes and categorize them into subcategories. The findings of this study indicate that the relationship between AI and the decision-making process requires consideration of multiple factors that previous studies have addressed only partially. However, through our meta-synthesis approach, we identified several additional important factors that influence the decision-making process, including the enhancement of skills and capabilities, the decision scope, challenges driven by AI, and the improvement of organizational performance.

Given the increasing use of AI in organizations, the results of this study can be particularly valuable for decision-makers, especially managers seeking to use AI to improve their decision-making. AI can provide managers with solutions that enable faster and more accurate decisions. Moreover, researchers can gain a deeper understanding of the important factors affecting the decision-making process. An initial version of this study was presented at the Conference of the Italian Chapter of AIS (Association for Information Systems)[3]. Subsequently, an extended version—incorporating received feedback—was developed and published as a book chapter in *Navigating Digital Transformation*[4]. It is currently under review at *Information Systems Frontiers*.

Chapter III: Exploring the forms of Human and AI collaboration in organizations

The third chapter focuses on conceptual research, building the fourth form of human-AI collaboration. As the modern world moves toward transformation and advancement in digitalization and robotics, AI systems have become one of the key factors in collaborating with humans in the workplace. These systems have expanded due to their capabilities in more accurate analysis and prediction, increased efficiency, and improved decision-making in work environments. In this study, we examined the relationship and collaboration between humans and AI, regardless of the type of technological system used. Our goal was to create a matrix for evaluating the overall relationship and collaboration between humans and AI. In this regard, based on Murray's study (2021), collaboration between humans and technology is classified into four types of conjoined agency. Each type represents a different combination of human-technology collaboration, depending on who is involved in "protocol development" and "action selection." Moreover, each combination requires a specific set of technological functions. In this context, conjoined agency refers to the shared capacity and ability of humans and non-humans (technology) to perform tasks more effectively to achieve specific organizational goals. Therefore, a conceptual model was developed focusing on collaboration between humans and AI. We distinguish between decision-making processes and execution processes. After reviewing the initial framework, we selected studies that examined human-AI collaboration and based on the analyzed literature—which was reviewed multiple times—we developed the final model. The final model identifies four modes of

[3] Javidan, A., Za, S. (2023). AI and Decision-Making Process: A Meta-synthesis of the Literature. 20th conference of the Italian Chapter of AIS (Association for Information Systems – www.aisnet.org

[4] Javidan, A., Za, S. (2024). AI and Decision-Making Process: A Meta-synthesis of the Literature. In: Agrifoglio, R., Lazazzara, A., Za, S. (eds) Navigating Digital Transformation. Lecture Notes in Information Systems and Organisation, vol 73. Springer, Cham. https://doi.org/10.1007/978-3-031-76970-2_16

collaboration between AI and humans, depending on who is responsible for decision-making and who executes the tasks. The first mode, called legacy mode, states that organizations rely less on AI and managers traditionally use their own experience and expertise to make decisions and perform tasks. In contrast, compliance mode indicates that organizations heavily rely on AI to make decisions and ensure accountability in decision-making. In the third mode, augmentation mode, organizations gradually anticipate and define operational changes, while AI acts as the agent responsible for executing the tasks. Finally, in autonomous mode, AI takes full responsibility for both decision-making and task execution due to features such as unlimited computational power and access to big data. The practical implications of this study relate to the field of business process management in organizations. Managers need to identify business processes along with the appropriate actions required for each process to design the best approach for human-AI collaboration. One way to improve collaboration is to understand the role of AI in each business process. Furthermore, from a strategic perspective, managers must carefully evaluate the opportunities and challenges associated with each AI process mode to choose the most suitable form of collaboration. If managers are not confident about which type of collaboration to adopt for their organization, they can rely on legacy or augmentation modes and gradually move toward mechanizing operations—namely, automated or compliance modes—to develop long-term organizational visions. This study was presented at the Conference of the Italian Chapter of AIS (Association for Information Systems) and published in AIS Electronic Library (AISeL)[5].

Chapter IV: Understanding factors influencing employee collaboration with AI in a work-related context

The fourth chapter marks the second part of the research project, which focuses on empirical research. AI has increasingly taken on a significant and essential role in organizations by enhancing interaction and collaboration with humans. One of the key factors shaping acceptance and collaboration with AI systems is the central role of trust in these technologies. The more employees trust AI, the more positive their attitudes and engagement with AI-based work environments will be. On one hand, when AI systems exhibit human-like characteristics, delegate tasks to AI, and trust these systems increases. Therefore, in this study, we examine two forms of trust—human-like trust and system-like trust—in relation to the delegation of authority to AI and, subsequently, collaboration

[5] Javidan, A., Za, S. (2024). "Exploring the forms of Human and AI collaboration in organizations". ITAIS 2024 Proceedings. 4. https://aisel.aisnet.org/itais2024/4

with it. Human-like trust includes attributes such as benevolence, competence, and integrity, while system-like trust incorporates characteristics such as functionality, helpfulness, and reliability. Both forms of trust can play an important role in shaping employees' willingness to delegate tasks to AI and ultimately collaborate with it. On the other hand, additional mechanisms can influence this collaboration, one of which is the delegation of tasks to AI, referring to the transfer of responsibility or decision-making authority from individuals to AI. In this study, we investigate the ambiguous role of delegating authority to AI in shaping perceptions of perceived usefulness (PU), perceived ease of use (PEOU), satisfaction, and collaboration. To address these gaps, this study develops and empirically tests a research model that integrates trust beliefs (human-like and system-like trust), AI delegation, PEOU, PU, satisfaction, and employee-AI collaboration. By analyzing 150 questionnaires from employees in French, Italian, UK, and US companies using PLS software. We examine how different types of trust influence the decision to delegate tasks to AI and how such delegation, in turn, shapes key technology perceptions and collaboration between employees and AI. Our findings indicate that both human-like and system-like trust significantly influence AI delegation. Delegating authority to AI enhances perceived usefulness, perceived ease of use, and satisfaction. PU and satisfaction emerge as strong predictors of employee-AI collaboration, underscoring their importance for the successful integration of AI in organizational settings. PEOU, however, does not have an impact on employee-AI collaboration. This study provides valuable insights for employees working in organizations in France, Italy, the United Kingdom, and the United States. To further encourage employee collaboration with AI, organizations must continuously foster positive attitudes toward AI systems, as more favorable employee perceptions lead to higher satisfaction and perceived usefulness. As a result, organizations offering better support can enhance satisfaction and improve interaction between humans and AI. An initial version of this study was presented at the European Conference on Information Systems (ECIS). Subsequently, an extended version – incorporating received feedback – will be published in the top ISI journal.

A timeline of the research project, along with a brief overview of each chapter's contribution to the overall study, is shown in Table 1 and Figure 1.

Table 1. Summary of the development

Period of the research project	Chapter	Paper	Type of study	Outcome
2023	I	• Javidan, A & Za, S. (2023). A bibliometric analysis of Artificial Intelligence and decision-making. 5th International Conference on Decision Economics, https://www.decision-economics.net. Portugal. • Javidan, A., Smacchia, M., Cipriano, M., & Za, S. (2024). A bibliometric analysis of Artificial Intelligence and decision-making. *Impresa Progetto. Electronic Journal of Management*, *2*, 1-26.	Bibliometric analysis	DECON 2023 Electronic Journal of Management (2024)
2023/2024	II	• Javidan, A., Za, S. (2023). AI and Decision-Making Process: A Meta-synthesis of the Literature. 20th conference of the Italian Chapter of AIS (Association for Information Systems – www.aisnet.org • Javidan, A., Za, S. (2024). AI and Decision-Making Process: A Meta-synthesis of the Literature. In: Agrifoglio, R., Lazazzara, A., Za, S. (eds) Navigating Digital Transformation. Lecture Notes in Information Systems and Organisation, vol 73. Springer, Cham. https://doi.org/10.1007/978-3-031-76970-2_16	Meta-synthesis	ItAIS 2023 Springer (Book Chapter) Under review (Information System Frontiers)
2024	III	• Javidan, A., Za, S. (2024). "Exploring the forms of Human and AI collaboration in organizations". ITAIS 2024 Proceedings. 4. https://aisel.aisnet.org/itais2024/4	Conjoined agency framework (Literature review)	ItAIS 2024
2025	IV	• Javidan, A., Pallud, j., Za, S. (2025). "Understanding factors influencing employee collaboration with AI in a work-related context" .https://ecis2026.it/call-for-submissions/	Empirical study	Under review (2025)

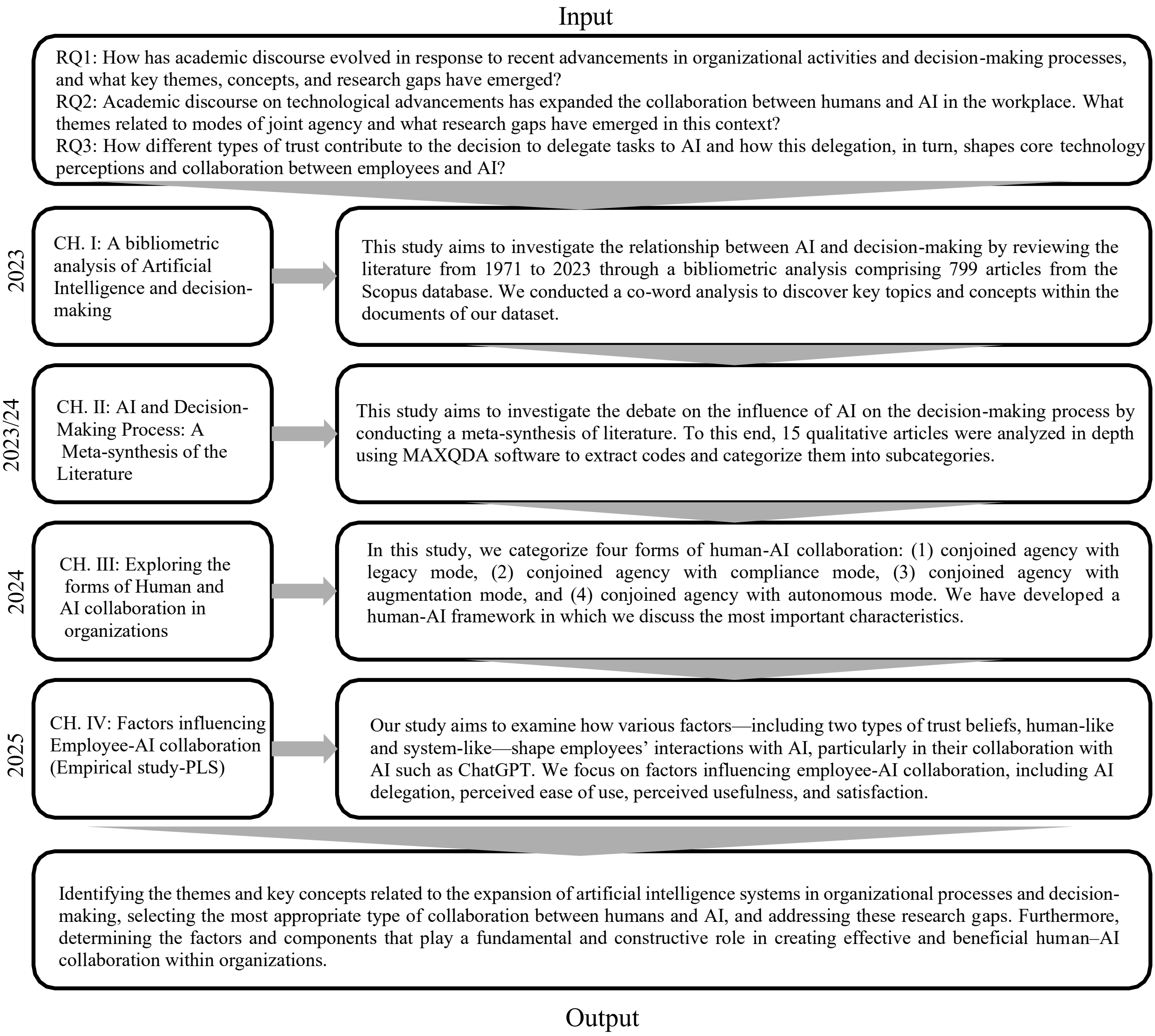

Figure 1. Research project overview

CHAPTER I

A Bibliometric Analysis of Artificial Intelligence and Decision-making

Abstract. Recent advancements in technological development are increasingly generating changes in organizational activities, as well as the decision-making processes. The employment of AI is significantly reshaping decision-making by providing advanced data analytics, predictive modeling, and real-time insights, highlighting its crucial role in organizational strategies. The present study aims to investigate the relationship between AI and decision-making by reviewing the literature from 1971 to 2023 through a bibliometric analysis comprising 799 articles from the Scopus database. We conducted a co-word analysis to discover key topics and concepts within the documents of our dataset. The results show an increasing interest in scientific literature exploring the role of AI in decision-making, highlighting its significance in healthcare, HR management, and education, among other fields. Beyond the comprehensive overview outlining the most significant topics of such a discourse, this work provides the groundwork for scholars and practitioners to further explore this field.

Keywords: Artificial intelligence, Decision-making, Bibliometric analysis

Introduction

Artificial intelligence (AI) is one of the branches of computer science that is receiving increasing attention among academics and practitioners. In recent years, several studies have also considered this technology a possible cornerstone for decision-making in various domains such as finance (Baporikar, 2014), culture (Glazer & Karpati, 2018; Sofo et al., 2013), and society management (Atrill & McLaney, 2020). Some scholars have attempted to recognize the potential effects of its use in firms, such as improving the workforce, reducing costs (Duan et al., 2019), increasing human interactions (Makarius et al., 2020), or creating favorable employment opportunities (Porter & Heppelmann, 2015). Other studies focused on the use and implementation of AI-based technologies explore its subfields, such as machine learning (Jahan & Tripathi, 2021), natural language processing (Tangiuchi et al., 2019), computer vision (Elgendy & Elragal, 2014; Ikeuchi, 2014), and data learning (Howard, 2013). Moreover, given its computational capacity and the increasing availability of data and information, it is not surprising that AI can improve the skills and capabilities of decision-makers (Lawrence, 1991). Accordingly, several scholars acknowledge AI as a communicative, informative, and decision-enhancing tool for managers and employees (Caputo et al., 2019; Dwivedi et al., 2021). For example, some research shows that using AI in the decision-making process in organizations can lead to accuracy, timeliness, efficiency (Ali et al., 2023), and improvement in accountability (Lehner et al., 2022). Furthermore, the greater the transparency and understanding of AI-based decision-making, the better the decision-makers will gain an understanding of AI, which will lead to improved decision-making effectiveness (Chernov et al., 2020). However, besides the benefits that this technology could generate, there is also scientific evidence showing an opposing view about AI in the decision-making process. In particular, other studies discuss concerns about the potential risks of using AI, including job losses and data breaches on an organizational and personal level (Çalışkan et al., 2017). Furthermore, from a decision-making perspective, AI does not always ensure outcomes aligned with ethical principles, such as objectivity (Trunk et al., 2020), privacy (Sahoh & Choksuriwong, 2023), transparency (Rajagopal et al., 2022), and accountability (Janssen et al., 2020). So, the lack of compliance with ethical principles could make employees reluctant to adopt this technology.

From this perspective, the literature on AI applications in decision-making is expanding. However, to the best of our knowledge, existing studies typically consider specific aspects or discussions of sub-categories (of such a scientific discourse). This may not provide a comprehensive overview that delivers a holistic perspective of the current discourse. So, this paper aims to contribute to research by proposing a comprehensive bibliometric analysis that systematically maps trends, key themes, and influential authors in such a domain. Then, by using a bibliometric approach to investigate the adoption and implications of AI inside the realm of decision-making, we seek to answer the following research questions:

What is the evolution of the discussion concerning AI and decision-making? And what are the most relevant trends in this field?

In doing so, we carried out a bibliometric analysis that could offer several benefits, such as improving the scientific groundwork (Fabregat-Aibar et al., 2019) and increasing the systematicity and quality of research (Van Raan, 1999). As a way of explanation, we adopt the bibliometric approach based on performance analysis evaluation (Aria et al., 2020) to explore and describe the documents composing our dataset, examining the role of authors, sources, and scientific collaboration. Afterward, we adopt the bibliometric approach based on science mapping investigations (Cobo et al., 2011) to analyze specific thematic structures and research areas from conceptual and social perspectives (given the documents in our dataset).

This work contributes to the literature by proposing a comprehensive review of the discussions concerning the applications and the role of AI in the decision-making process (Fabregat-Aibar et al., 2019), providing an understanding of top-ranking authors, journals, and countries, as well as providing insights into the most trending topics in the field. The paper is structured as follows: the second section reviews the pertinent literature, the third section explains the research methodology for the bibliometric analyses, the fourth section presents the results, and the conclusions close the study.

Theoretical Background: AI literature review

Exploring the literature, it appears that AI plays a crucial role in contemporary organizations, especially concerning their decision-making processes, by providing advanced tools for data analysis, predictive insights, and effective problem-solving, thereby revolutionizing organizational strategies (Davenport & Ronanki, 2018). The use of AI in the decision-making process has increased dramatically since the introduction of decision support systems (DSS), computer tools, and programs designed to help decision makers (Mintzberg, 1975). Interestingly, the implementation and impact of AI-based systems on the decision-making process have been studied in the literature (over time) in various fields.

Considering that decision-making has always been one of the central processes of our lives, in the organizational realm, the implementation and adoption of AI could significantly affect day-to-day activities and related decisions, impacting different areas or business units, as well as the efficacy of the entire organization. For example, managers who usually make decisions under high-risk contexts/situations should carefully understand DSS to make more effective and accurate decisions. Similarly, Intelligent Decision (ID) emerges as another way of automating decision-making that has attracted the attention of scholars. ID tools are usually based on predefined databases and don't require human intervention, enabling managers to make decisions independently (Chen et al., 2017), given the increasing availability and capacity to process information and data (Fogel et al., 1965). Besides, from the perspective of group decision-making, decisions in uncertain situations usually require the motivations and interests of a collaborative team of experts to find a common solution among the team. In this regard, the use and adoption of AI could help decision-making groups effectively manage complex situations to reach a consensual agreement (Cabrerizo et al., 2014; Heradio et al., 2020). Some examples are offered by research on green economy discussions (Govindan & Sivakumar, 2015), construction project management (He et al., 2019), and animal behavior management (Lu et al., 2008).

Further studies note that group decision-making using AI technology is one of the most important ways to facilitate decision-making in a digitalized industrial age (Yang et al., 2023). Furthermore, researchers from human resources (HR) and education domains show that AI in human resource management represents a dynamic and promising field with a growing future perspective in areas such as training, learning, and predictive analytics (Palos-Sanchez et al., 2022). In HR departments, the application of AI is still an evolving revolution (Bolton, 2018) that requires further action to achieve improvements and effective implementation (Vrontis et al., 2021). In comparison, Pan et al. (2021) noted that managers and researchers should deepen their understanding of how to apply AI in human resources and related decision-making practices by examining the scientific developments conducted in various departments, such as education or healthcare. The unprecedented growth of AI in higher education appears to reduce faculty workload and prioritize high-quality work for teachers (Akgun & Greenhow, 2021). AI algorithms such as chatbots and precision education (PE) can assist teachers with registration processes and identifying students at high risk for weaknesses (Greenhow et al., 2020; Luan et al., 2020).

Similarly, AI is becoming increasingly important in health care to improve the prediction and diagnosis of diseases and help medical staff make more informed decisions. Guo et al. (2020) call for further examination of how researchers, practitioners, and decision-makers could progress knowledge to better implement AI technologies for decision-making in medical care. Enriching such a scientific discussion might support practitioners and physicians who could benefit from harnessing AI in healthcare systems to make better decisions in medical prediction, detection, and treatment of patients (Mesko et al., 2018; Sandstedt et al., 2019).

In addition, although most studies in this field have addressed the positive outcomes of AI applications in decision-making processes, some studies have focused on “negative” consequences and drawbacks of incorporating AI into decision-making processes. In particular, concerns are discussed with regard to the potential risks associated with using sophisticated and integrated AI applications at technical and personal levels, such as privacy breaches and job losses (Caliskan et al., 2017). Moreover, concerning AI, research on the ethical challenges and risks associated with potential discrimination against people with disabilities suggests extending an understanding of strategy development that ensures the equitable expansion of AI (Tilmes, 2022). Other researchers are also concerned about how, using AI, the imbalance between accuracy and interpretability can negatively impact an organization’s performance and perspective. This imbalance could potentially erode trust between managers and decision-makers (Sahoh & Choksuriwong, 2023). For instance, in the context of AI's impact on gender inequality in the workplace, studies have shown that the absence of gender equality across various sectors, including healthcare, has diminished the efficacy of AI, concurrently exacerbating gender biases within AI systems (Young et al., 2023).

Interestingly, it has been observed that a reduction in transparency in decision-making tasks based on AI leads to a reduction in trust among employees and teamwork, which challenges the effectiveness of AI. Then, to achieve high effectiveness, organizations need to motivate and empower employees to use AI in order to improve performance and accuracy (Yu & Li, 2022). For example, identifying vulnerable individuals, such as long-term unemployed foreigners, using both traditional methods and novel AI models often brings organizations toward a form of statistical discrimination. From this perspective, setting preconditions within predictive models could hinder their ability to classify individuals accurately. Specifically, as the precision in identifying unemployed individuals improves, the risk of discrimination escalates (Desiere & Struyven, 2020). Thus, organizations should carefully address the potential implications dependent on the accuracy of novel AI models, which could have significant impacts in terms of social justice.

Aimed to support our assumptions, to conclude this section, we propose a comparative overview of some previous bibliometric analyses examining AI and decision-making in Table n. 1.

Table 1. "Bibliometrics Reviews" on AI and decision-making comparison

Authors	Journal	Tools	Scope
Heradio et al. (2020)	Mathematics	Bibliometrics	**Group decision-making**
Maphosa & Maphosa, (2022)	Theoretical & Applied Info Technology	Bibliometrics & VOS viewer	**Project Management**
Palos-Sa´nchez et al. (2022)	Applied AI	Bibliometrics	**Human resources management**
Li et al. (2022)	Cognitive Computation	VOS viewer, CiteSpace, Bibexcel & GPS visualizer	**Intelligent decision (ID)**
Yang et al. (2023)	Systems	GDM method & Bibliometrics	**Group Decision-Making in the Shipping Industry 4.0**
Kaushal et al. (2021)	Management Review Quarterly	Bibliometrics & Systematic Literature Review	**Human resource management**
Maphosa & Maphosa, (2023)	Applied AI	Bibliometrics, PRISMA, VOS viewer	**Higher education (HE)**
Jimma, (2023)	Telematics and Informatics Reports	Bibliometrics	**Health care**

Source: Authors' own elaboration

Although the literature offers several reviews, as shown in Table 1, we argue that most of the existing reviews focus mainly on specific topics. From this perspective, we believe that a bibliometric study, as comprehensive research, could better map such a domain, considering the interdisciplinary nature of decision-making and the different implications it could generate in organizations and society. To this end, in the following sections, we explore the discussions on AI in decision-making by examining the main topics, fields, and challenges emerging across multiple sectors.

Method

Among various statistical methods, bibliometric analysis is a quantitative technique useful for systematically analyzing scientific publications and evaluating the long-term development of a particular field of study (Cobo et al., 2018; Za & Spagnoletti, 2013). Scholars have extensively used this technique as a tool to examine the theoretical history of specific literature (Ellegaard & Wallin, 2015) and to better understand the related research groundwork (Van Raan, 1999). Bibliometric techniques consist of two main approaches to analysis. A descriptive approach based on performance explorations focuses on bibliometric data of the documents in a dataset, such as the authors, countries, and sources of publications (Aria et al., 2020). In comparison, a further approach is based on science mapping investigations, which support researchers in better comprehending and evaluating thematic densities and patterns concerning a particular topic (Cobo et al., 2011).

Inclusion criteria

To conduct a bibliometric analysis of the literature, we first focused on the study area to develop our research questions. Then, we identified the parameters for conducting the query search. In particular, we adopted the Academic Journal Guide released by the Association of Business Schools (ABS) to select suitable journals for our analysis. This guide is based on reputable and high-quality sources in various research areas, providing a rank according to several parameters, including the impact and credibility of research. Moreover, we used the Scopus database (as the data source) to collect articles published in scientific journals exclusively. Specifically, we performed a query restricting the search to the ISSN codes of journals ranked in the AJG and the keywords "artificial intelligence" and related technologies in "decision-making" (see Table n. 2).

Table 2. Search query terms

Construct	Search by terms
AI-related terms	("artificial intelligence") OR ("machine learning") OR ("deep learning") OR ("artificial neural network") OR ("big data") OR ("natural language processing") OR ("internet of things") OR ("data mining").
Decision-making related terms	(decision-making) OR ("decision support system").
Document types	Articles (we restricted the search by selecting all the ISSNs of the Journal in the AJG)
Language	English
Period	1971-2023 (automatically established by the query search)

Source: Authors' own elaboration

Exclusion criteria

Furthermore, we also applied some exclusion criteria. In this study, we do not consider the Indexed Keywords (i.e., keywords automatically generated by Scopus) when performing the search, because oftentimes they could generate excessive noise during the data analysis. As a way of explanation, we ensured to run our search considering the title, abstract, and authors' keywords exclusively. Accordingly, we decided to perform a co-word analysis based only on the author's keywords. We then examined the retrieved collection, searching for articles discussing unrelated subjects (eventually excluding such articles) to ensure the accuracy of the data. We applied no further restrictions, retrieving information from 896 articles in CSV format. The next phase involved data processing and dataset refinement. We ensured the compatibility of all articles with the selected topic of analysis. At the same time, we excluded all the articles with inaccurate or incomplete information (*e.g.,* no author, erratum, or withdrawal). After completing this process, we obtained a dataset composed of 799 articles. Lastly, the keywords were homogenized by all the authors who cross-checked and reviewed this process. Specifically, each keyword that referred to the same topic was associated with a unique keyword label (*e.g.*, artificial intelligence, AI, artificial intelligence (AI) = artificial intelligence). Afterward, we added the authors' keywords to the articles missing this information after carefully analyzing their titles and abstracts. Ultimately, we performed descriptive and science mapping analyses to examine the conceptual structure and the most important themes.

Visualization

We employed the software Bibliometrix (an R package) and the Biblioshiny IDE (Aria & Cuccurullo, 2017) for the analysis. This open-source tool helps analyze bibliometric data from various databases (e.g., Scopus, Web of Science, PubMed), supporting the development of various bibliometric analyses (Aria & Cuccurullo, 2017).

Figure n. 1 provides a graphical representation summarizing the research protocol we adapted from Za & Braccini (2017). In particular, such a research protocol is composed of three steps. The first step concerns a preliminary manual review of the available literature, the data collection process using the Scopus database – given its suitability relating to research in the field of social sciences (Rahal & Zainuba, 2019)–, and the setting of the query search. In doing so, during the multiple reviews of the articles, we crafted our research questions and developed a comprehension of the papers strictly related to our research boundaries. In the second step, we identified the inclusion and exclusion criteria for performing the dataset refinement. In addition, we also focused on keyword cross-checking and removed non-pertinent articles as well as those with missing data. Lastly, the Bibliometrix tool (Aria & Cuccurullo, 2017) was utilized for data analysis in the third step. We first developed the performance analysis (Aria et al., 2020) to describe our dataset and provide insights concerning the most relevant statistics on authors, sources, countries, and trends in cited papers. Afterward, to gain a deeper understanding of the research topic, we thoroughly analyzed the most used authors' keywords and examined their relations (Cobo et al., 2011).

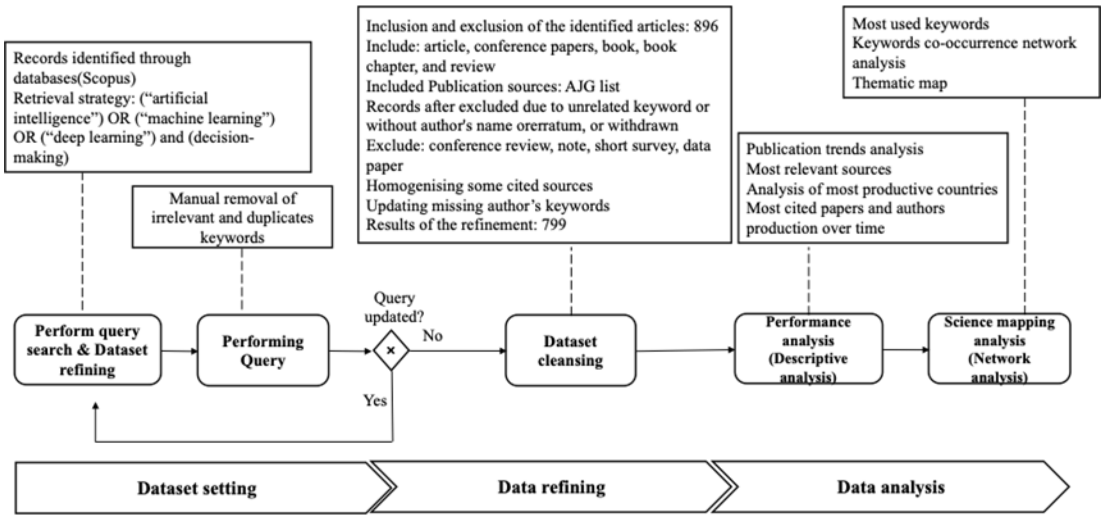

Figure1. Research protocol

Source: Authors owns elaboration

Results

This section presents the results of the bibliometric analyses. We first focus on the publication's trends, relevant sources, geographical distribution of publications, and most cited articles. Afterward, we present the results of the analysis of the authors' keywords, examining the most important themes and the related evolution of the discourse.

Publication growth rate

Figure n. 2 shows the trend of annual scientific publications from 1971 to 2023, based on the final dataset of 799 articles distributed across 309 sources. From 1971 until 2008, the number of publications was consistently very low or non-existent, with slight peaks in 1992 and 2006. However, since 2009, the number of publications has increased due to significant advances in the development of AI techniques. In particular, between 2019 and 2022, publications concerning AI in decision-making processes have increased significantly.

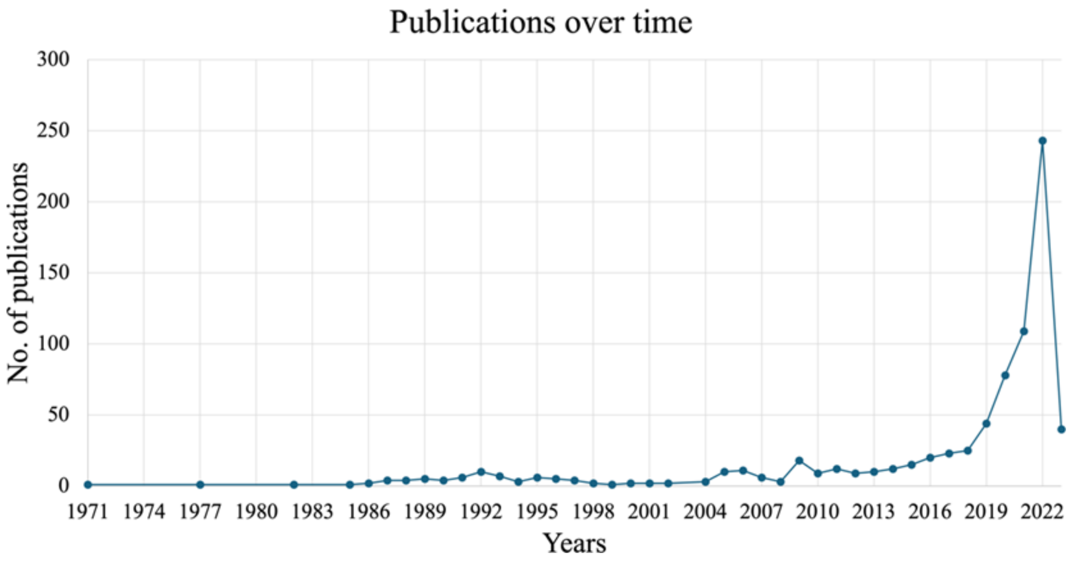

Figure 2. Annual scientific production of AI in decision-making since 1971

In this context, perhaps, it is possible that the increase in data volume, combined with the potential effects and impact of COVID-19 on the economy and society, has led to a rise in contributions highlighting increased applications of AI in decision-making. This is particularly evident in the healthcare sector, where AI is increasingly being used to manage the coronavirus crisis and assist in diagnosis (Adadi et al., 2022). As a matter of fact, in 2022, the number of articles published reached its highest peak, with 243 articles. In 2023, the number of articles is lower than in previous years, not representing the trend completely, as the data collection was performed in early June 2023.

Source of publications

After a detailed analysis of the refined dataset, it was found that the use of AI in decision-making represents multidisciplinary discussions examining technological, economic, social, and ethical issues. Focusing on the sources of publications, 33 articles were published in the *International Journal of Production Research* and 32 in the *Annals of Operations Research* journal. In addition, several other journals emerge among the top 16 sources with the highest publication rate. Table n. 3 lists such journals, providing their name, the number of publications, and the related AJF subject area. From this analysis, it is possible to note that 15 sources cover 33% of the dataset and are related to different AJG fields, emphasizing the multidisciplinary nature of such a discourse. Then, Table n. 3 shows that *Operations and Technology Management* (OPS&TECH), *Information Management* (INFO MAN), and *Operations Research and Management Science* (OR&MANSCI) are the fields in which researchers are most active, with 84, 76, and 67 publications, respectively. *Social Sciences* (SOC SCI) and *Economics, Econometrics, and Statistics* (ECON) follow with 15 and 12 publications, respectively.

Table 3. Publications distributed by the top 15 sources

Sources	Articles	AJG fields
International Journal of Production Research	33	OPS&TECH
Annals of Operations Research	32	OR&MANSCI
Expert Systems	27	INFO MAN
IEEE Transactions on Engineering Management	17	OPS&TECH
Cybernetics And Systems	15	OR&MANSCI
Journal of Decision Systems	15	INFO MAN
Journal of Environmental Management	15	SOC SCI
Decision Sciences	13	INFO MAN
Computational Economics	12	ECON
Journal of Intelligent Manufacturing	12	OPS&TECH
Benchmarking	11	OPS&TECH
Int. Journal of Computer Integrated Manufacturing	11	OPS&TECH
International Journal of Human-Computer Studies	11	INFO MAN
Ethics And Information Technology	10	INFO MAN
IEEE Transactions on Cybernetics	10	OR&MANSCI

Publications by country

Focusing on the affiliation of the authors in our dataset, we were able to preliminarily explore the extent of collaborations of the publications in terms of the country of the authors and gain insights about the most active countries in the discourse on AI and decision-making. Figure n. 3 provides an overview of the most productive countries, distinguishing single-country publications (SCP – all the authors are affiliated with the same country) and multi-country publications (MCP– at least one author is affiliated with a different country than the corresponding one). The United States of America leads with 135 articles, including 113 SCPs and 22 MCPs. China ranks second with 80 articles (56 SCPs and 24 MCPs). India is also notably active, with 48 articles (38 SCPs and 10 MCPs). The United Kingdom demonstrates solid international collaboration, producing 36 articles, with half (18) being multi-country publications (MCPs). Additionally, countries such as Iran, Germany, Australia, Canada, Korea, and Spain contribute to a lesser extent.

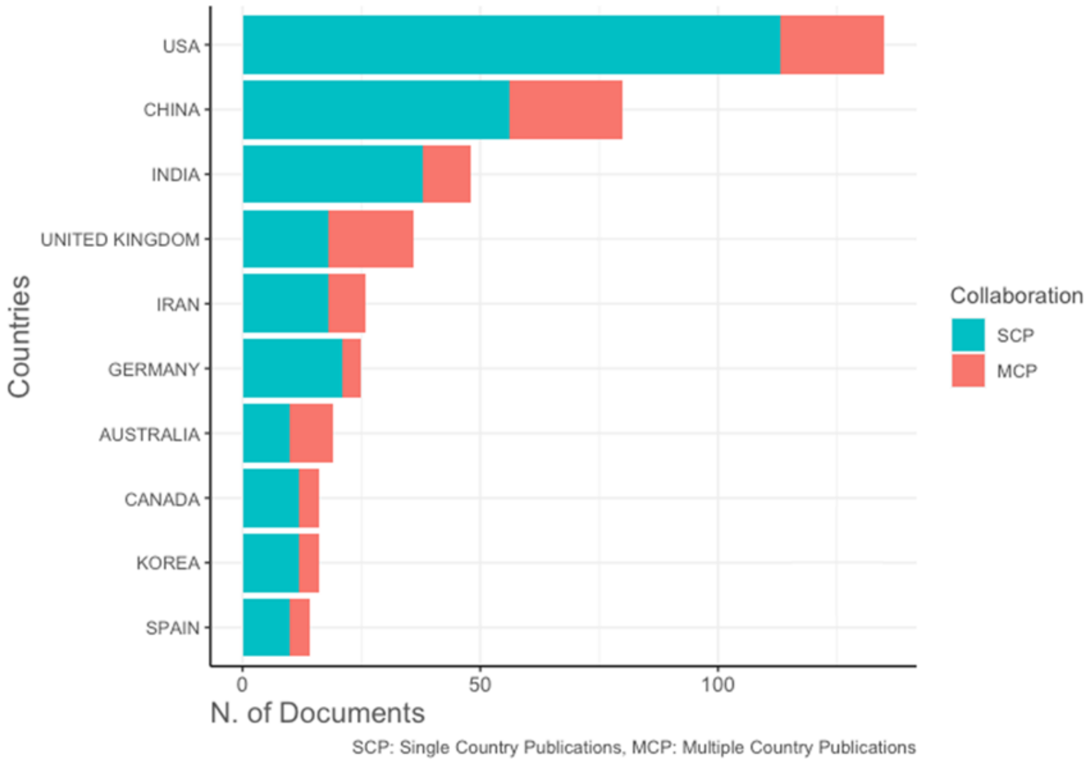

Figure 3. Most productive countries

Author productions

Figure n. 4 presents the most productive authors over time. In the graph, the dot size represents the total number of publications, while the color intensity shows the total number of citations per year for each author. The most productive author, Edward Szczerbicki, published four articles between 1998 and 2016. His research focused on how decision-making processes can be applied to technologies like the Internet of Things and decisional DNA for structural decision-making. Michael I.C. Nwogugu published three papers in 2005. His work is divided into three parts, focusing mainly on multifactor risk and decision-making models. Between 2010 and 2018, four authors, Ali H. Azadeh, Zhang Haoxi, Heboong Kwon, and Cesar Maldonado Sanin, published three papers. They primarily focused on medical research, the smartphone industry, and data-driven insights to make informed decisions (Azadeh et al., 2018; Kwon et al., 2016; Sanín et al., 2012). Sendhil Mullainathan, Keng Boon Ool, Jinil Persis, and V. Raja Sreedharan conducted similar research in recent years, between 2018 and 2023, analyzing the changes in healthcare operations and financial technology, given the COVID-19 crisis (Devarajan et al., 2023; Yuan et al., 2022). Moreover, Sendhil Mullainathan gathered the most citations (TC = 345) for his co-authored study published in the Quarterly Journal of Economics (Kleinberg et al., 2018).

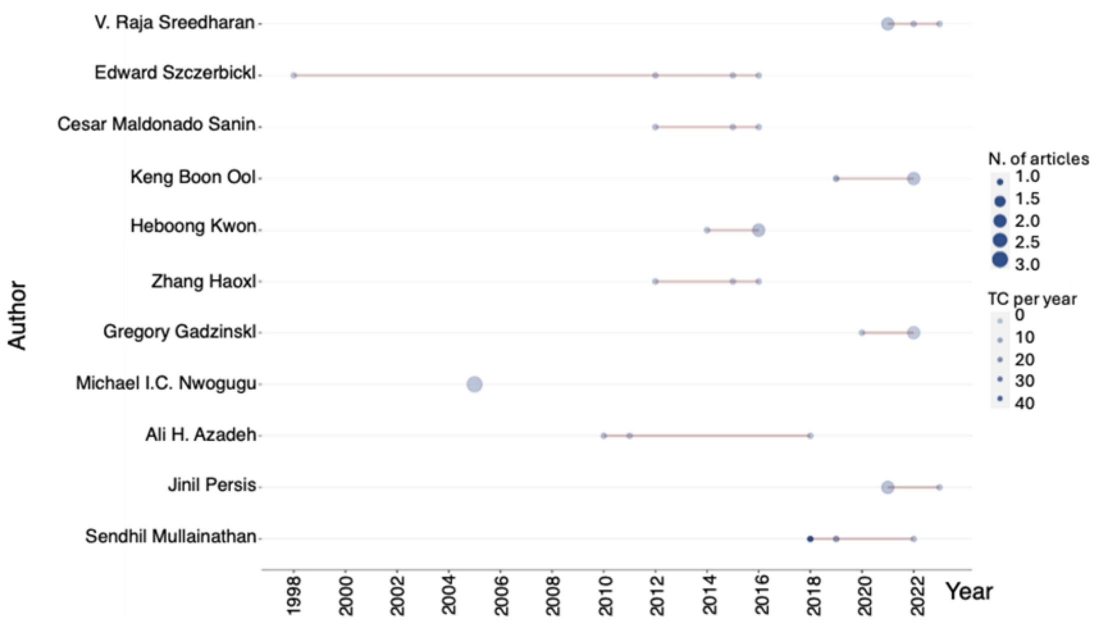

Figure 4. Top authors' production over time for the 11 authors

Document citations

Table 4 presents the top 16 most-cited papers, providing insights into the articles that garnered significant scholarly attention. For each paper, we report the number of total citations (TC), the percentage of total citations per year (TC per year), and the number of normalized total citations (Norm –TC–). The normalized metric offers an unbiased comparison between papers published in different years. That is, it compares the number of article citations with the global average of articles published in the same year.

Then, while Table n. 4 provides information concerning the metrics gathered by all the 16 most cited papers, we briefly describe the first five most cited articles hereafter. As mentioned earlier, we focus on the most productive authors. In addition to Sendhil Mullainathan, the most cited paper (TC = 345) in our dataset (published in The Quarterly Journal of Economics) has been co-authored by four other authors, where Kleinberg J. is the first author. In particular, this article focuses on a use case concerning the application of machine learning algorithms in the law enforcement sector. XU Z. et al. (2009) is the second most cited article (TC = 286). This study improves similarity measures for intuitionistic fuzzy sets, enhancing group decision-making analysis. A similar number of citations (TC = 281) is received by Zeng et al. (2020), emerging as the third most cited article and one of the most recently published. For this reason, it holds the highest value for TC per year. The paper explores the changes brought by COVID-19 in deploying robots inside the tourism sector. Saaty T. L. (2013) is the fourth most cited paper, with a total of 278 citations. This study aims to summarize the application of the Analytic Hierarchy Process (AHP) and its generalization, the Analytic Network Process (ANP), in decision-making. In a different context, the study by Shin D. (2021), with 182 citations, explores the impact of Explainable AI on user trust. The higher TC per year values of the five most cited papers may also indicate a sign of novelty in the topic or a renewed interest in the subject.

Table 4. Most cited papers

Paper	Tot. Cit. (TC)	TC per Year	Norm. TC
Kleinberg, J., Lakkaraju, H., Leskovec, J., Ludwig, J., & Mullainathan, S. (2018). Human decisions and machine predictions. The quarterly journal of economics, 133(1), 237-293.	345	49.29	11.22
Xu, Z., & Yager, R. R. (2009). Intuitionistic and interval- valued intutionistic fuzzy preference relations and their measures of similarity for the evaluation of agreement within a group. Fuzzy Optimization and Decision Making, 8, 123-139.	286	17.88	6.68
Zeng, Z., Chen, P. J., & Lew, A. A. (2020). From high-touch to high-tech: COVID-19 drives robotics adoption. Tourism geographies, 22(3), 724-734	281	56.2	15.46
Saaty, T. L. (2013). The modern science of multicriteria decision making and its practical applications: The AHP/ANP approach. Operations research, 61(5), 1101-1118.	278	23.17	6.71
Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. International journal of human-computer studies, 146, 102551.	182	45.5	15.97
Gosavi, A. (2009). Reinforcement learning: A tutorial survey and recent advances. INFORMS Journal on Computing, 21(2), 178-192.	169	10.56	3.95
Min, H. (2010). Artificial intelligence in supply chain management: theory and applications. International Journal of Logistics: Research and Applications, 13(1), 13-39.	156	10.4	3.87
Athanassopoulos, A. D., & Curram, S. P. (1996). A Comparison of data envelopment analysis and artificial neural networks as tools for assessing the efficiency of decision-making units. Journal of the Operational Research Society, 47(8), 1000-1016.	144	4.97	4.02
Zhou, G., Zhang, C., Li, Z., Ding, K., & Wang, C. (2020). Knowledge-driven digital twin manufacturing cells towards intelligent manufacturing. International Journal of Production Research, 58(4), 1034-1051.	139	27.8	7.65
Shrestha, Y. R., Ben-Menahem, S. M., & Von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. California management review, 61(4), 66-83.	139	23.17	5.02
Hochbaum, D. S., & Levin, A. (2006). Methodologies and algorithms for group-ranking decisions. Management Science, 52(9), 1394-1408.	138	7.26	3.2

Bertsimas, D., & Kallus, N. (2020). From predictive to prescriptive analytics. Management Science, 66(3), 1025-1044.	124	24.8	6.82
Cui, G., Wong, M. L., & Lui, H. K. (2006). Machine learning for direct marketing response models: Bayesian networks with evolutionary programming. Management Science, 52(4), 597-612.	120	6.32	2.78
Sannigrahi, S., Chakraborti, S., Joshi, P. K., Keesstra, S., Sen, S., Paul, S. K., ... & Dang, K. B. (2019). Ecosystem service assessment of a natural reserve region for	106	17.67	3.83
strengthening protection and conservation. Journal of Environmental Management, 244, 208-227.			
Kusiak, A. (2006). Data mining: manufacturing and service applications. International Journal of Production Research, 44(18-19), 4175-4191.	102	5.37	2.37
Rout, J. K., Choo, K. K. R., Dash, A. K., Bakshi, S., Jena, S. K., & Williams, K. L. (2018). A model for sentiment and emotion analysis of unstructured social media text. Electronic Commerce Research, 18, 181-199.	100	14.29	3.25

Keyword analysis

Moving on to the science mapping investigations, we first analysed the 42 most frequently used authors' keywords to identify and determine important topics over the years (here, the interpretative logic is that a keyword represents a topic). Accordingly, in

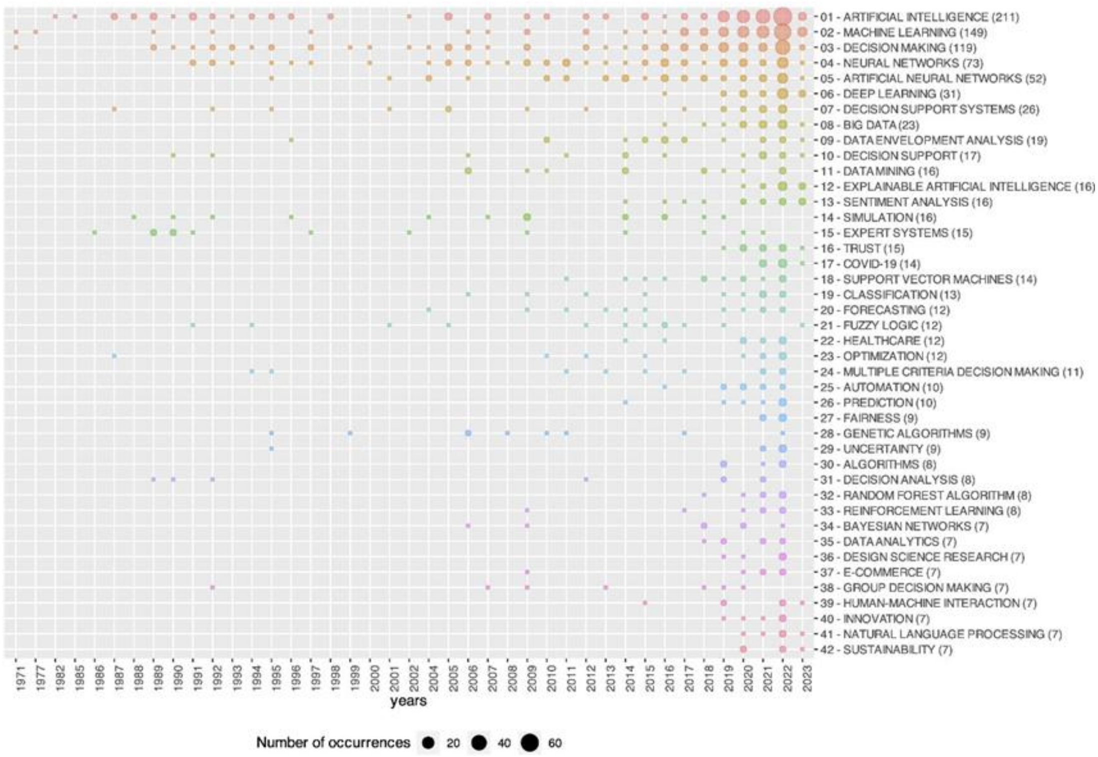

Figure 5. Top 42 used keywords

Figure n. 5, the dot size represents the number of keyword occurrences. Over the time span of the publications, *Artificial Intelligence* is the most used keyword, with 211 occurrences. Moreover, the most recurrent keywords appear to be used consistently throughout the years. The only exception is *deep learning*, which was used for the first time in 2016. Furthermore, keywords such as *explainable AI*, *trust*, *sustainability*, and *fairness* emerge among the most recently used by the authors, seemingly associated with the emerging trend concerning social and ethical aspects in AI over recent years. Concerning the research fields, the relevance of the healthcare and e-commerce sectors also emerges, as noted in the preliminary review of the literature and the descriptive analysis. Moreover, between 2019 and 2021, the use of keywords intensified significantly, considering the increase in the number of published articles in those years.

Thematic map

The thematic map is a further analysis useful to deepen an understanding of the most relevant themes in a discourse based on the most frequently used authors' keywords (intended as themes). In this analysis, emerging clusters of keywords are distributed across a two-dimensional map according to two network parameters: density and centrality (Cobo et al., 2011). Density (strength of internal connection in the clusters), on the vertical axis, reflects the development process of a theme, while centrality (connections between clusters), on the horizontal axis, indicates the overall importance of a theme. Figure n. 6 shows the thematic map, which depicts different themes related to the interconnection between AI and decision-making discussions. The four quadrants of the map include *Motor themes* that are well-developed and central to the topic (high centrality, high density). *Niche themes* refer to topics that are isolated in the network and highly developed inside a single cluster (high density, low centrality). Topics with low centrality and density are classified as emerging or declining themes, characterized by their limited development and impact. Finally, theoretically important but not fully developed themes (high centrality, low density) are represented in the *Basic themes*.

In the thematic map (i.e., Figure n. 6), each quadrant is characterized by its associated clusters and the defining keywords that provide context for each cluster. In this regard, the first quadrant (Motor themes) includes keywords such as *machine learning*, *deep learning*, *decision support*, *big data*, and *COVID-19*. This quadrant describes advanced technologies in organizational decisions that lead to value creation and improved efficiency and organizational performance. For example, Gupta et al. (2020) proposed a framework for technological developments in customer and market data. Specifically, according to their results, identifying changes in consumer behavior and AI developments leads to better decision-making and strategic insights.

Similarly, another study by Zhou et al. (2019) shows that with the development of information technologies, such as big data analytics, the Internet of Things, and AI, today's traditional production moved to intelligent production. However, these technologies require more advanced decision- making, such as learning and cognitive capacities, due to their autonomy in decision- making. Besides, Bertsimas & Kallus (2020) show that the combination of machine learning techniques in management sciences leads to effective and optimal decisions in complex conditions.

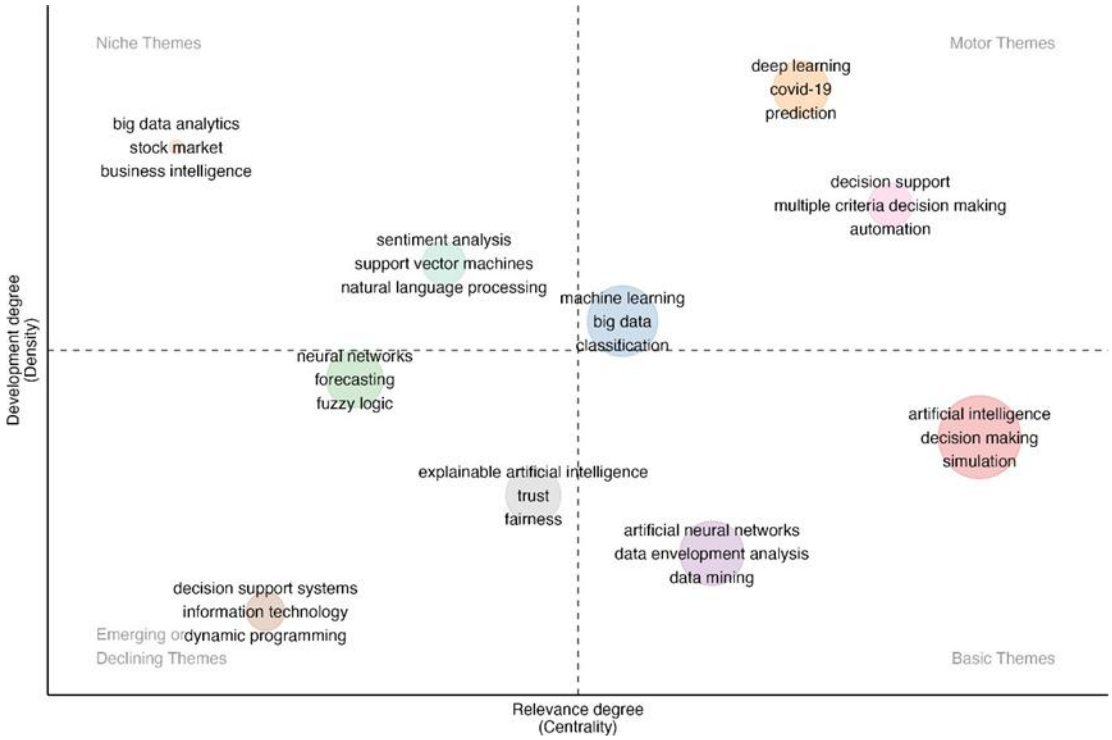

Figure 6. Thematic map

The second quadrant (Niche themes) includes the keywords *big data analytics*, *sentiment analysis*, *business intelligence*, and *natural language processing* (among others). The most representative studies of this quadrant refer to the advancement of AI in decision-support systems. Sentiment analysis, deep learning algorithms, and multi- criteria decision-making techniques emerge as important applications in AI, leaving room for further research, suggesting that such investigations could be useful for supporting managers in the use of such technology in their decision-making processes (Rout et al., 2017; Wang et al., 2022).

The emerging themes quadrant is composed of three clusters represented by keywords such as *neural networks*, *explainable AI*, and *decision support systems*. These clusters examine the impact of modern technologies such as machine learning, chatbots, and analytical software on the decision-making process in various fields and industries. For example, Moriuchi et al. (2020b) state that emerging technologies such as chatbots are being recognized as a solution to attract customers' attention. In the retail environment, these technologies, developed using psychological and motivational theories, lead to a more effective and efficient customer experience and improve organizational performance.

Kleinberg et al. (2017) showed how machine learning improves the quality of decisions made by judges in courts, which has relevant policy implications. Therefore, this technology uses available data to make real-world predictions, although there are challenges, such as the broad decision preferences of judges. In other words, given a coherent economic framework, these predictions can be used effectively to improve court decisions. Furthermore, trading software can improve decision-making processes by helping non-conservative investors make predictions for the stock market and market movements (Braun, 2017).

The basic quadrant is composed of two clusters. These clusters represent central themes in the discussions within this domain, such as artificial intelligence, artificial neural networks, and data mining, and their role in improving decision-making processes and organizational performance. For example, Shrestha et al. (2019) argue that, according to organizational needs, collaboration between AI and humans affects organizational members' decisions. Then, the combination and cooperation of humans and AI could lead to better quality organizational decisions and more accurate interpretation and analysis. For example, Chatterjee et al. (2021) notice that organizations have recently adopted advanced business analytics tools, leading to innovation and competitive advantage in information and communication issues.

Conclusion

This study draws on the assumption that AI can help achieve various economic, social, technological, and societal goals. This technology, which is growing and evolving rapidly, can be used to solve several problems within organizational and management functions. In this paper, we propose a bibliometric study that aims to integrate quantitative and qualitative insights to explore the role of AI in decision-making. Specifically, we reviewed papers published in journals belonging to the AJG list by performing descriptive (performance) and conceptual (science mapping) analyses. In the first part of the paper, we provided an outlook on the publication trend, the most relevant sources, documents, the most productive authors, and the most active countries. In the second part, we analyzed the most relevant themes in the field of AI and decision-making by qualitatively describing the most representative studies contributing to the development of the debate. According to previous works, our results show the remarkable growth of the literature on AI over the last five decades. Specifically, this upward trend in the number of publications on AI and decision-making underscores the increasingly important role of AI in improving decision-making in various sectors and domains. The adoption and implementation of AI applications in organizational processes, such as data analytics, is likely the reason for the significant increase in the growth rate of papers from 2009 onwards. This growth is consistent with the high level of attention from practitioners during these years.

In comparison, among the analyses based on the science mapping approach, reasoning emerging in the thematic map is that studies about the effects of AI on decision-making processes can be divided into 3 categories: studies on controlling factors, studies on facilitating factors, and studies on supporting factors. In particular, it appears that machine learning, deep learning, sentiment analysis, and neural networks represent controlling factors of AI that affect decision-making processes. Big data, prediction, business intelligence, and natural language processing are considered the facilitating factors, while support systems, AI, decision support systems, trust, and prediction direction are considered the decision-support factors for decision-making processes.

Some evidence appears with regard to the discussions about the health sector. From this perspective, we have found that healthcare professionals can provide more effective treatments with this technology because they are aware of newer and more accurate diagnostic methods (Jimma, 2023). From an organizational perspective, collaboration between humans and AI also appears to be central to improving the efficiency and effectiveness of decision-making. In this context, it is also important that HR departments address possible employee resistance to the introduction of this technology to achieve the best possible outcome (Palos-Sa´nchez et al., 2022). Further evidence emerges with regard to the discussions examining how AI has revolutionized the fields of science and education. Among others, several studies discuss the beneficial use of AI to support the human workforce in the education sector, to benefit students in their learning and skills or academics by reducing workload, teaching with high accuracy, and tracking learners' progress (Maphosa & Maphosa, 2023).

To summarize, the development and spread of AI have led many researchers to investigate the relationship between AI and decision-making in various dimensions. Drawing on these studies, we attempted to systematize the dimensions that represent this relationship. Hence, this work contributes to supporting the research community in the field of AI and its applications in organizational decision-making by i.) enriching existing groundwork and, at the same time, ii.) calling for further investigation that concurrently examines positive and negative factors affecting the various dimensions of the relationship between AI and decision-making (and related implications for society). In addition, as this study underlined a significant connection between applications of novel resources and tools in human resource management (HRM), room for further research refers to the impact of AI on decision-making, focusing on exploring strategies, appropriate training, effective mechanisms to utilize this technology and methods to mitigate potential issues that could lead to the emergence of bias in the outcome of AI tools.

Finally, this study has some limitations. First, the data set used in this study is exclusively composed of articles published in scientific journals. Future studies could consider a broader range of documents, including conference proceedings, to examine more recent data and related trends. Moreover, this analysis could be integrated with other techniques (e.g., citation and co-citation analyses) to advance an understanding of the intellectual and social structure of the AI and decision-making discourse.

CHAPTER II

Artificial Intelligence and Decision-Making Process: Meta-synthesis Literature

Abstract. Decision-making is one of the most significant challenges in various fields and has become an interdisciplinary endeavor. Therefore, it is crucial to identify the factors influencing decision-making in decision research. Although artificial intelligence is becoming increasingly important in decision-making, there are contradictory results regarding the relationship between the decision-making process and artificial intelligence. This study aims to investigate the debate on the influence of AI on the decision-making process by conducting a meta-synthesis of literature. To this end, 15 qualitative articles were analyzed in depth using MAXQDA software to extract codes and categorize them into subcategories. The results show that a comprehensive understanding of the relationship between AI and the decision-making process requires consideration of multiple factors and their interplay. Given the increasing use of AI in organizations, the results of this study may be particularly helpful for decision-makers, especially managers who intend to utilize AI to enhance their decision-making.

Keywords: Artificial intelligence, Decision-making process, Machine learning, Deep learning, Meta-synthesis approach

Introduction

Decision-making is one of the most common actions continuously performed by people and organizations in society (Nikoi, E. (ed.), 2013), economic (Ribbens et al., 2013), cultural (Fernandes et al., 2023), financial (Atrill, 2019), and technical (Chien et al., 2020) domains. Over the years, the multiple roles of digital technology and the factors that influence decision-making have been essential parts of decision research (Fernandes et al., 2023b). From the perspective of technologies used in decision-making, artificial intelligence is now widely used in organizational decision-making (Nalini, 2024) and can improve decision-making capabilities (Becker et al., 2022). In recent years, significant attention has been given to social work environments, like team motivation and leader-follower bonds in the workplace. This suggests that AI could play a more augmentative role for human decision makers, as employees demonstrate stronger human connection and identification with managers (Booyse & Scheepers, 2024). According to previous studies, AI has been shown to significantly improve accuracy, efficiency, enhance market competitiveness, and decision-making in organizations (Tuncalp, 2025). Therefore, collaboration between AI and humans in various areas such as leadership, creativity, and analytical skills can lead to greater trust between AI and managers in organizations (Roumbanis, 2025; Booyse & Scheepers, 2024). On the other hand, AI can make faster, more accurate, and more powerful decisions compared to humans due to its powerful and flexible capabilities (Metcalf et al., 2019). In healthcare, for example, the advancement and proliferation of AI technologies, such as machine learning and deep learning, have led to improved patient outcomes (Jillahi & Iorliam, 2024; Ribbens et al., 2013b). Despite the growth of qualitative research in this area, there is still no comprehensive overview of the positive and negative aspects of using AI in decision-making. This study aims to synthesize qualitative evidence to identify key themes and conceptual patterns in this field.

However, fundamental challenges in adopting AI may negatively affect employment. In countries, for example, with weaker economies, organizations face an ethical dilemma between increasing profits through AI and the resulting rise in unemployment and social impact on communities (Davenport & Harris, 2005; Booyse & Scheepers, 2024). Numerous studies have examined the lack of explainability and transparency in AI decision-making, which aligns with Babu et al. (2024), Papagiannidis et al. (2023), and Booyse & Scheepers (2024), finding that this leads to deep mistrust and even hostility.

Similarly, ethical concerns (such as security and privacy concerns, transparency, absence of AI responsibility and accountability, and lack of trust) in AI-based decision-making in organizations' financial reporting have become a significant challenge (Papagiannidis et al., 2023, et al, Booyse & Scheepers, 2024; Roumbanis, 2025). In this case, decision-makers in organizations must possess sufficient skills and potential to interpret AI explanations better and be aware of the ethical issues related to AI (Tuncalp, 2025; Barile et al., 2025). On the other hand, some studies have focused on ethical AI factors. For example, from an ethical consideration, organizational management has always been concerned about data privacy (Tuncalp, 2025; Papagiannidis et al., 2023), maintaining ethical standards. While significant concerns have been raised in the literature about the use of AI, such as job security risks, lack of confidence in AI, and loss of control and power, this evidence is presented at an individual level (D'Allura et al,2025; Jussupow et al., 2021; Daly et al., 2025).

In contrast, studies have shown that challenging aspects of AI at the organizational level, including data-led decision bias, costly infrastructure, and AI Biases and heuristics (Roumbanis, 2025; Booyse & Scheepers, 2024), can have a negative impact on organizational decision-making. Therefore, managers need to apply the necessary knowledge and skills to solve problems and make high-risk decisions (Kolbjørnsrud et al., 2017).

The contradictory results of previous studies on the relationship between AI and the decision-making process may affect the quality of decisions and limit the generalizability of AI applications, as companies, managers, investors, and society are not yet familiar with these new technologies. Therefore, this study uses a meta-synthesis approach to identify and explain the factors that lead to different outcomes. This framework can help managers select and implement a more appropriate form of AI to improve decision-making. Based on knowledge management theory, AI leads to accuracy, efficiency, and effectiveness in decision-making, which are the most effective characteristics of AI. However, previous studies have only used a one-dimensional approach to explain the relationship between AI and the decision-making process, while we have identified additional factors.

The first theoretical contribution of this paper is to explore the complex relationship between AI and the decision-making process, which, to our knowledge, has not yet been comprehensively addressed in the literature, especially from an interdisciplinary perspective. Second, given the increasing use of AI in organizational decision-making by managers and employees, it is necessary to comprehensively investigate the relationship between AI and decision-making (Vasconcelos et al., 2023). Finally, using a meta-synthesis approach, this study identifies several factors, including the value of information in decision-making, the increase in skills and capabilities, the scope of decision-making, the challenges raised by AI, and the improvement of organizational performance, which affect the relationship between AI and the decision-making process and provide a multidimensional perspective.

The structure of this paper is as follows: Section 2 provides an overview of various studies in the field of AI and their implications for decision-making. In Section 3, we outline the methods used for data collection. In Section 4, we discuss the AI factors and the conceptualization of the decision-making process in data, presenting the framework. Finally, in Section 5, we draw a three-part conclusion, outlining both theoretical and practical implications, as well as recommendations for future studies.

Theoretical Background

Since the beginning of the third millennium, there have been ongoing promises about developing machines capable of outperforming humans in various tasks and domains (Pesapane et al., 2018). The use of AI for decision-making is one of the most significant applications of AI in its history. AI systems can generally be used to either assist or replace human decision-makers (Edwards et al., 2000), and can collect data, predict trends, and analyze patterns (Murray et al., 2020). To investigate the relationship between AI and decision-making, Trunk et al. (2020) conducted a systematic literature review combined with content analysis to provide a comprehensive overview of the current research landscape characterizing AI in business decision-making. Their conceptual framework, developed under dynamic conditions, illustrates how humans can use AI capabilities effectively and efficiently despite challenges.

The literature review reveals that the relationship between AI and decision-making has been studied one-dimensionally, and there is limited evidence regarding the various factors that comprise this relationship. In other words, the relationship between AI and decision-making is multidimensional. It consists of multiple factors, which are discussed below, including *the value of information for decision-making*, *enhancement of capabilities and skills*, *decision scope*, *the improvement of organizational performance*, and *Challenges Driven by AI*.

From the data analysis, five main categories and thirteen subcategories were identified. Regarding the first theme, *the improvement of organizational performance*, we will review the following studies and discuss them in more detail in the results. Studies have shown positive emotional reactions to AI, stating that these technologies facilitate innovation, increase productivity, and lead to the adoption of these technologies in organizations (Daly et al., 2025). On the other hand, in recent years, several studies have examined the integration of AI in decision-making and highlighted significant benefits. For example, these studies noted that AI systems can increase decision-making accuracy (Condé & Münch, 2025; Nouis et al., 2025) and improve rapid workflow. These technologies also simplify processes and reduce decision-making processes by providing access to reliable and credible sources (Gezdur et al., 2024). Reducing these decision-making processes leads to cost savings. (Nouis et al., 2025). The more AI adapts to external conditions and complies with broader legal frameworks, the greater the organizational capabilities will be (Condé & Münch, 2025).

In the second category, the value of information in AI-supported decision-making has been discussed by several researchers (Gezdur et al., 2024; Barile et al., 2025; Babu et al., 2024). Research indicates that AI enhances data processing, provides more accurate information, facilitates access to information, and improves the predictive value of information (Tuncalp, 2025). In other words, from a knowledge management perspective, AI is driven by process monitoring and control processes (Booyse & Scheepers, 2024) and information and knowledge sharing/exchange (Barile et al., 2025).

Other studies explain the connection between AI and decision-making in terms of the skills of managers and employees. For example, AI in organizational settings can lead to a reduction in managerial errors and an increase in managers' self-confidence (Jussupow et al., 2021). On the other hand, managers and employees of organizations, due to their cognitive abilities such as experience, critical thinking, intuition, and most importantly, creativity, empathy, and compassion, can play an important role in job satisfaction (Tunkalp, 2024; D'Allura et al., 2024) and emotional intelligence (Das and Ranasinghe, 2025). As a result, collaboration between humans (due to cognitive characteristics and abilities) and AI systems (due to computational characteristics and fast decision-making) can lead to improved organizational performance, greater organizational commitment, and a positive work environment.

The next theme refers to decision scope. To develop AI capabilities, organizations need to integrate different resources across different conditions that are not transferable. In other words, organizations need to enhance their dynamic capabilities, such as data and information infrastructure (Young et al., 2024; Boys and Schippers, 2024) and human skills (technical skills, technology management ability, business know-how, and relational knowledge) (Yusupo et al., 2021). Another important issue that managers of organizations need to consider is organizational culture.

Management leadership attitudes toward AI can significantly influence the development of a culture that includes all team members. Therefore, management should remove barriers to an AI culture throughout the organization at various stages of the decision-making process and implement formal measures to promote shared organizational learning. Additionally, managers need to establish strong procedures for searching, acquiring, assimilating, and utilizing new and emerging knowledge to enhance AI capabilities (Babu et al., 2024).

Another part of the cycle derived from data analysis is the challenges driven by AI. According to the literature, these challenges, which include a lack of accountability and responsibility in decision-making, can undermine ethical standards (Booyse & Scheepers, 2024; Papagiannidis et al., 2023). In this case, organizations should develop mechanisms and strategies to identify, assess, and control these types of challenges in organizations. Evidence also suggests that the personal concerns of managers can affect the behavior of managers and employees when using AI in organizations (Cao et al., 2021). To address these concerns, it is recommended that organizations take proactive measures, such as training managers and increasing their knowledge in line with the principles of socio-technical systems theory, especially Theory Y (Deniz Tuncalp, 2025; Condé & Münch, 2025). Furthermore, the reduced transparency regarding AI-driven decision-making is a critical boundary condition for trust or accountability and affects the effectiveness of AI (Jussupow et al., 2021; Papagiannidis et al., 2023). Put differently, organizations need to motivate and empower their employees to use AI technology to optimize efficiency and increase performance and accuracy.

Research Design

A meta-synthesis approach is used to explain the relationship between AI and decision-making. This approach is an evidence-based qualitative study in which the results of other studies are used as data to investigate a particular topic (Dixon-Woods et al., 2007). In contrast to meta-analysis, a meta-synthesis combines the results of qualitative studies to present a new interpretation of a phenomenon and to understand and describe key issues, points, and recurring themes within a research stream (Sim & Mengshoel, 2022). We draw on the seven-step meta-synthesis method proposed by Sandelowski and Barroso (2007), which involves a sequence of steps to synthesize qualitative findings and create a process model. This method is outlined below.

Step 1: Raising the research question/Determining the research purpose

As a first step, this study examines the existing literature on AI and decision-making. To this end, the authors first reviewed theoretical research literature to identify the relevant factors. Our research question can, therefore, be formulated as follows: “Which AI factors do managers and organizations use (under certain conditions and circumstances) in their decision-making processes, and how do these factors affect optimal decision-making?” “Under what conditions are Challenges Driven by AI (e.g., human resources, organizational goals, and ethics) likely to have a negative impact on individuals and organizations?" In meta-synthesis research, the researchers formulate the research questions as shown in Table 1.

Table 1. Parameters and main research questions (Sandelowski & Barroso, 2007).

Parameters	Questions
What	Concepts and themes of AI and the decision-making process
How	Content & text analysis and synthesis
Who	Scopus, Google Scholar, and Web of Science
When	From 1987 to 2025

Steps 2 and 3: Searching and selecting relevant articles

As search engines, we used Scopus, Google Scholar, and Web of Science to search for related articles published in journals belonging to the AJG (https://charteredabs.org/academic-journal-guide/academic-journal-guide-2024) or in the SCImago (https://www.scimagojr.com/) Q1 ranking. The resulting dataset was composed of 297 papers published between 1987 and 2025. After that, we applied the specific CASP criteria (CASP, 2018; Yan et al., 2024). Using these criteria, 38 articles were excluded due to irrelevant titles, 31 articles due to irrelevant abstracts, and 79 articles due to irrelevant content; 113 articles were excluded due to irrelevant research method (literature review, conceptual papers, quantitative methodology). Thus, of the 36 studies assessed at the full-text review stage, 21 were excluded from the meta-synthesis because they did not provide sufficient qualitative data for code extraction and were not adequately aligned with the research question. In total, 15 studies met the inclusion criteria and were advanced to the coding and synthesis phase. Figure 1 shows a summary of our research protocol.

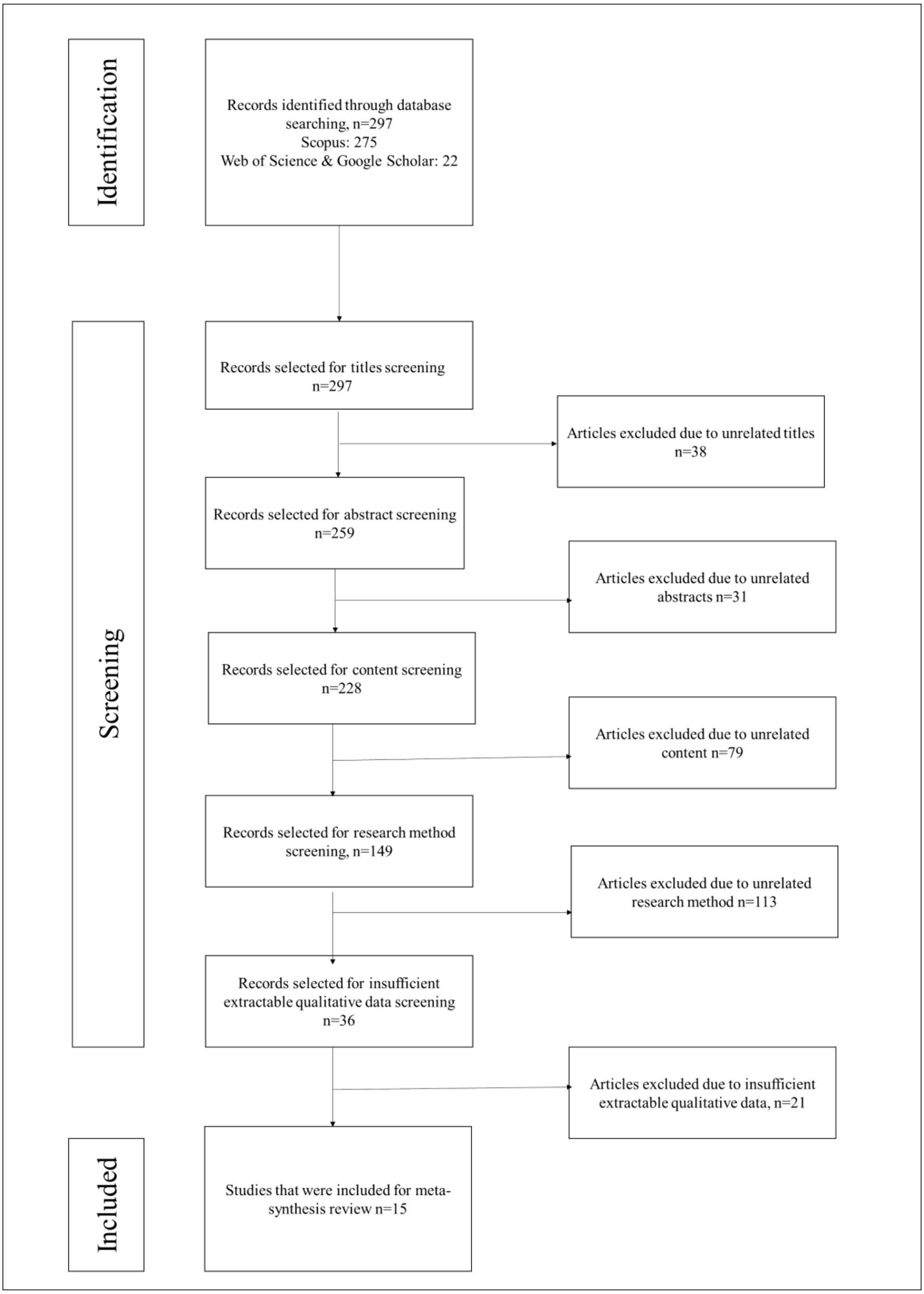

Fig. 1 Article selection algorithms

Steps 4 and 5: Extracting relevant data and analyzing categories

Extracting, coding, and classifying the data from the selected studies was the fourth phase of the meta-synthesis methodology (Noblit, 1988; Wang et al., 2024). The relevant data were extracted from the articles using the following steps of Elo and Kyngäs' comparative content analysis model (Elo & Kyngäs, 2008):

Prepare. We carefully analyzed the data and understood each text as a whole. We selected the unit of analysis and decided whether to consider the explicit or implicit content of the data. We reviewed the full text of the selected papers several times until the data was theoretically saturated. The sentences in the articles were analyzed as indicators of the units of analysis and the manifest and latent content according to the theme and purpose of the study.

Organizing. In the second phase, open coding, a more general classification with main categories and subcategories was created. After reviewing the data, an initial list of indicators (main themes) was created in a second step, and subcategories were defined based on the relationships between the initial codes. In contrast to inductive content analysis, comparative content analysis begins with the identification of main themes (AI and its factors, the decision-making process), which are already known at the outset. A matrix of codes and subcategories is then created after this step. Table (2-6) shows a categorization matrix. The initially collected codes reveal specific patterns. We have linked the identified concepts and factors in the reciprocal relationship between AI and the decision-making process. Since the initial factors are primarily about (*the value of information in decision-making, enhancement of skills and capabilities, decision scope, Challenges Driven by AI, and improvement of organizational performance*), we iteratively explored the collected data to arrive at a generalizable set of themes (Strauss, 1990; Young et al., 2024).

Reporting. There are various methods, including models, conceptual maps, conceptual categories, storytelling, etc., to report on the analysis process and results. We presented a conceptual model at the end of the meta-synthesis steps.

Step 6: Evaluating the quality of findings

The next step is to summarize the findings from the previous steps to make the results meaningful and provide well-founded recommendations. Once the relevant factors had been extracted and grouped into categories, the researchers repeated the coding extraction process to identify and minimize possible errors and biases (Miles & Huberman, 1994).

Step 7: Presenting findings and the conceptual research model

In the final phase, the meanings of the codes were similarly categorized based on their analysis. The factors obtained are then classified into more general categories. In this study, 268 codes were extracted from the analyzed sources. These codes were summarized into 13 subcategories and finally grouped into five main categories, as shown in Tables 2–7. Figure 2 shows a summary of these seven steps.

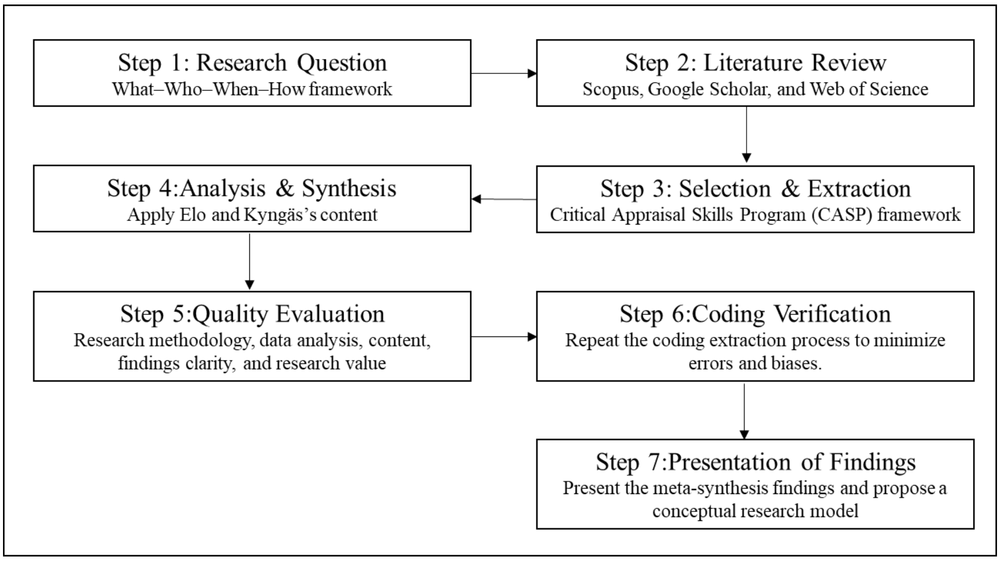

Fig. 2 The seven steps of the Meta-synthesis method of Sandelowski and Barroso (2007).

AI and the decision-making process conceptualization

Before examining the process model, we will discuss the AI factors and the conceptualization of the decision process in the data. Refer to Table 2-7 for a detailed categorization of the AI and decision-making process factors. Below, we summarize the characteristics of the top five factors in each subsection, namely (the value of information in decision-making, enhancement of skills and capabilities, decision scope, Challenges Driven by AI, and improvement of organizational performance).

In the meta-synthesis process, each reviewed study was assigned a specific code (S1 to S15). These codes were used in the analysis tables (2-7) to refer to the sources. A complete list of articles and their corresponding codes is provided in the appendix.

Improvement of Organizational Performance

One of the impacts of AI on decision-making is on organizational performance. Based on knowledge management theory, AI in organizations affects the decision-making process in two valuable ways: by enhancing the qualitative characteristics of information and by optimizing activities. The results of the meta-synthesis show that the main theme of this research is improving organizational performance, which encompasses other themes, including improvement of performance evaluation, criteria, developing business plans, and investments, creating a competitive advantage.

Based on a meta-synthesis, we therefore concluded that AI-based decisions lead to improvements in fairness (Roumbanis, 2025), cost efficiency (Babu et al., 2024), productivity (D'Allura et al., 2025; Das & Ranasinghe, 2025), Transparency (Booyse & Scheepers, 2024; Tuncalp, 2025; Condé & Münch, 2025), accountability, and responsibility (Nouis et al., 2025; Negash et al., 2025) in organizational activities, being increasingly emphasized by managers. Similar to previous findings in the literature (Negash et al., 2025; Nouis et al., 2025), our results showed that although decision makers are recognized as the primary stakeholders in decision-making, AI developers are also expected to be responsible for key decisions using diverse data sets, ensuring technical robustness, and minimizing bias. As a result, the precise allocation of responsibilities and liabilities remains unresolved.

The analysis of results shows that AI in the decision-making process leads to greater flexibility (Condé & Münch, 2025) and adaptability (Condé & Münch, 2025) for managers and employees by facilitating leadership, aligning goals (Roumbanis, 2025), driving innovation in organizational activities, and promoting effective communication. In this regard, these factors represent a shift in direction from traditional criteria for assessing organizational flexibility and sustainability to more intelligent criteria. In recent years, many studies have examined the benefits of adopting technologies in businesses. As Deniz Tuncalp (2024) states, AI has the potential to revolutionize business operations, customer interactions, and strategic decision-making, long-term sustainability, optimizing operations, and fostering innovation. This interpretation is consistent with the results of (Barile et al., 2025), which state that enabling companies to compete effectively in the market and stay updated with the latest technological advancements. These results may indicate the importance of these technologies in business and commercial fields. For example, these technologies significantly improved efficiency (Barile et al., 2025; Condé & Münch, 2025; Babu et al., 2024; Yang et al., 2024) for businesses by reducing and improving process times (Gezdur et al., 2024; Nouis et al., 2025), optimizing AI productivity (D'Allura et al., 2025; Das & Ranasinghe, 2025), and enhancing profitability (Tuncalp, 2025).

It is worth noting that from the perspective of creating innovative businesses, these technologies can develop new business models (Barile et al., 2025; Tuncalp, 2025), enhance market opportunities and create sustainable competitive advantages (Tuncalp, 2025), and lead to improved customer satisfaction (Tuncalp, 2025). For example, in the medical field, AI has positive applications such as improving the accuracy of disease diagnosis and providing personalized treatments for each patient (Jussupow et al., 2021; Condé & Münch, 2025; Negash et al., 2025). Doctors also emphasize that AI systems should be used with speed and discretion so that their professional autonomy is not compromised. They emphasize that technology is effective, safe, and ethical when supported by strong scientific evidence and should not operate in isolation but rather should be monitored and controlled by experts and regulatory bodies (Negash et al., 2025). A key factor for organizations in making effective strategic choices for innovation and adoption of technologies is social responsibility, as it increases energy efficiency and environmental sustainability (Barile et al., 2025; D'Allura et al., 2025). For example, organizations that prioritize social responsibility often use automation to protect the environment and increase energy efficiency. However, the social responsibility that drives innovation towards automation for sustainability can also have drawbacks, such as job losses or a lack of social responsibility commitments, leading many managers to hesitate to automate their operations (D'Allura et al., 2025). The findings of Jussupow et al (2021) showed that augmented intelligence is better than automation alone and emphasized that both human and technological aspects should be considered.

In recent years, there has been significant attention on AI in innovation cycles, as these technologies improve information sharing and maximize the impact of sustainable projects (Barile et al. 2025). These opportunities give AI a vital role in organizations, including facilitating data-driven decision-making, automating critical innovation processes, using predictive analytics to identify new market opportunities (Barile et al., 2025), and offering tailored advice to accelerate business growth (Barile et al., 2025; Condé & Münch, 2025; Yang et al., 2024). On the one hand, AI-based simulation models provide innovative solutions for organizations that enhance and accelerate the innovation process and increase product alignment with market needs (Tuncalp, 2025; Barile et al., 2025). In addition, innovative policies and strategies can significantly lead to the adoption of AI in organizations (D'Allura et al., 2025; Yang et al., 2024). The adoption of AI systems in organizations leads to increased innovation, productivity, and sustainable value creation (Barile et al., 2025; Booyse & Scheepers, 2024;

Tuncalp, 2025). On the other hand, by using technologies in organizations, managers can strengthen and promote environmental sustainability, social responsibility, and ethical governance. In other words, any initiative or collaboration between managers and AI is evaluated not only based on innovation, but also on environmental, social, and ethical impact (Barile et al., 2025) (See Table 2).

Table 2. Categorization matrix with first–order categories, second–order themes, and Aggregate dimensions (Improvement Organizational Performance)

First–order categories	Second-order themes	Aggregate dimensions
AI Efficiency Improvement (S1) (S2) (S6) (S7) (S8) (S11) (S14) (S15) Improving effectiveness (S1) (S15) Optimizing AI productivity (S2) (S3) (S14) Enhancing profitability (S2) Improving cost-effectiveness (S8) Improving decision-making processes (S2) (S7) AI's scalability (S10) Social responsibility (S3) (S6) Transparency Enhancement (S1) (S2) (S7) (S13 Reduces uncertainty (S4) AI alignment (S9) Enhancing human accountability and responsib (S13) (S2) (S15) Flexibility (S7) Adaptability (S7) Promoting fairness (S9) Promoting explainability (S9) (S4) The prevention of harm (S9) AI integration boosts accuracy (S4) (S7) (S13) (S15) Early Detection and Diagnosis (S4) Augmented Intelligence (S4) Enhancing sustainable value creation (S6) Promoting environmental sustainability (S6) Improvement in audit quality (S11) Facilitating trust in AI (S5) (S12) Non-profit-oriented development and financing (S15) Voluntariness regarding the use of AI (S15) Ensuring technical functioning (S15) Reducing time processes with the ability of AI systems (S13) (S2) (S5) Saving time and costs (S5) Cost efficiency (S14)	Improvement of performance evaluation criteria	Improving Organizational Performance
Upgrading the business model (S2) (S6) Accelerating the pace of investment (S2) Legacy preservation (S2) Incremental integration (S2) Accelerate business growth (S6) Improving product-market alignment (S)	Developing business plans and investments	
Creativity and innovation strategies and policies (S3) (S11) Enhance co-innovation initiatives (S6) Improving innovation efficiency (S6) (S1) (S2) (S6) Responsible Innovation (S9)	Creating a competitive advantage	

Expanding market opportunities (S2) (S6) Creating sustainable cash flows(S2) Dynamic business environment (S1) Gain a competitive edge (S2) (S3) (S6) (S7) (S11)

Enhancement of the capabilities and skills

Improving human resource skills and capabilities is one area in which organizational performance has undergone significant evolution. The results of the meta-synthesis reveal that the primary theme of this research is enhancing the capabilities and skills, which encompasses other key themes, including managerial decision-making, cognitive characteristics of managers, and characteristics of an Employee. By reviewing the literature, we found that organizations can increase the skills and expertise of their employees by applying one of the principles of organizational development (Jussupow et al., 2021; Babu et al., 2024). AI systems in organizations have a significant impact on organizational decision-making through better support for strategic decision-making (Tuncalp, 2025), digital literacy (AI) (Tuncalp, 2025; Yang et al., 2024), team motivation (Booyse & Scheepers, 2024; Barile et al., 2025), and the ability to detect errors (Jussupow et al., 2021). Also, managers increase their self-confidence in performing tasks by recognizing their skills and abilities (Jussupow et al., 2021). In this case, the more self-confidence in managers, the fewer management errors are reduced and the more cooperation between colleagues increases (Barile et al., 2025; Papagiannidis et al., 2023; Nouis et al., 2025). Consequently, this shows that AI systems have a potential impact on organizational performance.

Much research has shown that economic factors alone do not influence organizations' decisions to automate; other factors, such as emotions and ambivalence (conflicts in goals or perspectives), also play an important role. These conflicting goals can affect organizations' strategic decisions regarding automation (D'Allura et al., 2025). To be more precise, ambivalence can lead to narrow thinking, indecisiveness, uncertainty, risk perception, and poor decision-making (Rothman et al., 2017). In opposition to the perspective outlined above, several researchers contend that it may also foster cognitive flexibility, divergent thinking, situational awareness, and adaptive decision-making, thus facilitating the management of demanding situations (Randerson & Radu-Lefebvre, 2021).

In today's digital world and market, AI is no longer just a tool; its use and application are now inevitable for continued progress and success. Inevitability is recognized as a social ability that individuals and organizations must understand and engage with. One of the most important aspects is understanding of AI principles, which includes elements such as open-mindedness and ongoing education. They should also be realistic about its use. Understanding the capabilities and limitations of AI helps people avoid the common misconception that it can detect and solve every problem, especially rare or random anomalies (Condé & Münch, 2025).

The results of data analysis indicate that (Condé & Münch, 2025), neutrality as a social ability refers to the idea that, unlike humans, AI is not affected by internal organizational sensitivities or personal preferences and always remains impartial, focusing instead on improving and achieving defined objectives. The social ability of flexibility is the ability of AI to adapt to changing conditions. For example, AI-driven tools can help organizations achieve greater accuracy and efficiency in tasks such as systematic scanning and analysis of a vast array of external data sources. This results in operational efficiency and improved decision-making processes (Condé & Münch, 2025). Another social skill is adaptability, which refers to the ability of AI to learn independently, adapt to new situations, and not be limited to predetermined data (Condé & Münch, 2025). The third social ability is reliability, which must be designed as a sustainable and reliable operational tool for utilizing AI. This ability has four main considerations: the first of which is the ability of AI systems to acquire all necessary data independently, that is, trust in the system and access. Second, it must be integrated seamlessly into the existing infrastructure.

In recent years, much attention has focused on how combining different resources leads to the development of organizational capabilities. These capabilities are essential strategic tools for any organization formed in response to environmental conditions (Booyse & Scheepers, 2024; Tuncalp, 2025). To achieve this, AI capabilities require organizations to pay sufficient attention to their dynamic capabilities, such as the infrastructure (which encompasses the systems and tools collecting, storing, processing, and managing data, serves as the prerequisite for adoption of AI (Yang et al., 2024), database, skills (technical skills, capability to manage technology, business know-how and relational knowledge) (Babu et al., 2024), and relevant technology, and intangible factors such as the organizational culture for technology orientation, employees' skills, and knowledge sharing. Focusing on these capabilities increases operational efficiency, cost effectiveness, and data management and processing technology (Babu et al., 2024).

One of the important characteristics of managers in organizations is a positive attitude towards AI, meaning that they are receptive to the use of AI and consider it a useful and efficient tool. What is more, a positive attitude among managers can improve efficiency, enhance the quality of their work, and create organizational advantages (future orientation) (Daly et al., 2025). Users with a positive attitude toward AI, however, are not always willing to share their knowledge because they feel it would take away their personal advantage and put their contractual payments at risk (Daly et al., 2025). On the other hand, negative attitudes toward AI have been described as concerns about threats to future employment, livelihood, happiness, personal privacy, and a loss of agency and control. For example, one of the main concerns among employees is the fear of losing their jobs due to the increasing use of AI systems. Threats to job security can be one of the barriers to trust and acceptance of these technologies by employees in organizations (Daly et al., 2025). In this case, negative attitudes of employees about job threats, privacy, or loss of control can limit the adoption of AI. Despite these challenges, AI offers organizations numerous opportunities and capabilities, the most important of which are improving audit quality and increasing work productivity (Yang et al., 2024). In addition, studies have shown that AI offers immense benefits for managers, including risk management (Das & Ranasinghe, 2025; Booyse & Scheepers, 2024), personalization of customer experience, enhanced decision-making, risk assessment, and fraud detection (Das & Ranasinghe, 2025) (See Table 3).

Table 3. Categorization matrix with first–order categories, second–order themes, and Aggregate dimensions (Enhancing the capabilities and skills)

First–order categories	Second-order themes	Aggregate dimensions
Problem-solving skills and abilities (S4) (S8) Extrapolating a reasonable judgment (S1) Enhancing employees' capabilities (S1) (S2) Strategic decision-making (S2) Risk management (S14) (S1) Decision maker training (S7) (S13) Accelerated and effective collaboration (S6) Inevitability (S7) Open-mindedness (S7) Hybrid intelligences (S9) Meta-algorithmic discretionary (S9) Human oversight authority (S15) (S13) (S14)	Managerial decision-making	Enhancing the capabilities and skills
Digital (AI) literacy (S2) (S11) Increasing self-confidence (S4) Reducing the personal concerns of the manager (S1) Reskilling of employees(S1) (S5) (S6) Increasing collaboration, interaction, and teamwork (S1) (S6) (S10) (S13)	Cognitive characteristics of managers	

Team motivation (S1) (S6) leader-follower bonds (S1) Ability to detect errors (S4) Emotions and ambivalence (S3)		
Continuous improvement of employee participation (S1) Social interactions and norms (S1) Employees' training (S2) (S4) (S6) (S7) (S15) Neutrality (S7) Employees' satisfaction and well-being (S3) (S4) Improving Employees' Digital Skills (S8) (S11) Reduce employees' overload (S10) Positive attitudes towards AI (S12) Negative attitudes towards AI (S12) Openness towards incorporating AI systems (S15) (S12)	Characteristics of an Employee	

The value of information in decision-making

The value of information in decision-making is another part of the results that show that data processing techniques, e.g., machine learning (ML), contribute to improvements in relevance and reliability (Gezdur et al., 2024), the predictive value of information (Tuncalp, 2025), and the accuracy of information (Gezdur et al., 2024). In other words, based on the management information systems frameworks, the use of information technology tools leads to improving monitoring and control processes (Booyse & Scheepers, 2024; Jussupow et al., 2021), improving collaboration, interaction, and teamwork (Mikhaylov et al., 2018; Yu & Li, 2022b). Even if these effects have been noticed and highlighted by the internal side of the organizations. On the contrary, there is evidence of external effects, such as the timeliness of information (Condé & Münch, 2025), and information and knowledge sharing/exchange (Barile et al., 2025; Babu et al., 2024). In general, the findings related to information processing can be analyzed using a meta-synthesis approach, considering both internal and external organizational aspects, and data processing can be regarded as influencing the understanding of external users. (see Table 4).

Table 4. Categorization matrix with first–order categories, second–order themes, and Aggregate dimensions (The value of information decision-making)

First–order categories	Second-order themes	Aggregate dimensions
Information reliability (S5) Improving the accuracy of information (S5) Information and knowledge sharing/exchange (S6) (S8) (S7) (S12) Timeliness of information (S7)	Information issues	The value of information in decision-making

Shortening development timelines (S6)	
Improving monitoring and controlling processes (S1) (S4) Predictive value of information (S2)	Information goals

Challenges driven by AI

The results of the meta-synthesis show that the main theme of this research is challenges driven by AI, which encompasses other themes, including human resources, professional and organizational ethics, and organizational goals. Although the findings have highlighted the positive impact of AI on decision-making, the use of AI also harbors risks. One of the most prominent challenges in traditional hiring methods is the lack of efficiency (Booyse & Scheepers, 2024; Roumbanis, 2025) and human bias (Roumbanis, 2025). The time and energy spent evaluating backgrounds and reading CVs make the process immensely inefficient and prone to cognitive biases and gut feelings, which can unintentionally lead to discrimination and the neglect of qualified candidates (Roumbanis, 2025). Decision makers play a crucial role in mitigating the biases in AI-based systems and transferring AI insights into concrete actions (Jussupow et al., 2021). Therefore, managers in organizations need to ethically assess transparency and accountability by conducting regular audits of AI systems (Tuncalp, 2025). However, successful decision-making occurs when decision-makers use both system-monitoring and self-monitoring cognition. This cognition enables managers to gain confidence in AI systems (Jussupow et al., 2021). This leads to improved information accuracy (Gezdur et al., 2024) and information confidence (Gezdur et al., 2024).

One of the main challenges to AI adoption is the lack of resources and expertise (Tuncalp, 2025; Babu et al., 2024). These include infrastructure and the talents of employees and managers. In other words, high costs for accessing reliable sources (Booyse & Scheepers, 2024; Tuncalp, 2025; Babu et al., 2024) and a lack of internal expertise and skills (Tuncalp, 2025) for implementing and managing these technologies are considered to be the most important barriers. Other barriers that can be mentioned here are fear of losing family heritage (Tuncalp, 2025), low self-confidence (Booyse & Scheepers, 2024; Jussupow et al., 2021), and low employee satisfaction (Jussupow et al., 2021). This can create barriers to the adoption of innovative technologies.

The analysis shows that the challenges of algorithm aversion have been addressed in qualitative studies. Senior managers and HR professionals in organizations often fear the consequences of using AI, leading to something bad, which generates ‘algorithm aversion’. However, this fear is not solely due to aversion to algorithms; it can also reflect managerial motivation when using AI (Roumbanis, 2025). On the other hand, there is always a potential risk associated with over-reliance on AI recommendations (i.e., “algorithm appreciation”), as following them blindly may unintentionally mislead human decision-makers (Booyse & Scheepers, 2024; Roumbanis, 2025).

Some studies focus on the social and cultural aspects of AI. One of the major problems and challenges in implementing AI technologies is having unrealistic expectations (AI false expectations). Expecting too much from these technologies can result in a lack of business value and sometimes unexpected outcomes. Therefore, it is necessary to use alternative methods and manual mechanisms to correct and prevent errors (Papagiannidis et al., 2023). Over-reliance on AI-enabled employees leads to loss of their competence and deskilling, ultimately reducing their abilities over time (Papagiannidis et al., 2023). Studies have also shown that organizations' use of AI can cause employees to lose interest in their jobs and reduce their motivation.

Data analysis shows that security and ethical challenges have been addressed in qualitative research. Therefore, another important challenge is cybersecurity (Papagiannidis et al., 2023; Das & Ranasinghe, 2025), which can cause financial and reputational damage to the company if a security breach occurs. However, many organizations are trying to use AI systems to develop and create new strategies and tactics that would be impossible without the use of AI (Papagiannidis et al., 2023). From an ethical consideration, organizational management has always been concerned about data privacy (Tuncalp, 2025; Papagiannidis et al., 2023), maintaining ethical standards, and potential bias in AI algorithms (Tuncalp, 2025). In the adaptation of AI, three main areas of ethical concerns have emerged: Life-or-death decisions and the principles on which they are based; potential discrimination against certain groups embedded in the design of AI; and the replacement of humans with machines, and resulting employee unemployment, which is considered an ethical issue within organizations (Tambe et al., 2019; Booyse & Scheepers, 2024).

Unemployment is considered one of the main factors preventing the adoption of technologies in organizations. Some governments, such as South Africa, generate revenue from the use of AI but still face ethical and negative social dilemmas, including rising unemployment. The work of Davenport and Harris (2005), Booyse & Scheepers (2024) is thus supported by our research. Another important theme, like creativity (Booyse & Scheepers, 2024), remains a defining characteristic that sets humans apart from AI. This shows that humans are still the main decision makers in organizations. As a result, managers are encouraged to provide training to develop and expand the skills of employees (Gezdur et al., 2024). By creating this training, employees strengthen their creative and imaginative abilities, which AI systems lack (Schoemaker and Tetlock, 2017; Booyse & Scheepers, 2024).

AI is described as a "black box" due to the difficulty in analyzing and understanding the logic and decisions behind it for managers and employees of organizations (Booyse & Scheepers, 2024). In this case, the lack of transparency and understanding in AI decisions can undermine employee trust. As a result, organizations can reduce this uncertainty and potential hostility and bias by regularly auditing AI algorithms (Booyse & Scheepers, 2024) and monitoring and controlling AI systems (Yang et al., 2024). In addition to creating an environment that facilitates the adoption of AI, organizations should reduce barriers and challenges through appropriate management practices and provide necessary training. With this management approach, not only will the acceptance of AI by employees increase, but hostility towards these technologies will also decrease (Ransbotham et al., 2018; Booyse & Scheepers, 2024).

Regarding responsibility and accountability (Booyse & Scheepers, 2024; Papagiannidis et al., 2023), there is considerable confusion about who should be held accountable for the outcomes and use of AI: on one hand, AI developers, and on the other, the users who primarily supervise AI systems. In this context, the lack of explainability of these technologies (Booyse & Scheepers, 2024; Jussupow et al., 2021; Babu et al., 2024; Nouis et al., 2025) may increase concerns about transparency and bias (Nouis et al., 2025; Papagiannidis et al., 2023). Studies have shown that the dualities of using and designing AI can be summarized as follows: the ability to predict depends on the internal structure of these technologies, which is very important but often has poor accuracy, while explainability and interpretability are important features for building trust. However, these dualities indicate which of these two aspects should be prioritized by users of AI systems. This creates an ethical dilemma, as users are not willing to sacrifice accuracy to maintain a certain level of interpretability (Nouis et al., 2025).

AI systems also face challenges and limitations, such as a lack of emotional intelligence (Das & Ranasinghe, 2025), an inability to make judgment-based decisions, an inability to analyze problems in depth, limited situational analysis, data bias, and low adaptability (Das & Ranasinghe, 2025). Studies have shown that

AI cannot replace human intelligence in judgment-based decision-making and emotional cognition, as these require contextual and situational awareness for proper evaluation. Furthermore, from an ethical perspective, AI systems cannot take responsibility for the ethical aspects of the decision-making process (Das & Ranasinghe, 2025) (see Table 5).

Table 5. Categorization matrix with first–order categories, second–order themes, and Aggregate dimensions (Challenges Driven by AI)

First–order categories	Second-order theme	Aggregate dimensions
Job security risks (S1) (S3) (S8) (S10) (S12) (S15)	Human Resources	Challenges driven by AI
Need for continuous learning (S1)		
Lack of confidence in AI (S1) (S4)		
Lack of trust (S1) (S9) (S10)		
Safely Concern (S3)		
Costly Infrastructure (S1) (S2) (S8)		
Lack of creativity (S1)		
Loss of control and power (S1) (S12)		
Decision complexity and ambiguity (S1)		
Lack of resources (S2) (S8) (S11)		
Lack of in-house expertise (S2)		
Lack of skills (S2)		
Insufficient cognitive control (S4)		
Realistic use of AI (S7)		
Shortage of skilled human resources (S8) (S7)		
Negative perception (S8)		
Deskilling (S10)		
Losing interest in work (S10)		
Concerns about overreliance on AI (S13)		
New work organization (S15)		
Irreplaceability of interpersonal relationships (S15)		
Possible extinction of specialist areas (S15)		
Algorithm Aversion (S1) (S9)		
Algorithm appreciation (S9)		
Traceability in an AI system (S15)	Professional and Organizational Ethics	
Lack of accuracy (S1)		
Lack of transparency (S1) (S4) (S10)		
Lack of emotional intelligence (S14)		
Cyber security concerns (S10) (S14)		
Absence of AI responsibility and accountability (S1) (S10)		
Ethical AI (S1) (S2) (S14) (S6) (S9) (S10)		
Lack of judgmental decision making (S14)		
Preventing discrimination(S1)		
AI Biases and heuristics (S1) (S2) (S10) (S13) (S4) (S8)		
Human biases (S9)		
Cognitive biases and gut feelings (S9)		
Lack of Efficiency (S1) (S9)		
Lack of explainability (S1) (S4) (S8) (S13) (S10)		
Security and Privacy Concerns (S2) (S10)		
Data-led decision bias (S11) (S14)		
Regulatory and liability concerns (S1)		
Restrictive regulatory environments (S1)		

Compliance with regulations (S7) Economic concerns (S1) Protection of intellectual property (S1) Reputation damage (S1) AI false expectations (S10) Lack of AI decision (S10) Negative developments of superintelligence (S10) Need for simplified AI outputs (S13) Lack of understanding context (S14) Lack of analysis of the problem deeply (S14 Lack of situation analysis (S14) Less adaptability (S14) Reservation about AI autonomy (S15) AI-based confirmation (S4)		
Establishing a robust regulatory and governance framework (S13) Human resistance (S1) (S2) Lack of data management policy and culture (S1) AI governance (S2) Lack of data availability (S8) Ethical compliance (S2) Financing of AI systems (S15)	Organizational goals	

Decision Scope

Decision scope is a comprehensive process that encompasses information on social and organizational dynamics, as well as data. Thanks to AI, organizations simplify problems, improve data collection (Booyse & Scheepers, 2024; Babu et al., 2024), and enhance data quality (Booyse & Scheepers, 2024; Babu et al., 2024). What is more, decision makers use available data and information to manage data and process technologies (Babu et al., 2024), regulate data governance (Yang et al., 2024), analyze large datasets (Das & Ranasinghe, 2025), and make more informed decisions (Liao et al., 2015). Thereby, one of the most critical factors for the success of collaboration and interaction between decision-makers and AI is facilitative leadership (Booyse & Scheepers, 2024) (see Table 6).

Table 6. Categorization matrix with first–order categories, second–order themes, and Aggregate dimensions (Decision Scope)

First–order categories	Second-order themes	Aggregate dimensions
Enhancing Data Collection (S1) (S8) Enhancing data quality (S1) (S8) Facilitating value co-creation (S6) (S10) Data protection (S7) Leveraging predictive analytics (S6) Optimal resource allocation (S6) (S11) Enhancing the data infrastructure (S8) (S1 Organizational culture (S8) Data management and processing technol((S8) Data sovereignty regulation (S11)	Performance Dynamics	Decision Scope

Bulk data analysis (S14) Data-based confirmation (S4)	
Facilitative Leadership (S1) Mitigating the agency problem (S1)	Societal and Organizational Dynamics

A model explaining the role of Artificial Intelligence and the Decision-making Process

To clarify how AI influences the decision-making process and to define the underlying patterns identified in qualitative research, it is essential to model a series of events, including what happens in specific situations and the effects that result. Table 2-6 summarizes the factors discovered in each study that influenced the integration of AI into the decision-making process. Table 7 provides an overview of the AI used in decision-making. Specifically, "Improvement of organizational performance" refers to the implementation of AI technologies that can lead to significant improvements in decision-making processes in organizations (e.g. increasing efficiency, effectiveness, transparency and accuracy); "Enhancement of skills and capabilities" includes improving the skills and capabilities of managers and employees in organizations (e.g. increasing managerial participation, trust, continuous improvement of employee participation and learning process); "value of information in decision-making" refers to the usefulness and impacts awareness of information on decision making (e.g., information reliability, information and knowledge sharing/exchange an improving monitoring and controlling processes); "Challenges Driven by AI" refers to a kind of interruptions of the decision-making process due to various types of noise related to ethical issues, organizational goals, and human resources associated with the implementation of this technology (e.g. job security risks, trust challenges, reducing transparency, responsibility and accountability, discrimination, bias, and security and privacy concerns); the term "Decision scope" alludes to the strengthening of the decision dynamics, which is a comprehensive process that includes data and information, as well as social and organizational aspects (e.g. Improving data collection and recording, data protection, facilitative leadership). A meta-synthesis that combines and organizes these factors from different studies reveals underlying trends (see Table 7). This method, applied to our dataset, provides a comprehensive understanding of the decision-making process, contextual elements, and outcomes that organizations experience when using AI.

Table 7. AI and decision-making process factors and their codes for each study

Paper	Improvement Organizational Performance	Enhancement Capabilities & Skills	The value of information in decision-making	Challenges Driven by AI	Decision scope
(Tuncalp, 2025)	Performance evaluation criteria Developing business plans and investments Creating a competitive advantage	Managerial decision-making Cognitive characteristics of managers Characteristics of an Employee	Information goals	Human Resources Organizational Ethics Organizational Goals	N/A
(Barile et al., 2025)	Performance evaluation criteria Developing business plans and investments Creating a competitive advantage	Managerial decision-making Cognitive characteristics of managers Characteristics of an Employee	Information issues Information goals	Organizational Ethics	Performance dynamics
(Condé & Münch, 2025)	Performance evaluation criteria Creating a competitive advantage	Managerial decision-making Characteristics of an Employee	Information issues	Human Resources Organizational Ethics	Performance dynamics
Babu et al., 2024)	Performance evaluation criteria	Managerial decision-making Characteristics of an Employee	Information issues	Human Resources Organizational Ethics Organizational Goals	Performance dynamics
(Yang et al., 2024)	Performance evaluation criteria Developing business plans and investments Creating a competitive advantage	Cognitive characteristics of managers Characteristics of an Employee	N/A	Organizational Ethics	Performance dynamics
(Das & Ranasinghe, 2025)	Performance evaluation criteria	Managerial decision-making	N/A	Organizational Ethics	Performance dynamics
(Negash et al., 2025)	Performance evaluation criteria	Managerial decision-making Characteristics of an Employee	N/A	Human Resources Organizational Ethics Organizational Goals	N/A
(Booyse & Scheepers, 2024)	Performance evaluation criteria Developing business plans and investments Creating a competitive advantage	Managerial decision-making Cognitive characteristics of managers Characteristics of an Employee	Information issues Information goals	Human Resources Organizational Ethics Organizational Goals	Performance dynamics Societal and Organizational Dynamics
(D'Allura et al., 2025)	Performance evaluation criteria Creating a competitive advantage	Cognitive characteristics of managers Characteristics of an Employee	N/A	Human Resources	N/A
(Jussupow et al.,2021)	Performance evaluation criteria	Managerial decision-making Cognitive characteristics of managers Characteristics of an Employee	Information goals	Human Resources Organizational Ethics	N/A
(Gezdur et al., 2024)	Performance evaluation criteria	Cognitive characteristics of managers	Information issues	N/A	N/A
(Roumbanis, 2025 .,2025)	Performance evaluation criteria Creating a competitive advantage	Managerial decision-making	N/A	Human Resources Organizational Ethics	N/A
(Papagiannidis et al., 2023)	Performance evaluation criteria	Cognitive characteristics of managers Characteristics of an Employee	N/A	Human Resources Organizational Ethics	Performance dynamics
(Daly et al., 2025)	Performance evaluation criteria	Characteristics of an Employee	Information issues	Human Resources	N/A
(Nouis et al., 2025)	Performance evaluation criteria	Managerial decision-making Cognitive characteristics of managers	N/A	Human Resources Organizational Ethics Organizational Goals	N/A

Based on the coding performed and the review of the meta-synthesis, the conceptual model shows two types of relations among the main categories. The first type of direct relation we examine is the relationship between "*value of information in decision making*" and "*enhancement of capabilities and skills*," followed by the direct relationship between "*enhancement of skills and capabilities*" and "*decision scope*." Additionally, "*decision scope*" has a direct relationship with "*improvement of organizational performance*," which ultimately leads to "*improvement of organizational performance*" through the "*value of information in decision making*." The impact of these direct relations is explained in detail in the following section. However, it should be noted that Challenges Driven by AI also have direct (in terms of the value of information in decision-making and the enhancement of skills and capabilities) and indirect (in terms of decision scope and the improvement of organizational performance) relationships. We will explain these direct relationships to the main categories in tables 8-13. (see Fig. 3).

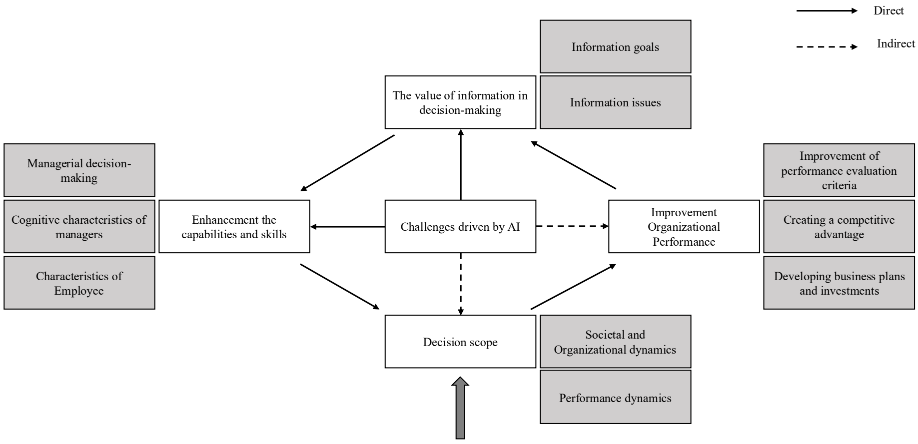

Fig. 3 Conceptual Mode

Direct and indirect connections

In this section, we examine the direct and indirect relationships between the challenges of AI, the value of information for decision-making, skill and capability improvement, the scope of decision-making, and its impact on enhancing organizational performance. These relationships have an impact on organizational decision-making and are discussed in more detail below.

The results show that the AI-driven challenges in the main categories are directly and indirectly related to other factors in the conceptual model. On the one hand, the Challenges driven by AI are directly related to the "value of information in decision making," which leads to a weakening of the planning process and the personal concerns of managers and employees. On the other hand, there is a direct relationship with the "enhancement of skills and capabilities," which leads to a decrease in the participation and coordination of managers and employees in decision-making, as well as a decline in training. There is also an indirect relationship with “decision scope,” which leads to a weakening of leadership and a reduction in data collection and recording. Ultimately, this results in a decrease in “improvement of organizational performance,” characterized by a decline in efficiency, effectiveness, and accountability.

Table 8 provides examples of the relationships between the challenges posed by AI and the skills and capabilities of managers and employees, as well as their direct impact on the value of information in decision-making. Although the papers did not report on a direct relationship between these concepts, this relationship was obtained through interpretive and comparative analysis in the meta-synthesis. As Booyse & Scheepers (2024) state, the limitations of AI creativity can lead to an increased importance of human judgment. Furthermore, the weakness of AI in creativity and the biases and discoveries of AI can highlight the importance of the human role in improving the quality of information, because the inability of AI in creative decision-making requires organizations to establish monitoring and control mechanisms to compensate for these limitations and weaknesses of AI. From the perspective of ethical considerations in the use of AI (Tuncalp, 2024) – which include issues such as privacy protection, transparency, and accountability – organizations are required to increase human oversight, improve data quality, and strengthen accountability and trust through human participation. This requires increasing the skills of employees and managers when using AI and providing them with the necessary training. By improving employee skills, investing in training, and using external technical experts, the predictive value of information is strengthened and ultimately leads to improved information quality. Our analysis of the codes showed that the more negative attitudes there are towards AI, the more trust in AI decreases. This distrust among employees reduces their willingness to adopt the technology and limits the effective use of AI systems. As these negative attitudes and distrust persist, employees develop concerns about job turnover, threats to their well-being, and risks to their privacy. In such a situation, increasing the quality of data and information and ensuring the effective use of AI requires a strong emphasis on data exchange and knowledge sharing between employees and managers in organizations (Daly et al., 2025). Furthermore, based on the study conducted by Condé & Münch (2025), we found that organizations should be aware of the capabilities and limitations of AI and should not expect AI to perform beyond its actual capacity. The lack of AI-related expert staff and the lack of clear regulations require organizations to provide the necessary training to decision makers. In this case, it is essential to create mechanisms to increase the adoption of innovation and new technologies and prevent bias in data.

Table 8. Challenges driven by AI, enhancement of skills and capabilities, and improvement of organizational performance

paper	Challenges Driven by AI	Enhancement skills & capabilities	The value of information in decision-making
(Booyse & Scheepers, 2024)	-A machine cannot be creative	-The human mind can extrapolate reasonable judgment and understanding of multiple debates	-Improving monitoring and control processes

(Booyse & Scheepers, 2024)	-AI Biases and Heuristics	-Needs continuous improvement of employee participation	-Improving monitoring and controlling processes
(Deniz Tuncalp, 2024)	-Ethical considerations in AI adoption - Risk of bias in AI algorithms	- leveraging external partnerships for technical expertise -Investing in training, -Seeking external expertise and fostering a culture of innovation	-Predictive value of information
(Daly et al., 2025)	-Negative attitudes to Wards AI decreases trust in AI	-Threat to the user's livelihood, happiness, or personal privacy, and a lack of agency	-Information and knowledge sharing/exchange
(Lansiné Condé & Christopher Münch, 2025)	-Realistic use of AI -Shortage of skilled human resources -Compliance with regulations	-Decision maker training -Open-mindedness -Employees' training -Neutrality	-Information and knowledge sharing/exchange -Timeliness of information

Another part of the results shows that the challenges posed by AI are indirectly related to the scope of decision-making and indirectly related to improving organizational performance, as explained in Table 9. One of the challenges and limitations identified in this study is the lack of transparency and complexity of AI systems. The lack of transparency and the inability to explain AI systems can cause confusion among employees about the use and application of AI. In such cases, organizations should increase the quality of their data and the accuracy of their information and clearly state the logic and basis of AI-based decisions to increase the trust of decision-makers. The greater the transparency, monitoring, and continuous evaluation of AI performance during the data collection stages, the more bias and errors will be reduced. One effective way to improve productivity and prevent decision-making biases and errors is to combine human capabilities with AI. In this case, organizations do not necessarily need to invest in technical infrastructure and training of skilled professionals (Booyse & Scheepers, 2024). Moreover, other challenges, such as insufficient financial and human resources, a lack of appropriate and high-quality data, and biases in data, can undermine the performance of AI systems. Organizations need to process and manage data using appropriate tools to eliminate these biases and provide more accurate and transparent data. What is more, to adopt new technologies, organizations need to create a supportive organizational culture. By creating such an organizational culture and ensuring the availability of high-quality data, AI systems can perform tasks more efficiently. By increasing this efficiency, costs are reduced, leading to resource savings and improved productivity in the organization (Babu et al., 2022). From the perspective of ethical issues in AI systems - such as transparency, fairness, and privacy protection - organizations can make more transparent, fair, and informed decisions by analyzing data, trends, and allocating sufficient resources to support employees and managers. Also, by analyzing these data and trends, organizational leaders can enter new markets and compete with their competitors faster and at lower costs, thereby achieving a competitive advantage. Adopting and applying AI in organizations can accelerate business operations and increase the organization's competitive advantage in the market (Baril et al., 2025).

Table 9. Challenges Driven by AI, the Value of Information in Decision-Making, and Improvement of Organizational Performance

paper	Challenges driven by AI	Decision scope	Improvement of organizational performance
(Booyse & Scheepers, 2024)	-Lack of trust due to unknown AI algorithm. -Lack of transparency -High-end systems cannot be explained.	-Mitigating the agency problem -Data Collection	-Disclose reasoning behind decisions -Need transparency Enhancement -Audits required -Creativity, spontaneity, and intuition are required in environments -Funding human-machine teams -Change management process -Capital investment in web space, programming, and AI talented programmers
(Babu et al., 2022)	-Lack of resources -AI Biases and heuristics -Lack of explainability -Lack of data availability	-Data Collection -Data quality -Organizational culture -Data management and processing technology	-AI Efficiency -cost-effectiveness
(Barile et al., 2025)	-Ethical AI	-Predictive analytics -Optimal resource allocation	-Upgrading the business model -Accelerate business growth -Enhance co-innovation initiatives -Expanding market opportunities -Gain a competitive edge

In the following table (10), we discuss studies that examine the direct relationship between the value of information in decision-making and the enhancement of skills and capabilities. According to data analysis, organizations should rely on human analysis – not just on recommendations generated by AI – when making managerial and organizational decisions. Overreliance on AI suggestions can increase decision-making errors and reduce human oversight. As decisions are supported by human analysis and monitoring, assessments become more accurate and reliable. Which in turn reduces decision-making uncertainty and increases managers' trust and satisfaction with their decisions (Yusupo et al., 2021). Also, managers can make more effective organizational decisions by having more reliable and valid information. Which leads to increased collaboration between managers and AI systems in different parts of the organization. This is because trust in data and its output increases coordination and knowledge sharing among employees during organizational decision-making. With high-quality data and enhanced collaboration, employees are encouraged to develop their skills to analyze data more effectively when working with others. In an effort to gain a competitive advantage and make accurate decisions, employees strive to acquire new competencies and enhance their capabilities (Gezdur et al., 2024). As qualitative data analysis showed, the less knowledge and experience is shared among employees, the more their ability to learn and understand AI systems decreases. Knowledge sharing is essential to improve the quality of decision-making and eliminate information gaps among employees. Lack of knowledge exchange in organizations can reduce employees' competitive advantages and erode their personal professional leverage. It may also threaten employees' job security, as a lack of collaboration and knowledge sharing with other colleagues leads to job and professional vulnerability (Daly et al., 2025). In this regard, organizational decisions are valid when the information provided to decision makers is accurate and reliable. As a result, organizational decision-making performance improves. In this context, one of the key strategies for organizations to ensure the correct use and full understanding of accurate and reliable information is to provide employees with the necessary training to upgrade their skills and create a comprehensive understanding of the situation and data analysis. Such training and new skills increase employees' trust in information and strengthen their ability to recognize which data is valid and appropriate for decision-making (Gezdur et al., 2024).

Table 10. The value of information in decision-making & Enhancement of skills and capabilities

paper	The value of information in decision-making	Enhancement of skills & capabilities
(Jussupow et al., 2021)	-Managers and employees need to focus on extensive data analysis (AI-based confirmation) instead of AI advice	-Reduces uncertainty -Increasing self-confidence -Employees' satisfaction and well-being
(Gezdur et al., 2024)	-Information reliability	-Increased collaborative discussions among our departments -Facilitating greater trust in the forecasting process -Expanding skillset
(Daly et al., 2025)	-Lack of sharing knowledge	-Take away the employee's personal advantage and place their contract payments at risk
(Gezdur et al., 2024)	-Information reliability -Accurate and relevant information improves Predictive value enhances information	-Promote reskilling of employees and offer a A comprehensive understanding of the situation

	accuracy, and timely access to information	

Another issue considered in improving organizational performance is enhancing the skills and capabilities of the organization's human resources. In this context, Table 11 presents results related to increasing skills and capabilities in direct relation to the decision scope. One of the main ways to create creativity and innovation in organizational decision-making is to foster an entrepreneurial mindset among future generations in the organization. To make employees more enthusiastic about adopting new technologies, organizations should encourage creativity and innovation and provide employees with solutions to adapt to organizational changes. The more employees and future leaders are aligned with technological advances, the greater the business growth, sustainability, and competitive advantage (Deniz Tonkalp, 2024). Factors that improve data quality and integrity in organizations include employees' problem-solving skills and increased digital competencies. With these skills and abilities, employees can evaluate the information and recommendations provided by AI and make appropriate decisions by interpreting these recommendations more effectively. As qualitative data analysis shows, improving data quality, along with strengthening employees' digital and problem-solving skills, ultimately increases the speed and effectiveness of the decision-making process (Babu et al., 2024). An important factor that employees in organizations pay special attention to is satisfaction and well-being. Increasing satisfaction, reducing work-related stress, and improving work experience can increase AI productivity. As AI productivity increases, employees' willingness to cooperate with and accept AI systems also increases. Organizations are required to avoid discrimination and bias to create more effective interactions between humans and AI systems. Also, they should maintain their social responsibility when implementing such technologies, as these practices create more trust. In addition, organizations should adopt creative and innovative strategies to encourage employees to accept and collaborate with AI. The more these strategies and policies are implemented, the more supportive, innovative, and safe the environment for employees will be, which ultimately creates a competitive advantage (D'Alara et al., 2025).

Table 11. Enhancement of skills and capabilities, & Decision scope

paper	**Enhancement of skills & capabilities**	**Decision scope**

(Deniz Tuncalp, 2024)	-Fostering an entrepreneurial mindset among the next generation (encouraging innovation, experimentation)	-Facilitate a smoother transition of leadership and ensure that the business's strategic direction remains aligned with evolving technological landscapes.
(Babu et al., 2024)	-Problem-solving skills and abilities -Improving Employees' Digital Skills	-Improve the quality and integrity of data that eventually enhances the speed and efficacy of the decision-making process
(D'Allura et al., 2025)	-Employees' satisfaction and well-being	-Optimizing AI productivity -Social responsibility -Creativity and innovation strategies and policies -Gain a competitive edge

Decision-making scope is a comprehensive process involving organizational performance and information dynamics. As shown in Table 12, decision-making scope is directly related to improved organizational performance. One key factor that all decision-makers, including physicians, rely on to build trust and increase satisfaction with their final decision or diagnosis is the use of data and accurate information analysis. When decision-makers use reliable and valid data, the likelihood of making incorrect decisions or encountering errors in the decision-making process is significantly reduced (Jussupow et al., 2021). Our data analysis showed that improving the efficiency and effectiveness of AI in organizations depends on increasing data collection, enhancing data quality, and strengthening data infrastructure. The more data comes from trusted, high-quality, and relevant sources – and the stronger the supporting security and storage infrastructure – the better AI systems will perform, resulting in more effective and accurate decision-making (Babu et al., 2022). Additionally, data protection strengthens the trust of employees and managers when making organizational decisions. This trust in data and confidence in information confidentiality led to improved decision-making processes and more accurate and timely analyses. Advanced decision-making also contributes to greater data transparency, clearer justification of decisions, and reduced uncertainty about AI-generated results. Moreover, secure and protected data encourages investors and decision-makers to pursue competitive advantages and respond more effectively and quickly to market changes, ultimately improving service quality and overall organizational performance (Condé & Münch, 2025).

Table 12. Decision Scope and Improvement of Organizational Performance

paper	Decision scope	Improvement of organizational performance
(Jussupow et al., 2021)	-Data-based confirmation	-Reduces uncertainty, increases physicians' final confidence in their diagnosis, and their satisfaction

(Babu et al., 2022)	-Enhancing Data Collection -Enhancing data quality -Enhancing the data infrastructure	-AI Efficiency Improvement -Improving effectiveness
(Condé & Münch, 2025)	-Data protection	-Improving decision-making processes -Transparency Enhancement -Gain a competitive edge

Table 13 shows that the value of information in decision-making is directly related to improved organizational performance. According to data analysis, information accuracy is one of the most important factors in enhancing the decision-making process. The more accurate, reliable, and trustworthy the information – and the more credible the predictions for employees and managers – the higher the quality of decision-making, ultimately reducing errors in organizational decisions (Gezdur et al., 2024). As previously noted, sharing information and knowledge among colleagues and managers leads to transparency, greater collaboration, and the generation of new ideas. These new ideas form the foundation for improving innovation efficiency, identifying new opportunities, and transforming traditional business models into advanced digital models. This transformation ultimately increases organizational productivity and performance (Barile et al., 2025).

Table 13. Improvement of Organizational Performance and the Value of Information in Decision-Making

paper	Improvement of organizational Performance	The value of information in decision-making
(Gezdur et al., 2024)	-Enhancing decision-making	-Information reliability -Improving the accuracy of information
(Barile et al, 2025)	-Upgrading the business model -Improving innovation efficiency	-Information and knowledge sharing/exchange

Discussion and conclusion

In this study, we aimed to summarise the findings from qualitative studies in a process model. In this model, AI and the decision-making process play a dual role: on the one hand, they shape the value of decision information and promote management development, and on the other hand, they can effectively overcome the challenges driven by AI. We have identified the following categories: v*alue of information in decision-making, enhancement of skills and capabilities, decision scope, Challenges Driven by AI, and improvement of organizational performance*. With the meta-synthesis, we aim to enrich the literature on AI and decision-making by highlighting the particular and extensive contextual knowledge gained through qualitative studies.

The following section discusses the theoretical insights, future research directions, study limitations, and practical implications.

Theoretical Contributions

The results of the meta-synthesis of this research show a new interpretation of the original studies on the relationship between AI and decision-making, and several important factors were identified. Based on knowledge management theory, implementing AI leads to accuracy, efficiency, and effectiveness in decision-making through the qualitative characteristics of information. However, meta-synthesis has identified several additional factors to improve the decision-making process. For example, AI influences the decision-making process by increasing the capabilities and abilities of managers and employees, the scope of decision-making, and organizational performance. However, previous studies have only used a unidimensional approach to explain the relationship between AI and the decision-making process. In this study, additional factors suggest that the relationship between AI and the decision-making process is multidimensional and not unidimensional. Moreover, most of the papers examined in this study adopted a qualitative interview approach to address the qualitative characteristics of information in the decision-making process (e.g., AI efficiency improvement (Booyse & Scheepers, 2024; Tuncalp, 2025), transparency enhancement (Condé & Münch, 2025; Nouis et al., 2025), employees' training (Tuncalp, 2025; Jussupow et al., 2021; Barile et al., 2025), and job security risks (Booyse & Scheepers, 2024; D'Allura et al., 2025; Babu et al., 2024). Accordingly, the findings on managerial capabilities, decision scope, and organizational performance improvement confirm that organizational performance and efficiency are critical elements in explaining the relationship between AI and decision-making.

Our findings indicate that, in addition to self-monitoring by managers and decision-makers in organizations, another factor that can affect decision-making outcomes is the monitoring of technology system performance by decision-makers. These distinctions between self-monitoring and system monitoring can be influenced by the decision-maker and lead to better decision-making (Jussupow et al., 2021). These decisions by managers can be influenced by AI-based systems, causing human decision makers to lose much of their power and control without even noticing it. Specifically, this leads to the indirect replacement of human decisions by AI-based systems, which play a vital role in organizations. Therefore, human decision makers must explicitly consider cognitive factors such as self-monitoring and system-monitoring, Biases (actual completeness of the data (Yang et al., 2024), and heuristics (which lead to over-reliance on AI or overlooking AI), the ability to detect errors and critically assess data without relying on their intuitive judgment when making decisions with AI-based systems (Jussupow et al., 2021). For example, during the COVID-19 pandemic, AI played a significant role in responding to patients and processing medical information (Condé & Münch, 2025). In other words, as new data and updates become available to AI systems, these systems will be able to adapt to new and critical situations (Condé & Münch, 2025). However, one of the key ways organizations can address the challenges of AI is to establish legal and regulatory frameworks. These frameworks require organizations to effectively manage challenges such as bias, transparency, and accountability. By establishing these guidelines, organizations can specify who is responsible for AI decision-making, how transparency in decision-making is maintained, and how biases should be identified and mitigated (Nouis et al., 2025).

One key feature of AI in decision-making is impartiality or neutrality, which refers to the absence of human sensitivities in AI-driven decision-making. Unlike humans, AI systems are not influenced by departmental biases or interpersonal dynamics. However, because AI algorithms are trained on biased data, their results may not always be impartial or unbiased (Condé & Münch, 2025). Other studies in social psychology have shown that AI can play an important role in reducing human biases. However, AI cannot replace humans in soft skills such as social understanding; instead, complementary interactions between humans and AI are necessary to establish an augmented decision-making process (Roumbanis, 2025). To achieve effective collaboration between humans and AI and to pave the way for new forms of 'hybrid intelligences', algorithms should first perform the necessary screening. In the second stage, human judgment can then make the required evaluations. Incorporating human judgment at this stage can help reduce discrimination and bias (Roumbanis, 2025). If these future hybrid intelligences are developed through mutual augmented human-AI learning processes, they could significantly impact meta-algorithmic discretionary judgments in the years to come (Roumbanis, 2025).

Integrating AI into organizations has become an inevitable necessity, requiring substantial educational effort by managers for the successful implementation of AI systems. These efforts and training prepare managers and decision-makers to integrate AI into organizations and increase their awareness of its capabilities and limitations (Daly et al., 2025). However, the absence of such training programs can result in organizations not accepting AI and falling behind their competitors (Condé & Münch, 2025). One of the most important challenges employees face in adopting AI in organizations is the risk of being replaced by AI, leading to higher unemployment rates. Organizations and governments need to reduce the impact of technology on job security and employment levels by upskilling and diversifying employee skills (Babu et al., 2024).

To address challenges such as (cost of establishment, lack of explainability, legislation, negative perception, data availability, and data), organizations should support not only tangible resources but also intangible resources, such as employee skills, organizational culture, knowledge, and change management ability, when developing the dimensions of AI capabilities. Additionally, to address the challenges of technological complexity, organizations should focus on developing talent resources, as having the best resources and infrastructure requires skilled people to implement successful projects (Babu et al., 2024). In addition, the lack of transparency of AI-based systems makes it difficult to determine whether decision makers are using appropriate explanations. Therefore, to reduce decision-making errors, human decision makers can use explainable AI to understand the reasons behind AI explanations. To benefit from new insights gained by analyzing system patterns, decision makers should actively review and evaluate AI explanations (Babu et al., 2024).

Equally important for research is that the benefits of AI, such as AI can add value through co-creation, are significant; it is also important to examine its negative implications and co-destruction. Co-destruction in aspects that range from job loss to privacy concerns, machine ethics, security issues, and negative developments of superintelligence. Negative implications such as AI-related fear, deskilling, and unemployment have raised concerns for organizations, requiring them to establish the necessary procedures and mechanisms. These processes must be aligned with the business goals and broader objectives of organizations to effectively develop and integrate AI applications (Papagiannidis et al., 2023). Therefore, organizations need to effectively govern AI because AI governance bridges the gap between accountability and ethics in technological advancements and ensures that AI aligns with business goals (Papagiannidis et al., 2023).

Practical Implications

As can be seen from the meta-synthesis model, the relationship between AI and decision-making is multidimensional and cannot be explained from only one aspect. In other words, as the results show, AI-based decision-making can be categorized into different groups, including *the value of information in decision-making, the enhancement of skills and capabilities, the decision scope, Challenges Driven by AI, and the improvement of organizational performance*. This framework can help managers select and implement a more appropriate form of the various factors of AI to improve decision-making in their organization.

The findings of this study have several practical implications. AI algorithms can provide managers in organizations with solutions based on data relevant to a specific issue or task. These algorithms are not a magic solution but serve as an augmentation and reinforcement tool to achieve greater accuracy and speed in decision-making (Booyse & Scheepers, 2024; Jussupow et al., 2021). Therefore, one important key factor that managers should consider when implementing AI is whether there is a willing need among employees and sufficient support from top-level management. Additionally, Managers also need to be aware that implementing AI is considered expensive because it requires human resources, which increases costs (Booyse & Scheepers, 2024). The deployment and use of AI in organizations must be accompanied by a careful cost-effectiveness assessment to determine whether these systems provide operational benefits and added value (Nouis et al., 2025).

Moreover, by understanding the role of emotions and ambivalence in decision-making, managers can learn from the complex processes involved in innovation and automation within organizations. In other words, by understanding this perspective and these roles, managers can make decisions that benefit both the organizational well-being and economic goals (D'Allura et al., 2025). In addition, as mentioned, the successful implementation of AI requires managers to have access to large amounts of data. Therefore, organizations with a data-driven policy and culture will achieve greater success than their competitors (Ransbotham et al., 2020). For successful AI adoption, managers must be aware of organizational laws and regulations and follow quality control procedures (Yang et al., 2024), as a lack of awareness of the legal and regulatory environment and unsupervised managers can lead to negative and ethical consequences for employees, including unemployment and loss of control (Booyse & Scheepers, 2024). The findings by Yang et al. (2024) indicate that the comprehensiveness of policies and the diversity of linking agents are important measures of innovation management. In this regard, regulatory bodies help align AI with ethical standards by developing guidelines that reduce inequalities and injustices among vulnerable groups (Nouis et al., 2025).

Another important consequence of the barriers organizations face in adopting AI is resource constraints (Yang et al., 2024), digital literacy gaps (De Massis et al., 2015; Tuncalp, 2025), and resistance to change. Leaders must adopt strategic approaches, including investing in training, seeking external expertise, and fostering a culture of innovation. Importantly, it is essential that human decision makers become aware of the different steps of decision-making, as this helps them identify errors and benefit from AI-based systems. In other words, unawareness of the decision-making steps can lead to failing to recognize the benefits of AI advice. Therefore, raising awareness of decision-making processes can lead to reaping more benefits in AI-based systems (Jussupow et al., 2021).

Furthermore, many scholars have emphasized the need for “ethical AI” (Booyse & Scheepers, 2024; Tuncalp, 2025; Barile et al., 2025), “responsible innovation,” and “AI alignment,” which require stricter rules and regulations. However, despite new laws, there is no guarantee that AI will be used with care and caution (Roumbanis, 2025). Finally, AI developers should use explainability tools to make AI decisions transparent, as these tools foster a greater sense of accountability among employees and help them feel safer when using AI in the decision-making process. This approach leads to a better understanding of the technology, establishes public trust among employees, and makes it easier to monitor AI. By doing this, instead of causing unemployment and job losses, employees can be transferred to areas where AI is not involved. What is more, by creating appropriate infrastructure for the use of AI systems, inequality can be reduced and promote social empowerment, allowing individuals in society to benefit from these advancements (Papagiannidis et al., 2023).

Study Limitations

This research project has certain limitations. First, we used a limited number of articles in this study, which may limit the generalizability of the results. Extending the dataset to a broader range of articles will help future research. Second, we attempted to ensure the completeness and relevance of the study by searching electronic databases. However, our focus on journal articles may overlook valuable findings from other sources. In other words, a broader range of literature could improve the robustness of the conceptual framework.

Furthermore, we employed a systematic, explicit, and transparent search process to ensure the accuracy of article selection and evaluation based on relatively objective criteria. We followed the criteria proposed by Sandelowski and Barroso (2007) for evaluating the qualitative data to determine whether the article was relevant to the synthesis. Furthermore, both researchers evaluated each article to validate the conceptual model. Although we applied transparent search processes in this paper, conducting qualitative studies remains a challenging endeavor. Therefore, researchers should consider these limitations in their studies as they will make an essential contribution to the development of future research efforts.

Future Research Directions

We coded the data extracted from the qualitative articles and then examined the role of AI in improving decision-making outcomes, optimizing resource allocation, and facilitating strategic planning. Otting and Maier (2018) argue that factors such as job satisfaction, emotional intelligence, and employee trust in the work environment can enhance employee performance, improve employee-organization relationships, and improve management ability. These elements also help reduce management errors and motivate employees to utilize AI to solve problems and capitalize on various opportunities. However, efficient distant collaboration between managers and staff through AI tools is a crucial component that has not been adequately addressed in this research. Furthermore, by comparing the perspectives presented in the theoretical literature with the reality of the workplace, researchers can gain a deeper understanding of how AI influences the decision-making process.

CHAPTER III

Exploring the form of Human and AI collaboration in an organization

Abstract. Technological advances have expanded the collaboration between humans and artificial intelligence (AI) in the workplace, driven by the use of large data sets that enable more accurate analysis and predictions. In this study, we categorize four forms of human-AI collaboration: (1) conjoined agency with legacy mode, (2) conjoined agency with compliance mode, (3) conjoined agency with augmentation mode, and (4) conjoined agency with autonomous mode. We have developed a human-AI framework in which we discuss the most important characteristics. We then explain each one of the conjoined agency modes by reviewing the literature. In doing so, we discuss in detail the different ways in which organizations can select depending on the type(s) of conjoined agency they use in their organizational decision-making.

Keywords: Decision Delegation, AI Delegation, Conjoined agency, Human-AI Collaboration Matrix

Introduction

Advances in technology have expanded collaboration between humans and artificial intelligence (AI) in the workplace, driven by the use of extensive datasets that enable more accurate analysis and forecasting. This integration reduces risks, enhances efficiency, and offers more effective decision-making (Candrian & Scherer, 2022). Based on Husairi and Rossi's (2024) perspective," AI refers to programs, algorithms, systems, and machines that imitate human intelligence in tasks such as learning, planning, and problem solving through higher-level, autonomous knowledge creation." (Ahmad Husairi & Rossi, 2024). In today's world, as we move towards a remarkable transformation in digitalization and robotics, the implementation of AI and its various aspects, including machine learning, deep learning, neural networks, natural language processing, and rule-based expert systems, can have a significant impact on the economic, social, cultural, and financial sectors (Brynjolfsson & McAfee, 2014). Despite this broad spectrum, we have aimed to describe the relationship between humans and AI at a general level, without distinguishing between different classifications of AI. Studies such as Crowston and Bolici (2019) have specifically addressed the relationship between humans and AI by focusing on machine learning with an emphasis on human jobs and discussing three different types of automated tasks, including decision support, blended decision-making, and complete automation. In contrast, our study focuses on a broader analysis of the relationship between humans and AI in different modes. Our goal in this study is not to analyze the relationship between each classification of AI and humans. Therefore, we developed a matrix to examine the overall relationship between humans and AI.

Existing studies reveal contrasting attitudes towards the collaboration of AI and human agents in decision-making processes and their execution. On the one hand, it has been traditionally held that humans are responsible for controlling and supervising AI. However, some technologies have achieved a level of autonomy in decision-making that has significantly reduced the need for human intervention (Murray et al, 2021; ServiceNow, 2020). In other words, these technologies may limit, complement, or completely replace human performance, genuinely possessing capabilities surpassing human intelligence in business and investment domains (Schrage, 2017). Conversely, an opposing viewpoint asserts that recent advancements in AI have outperformed human intelligence in terms of productivity, efficiency, and safety (Kaasinen et al., 2015). However, in fields such as medicine, human experience, and knowledge management, particularly with access to sensitive data that AI cannot comprehend, this often results in higher predictive accuracy (Hemmer et al., 2023). From a human-centric perspective, employees consider satisfying work experience and job satisfaction significantly more valuable [9, 10]. While previous studies have explored contrasting viewpoints, collaboration between humans and AI can significantly improve decision-making performance. AI is capable of processing large, time-consuming datasets, contributing to increased job satisfaction among employees (Pink, 2011). On the other hand, managers, endowed with extensive experience (Fügener et al., 2021) and capable of actively rethinking decisions, can achieve greater decision-making accuracy, reduce biases (Lu & Zhang, 2024), and enhance employee motivation and career prospects (Pink, 2011). The collaboration between humans and AI results in improved operational efficiency and economic performance compared to what either AI systems or humans could achieve alone (Fügener et al., 2021).

Previous studies have documented both acceptance and resistance among human decision-makers when integrating AI into their processes (Kleinmuntz, 1990; Dawes, 1979). However, further research has challenged this perspective by focusing on individuals' responses to algorithmic errors (Dietvorst et al., 2014). Although the exploration of collaboration between humans and AI, as well as the factors influencing individuals' trust in delegating tasks to AI, remains limited, a few studies have addressed the motivations for delegating decision-making to AI. For example, a recent study (Hemmer et al., 2023) explores how task delegation to AI could enhance job satisfaction and self-efficacy. The authors investigate how algorithms delegate tasks to humans based on the evaluation of their skills and expertise. Furthermore, they examine the impact of this task delegation, highlighting a reduction in repetitive and tedious work, increased job satisfaction among employees, and enhanced long-term organizational success (Hemmer et al., 2023).

Factors contributing to humans' distrust in delegating decision-making to other humans (human agents) or algorithms (AI agents) have not been fully explored. For instance, studies have shown that even when accepting lower expected outcomes, individuals display less inclination to delegate decision-making to another person (Dominguez-Martinez et al., 2014). Additionally, other studies have shown that managers often exhibit a reluctance to delegate tasks to humans for several reasons, such as risk aversion (Di Vaio et al., 2022) or to AI systems, since managers perceive inadequacies in AI expertise and knowledge (Soni et al., 2020).

This paper aims to shed some light on the forms of collaboration between AI and Humans in decision-making. Starting from the conceptual framework of the conjoined agency proposed by Murray et al. (Murray, Rhyme, & Sirmon, 2021), we develop a similar framework focused on Human-AI collaboration. Based on the literature review, we identify four different collaboration modes based on who, between AI and Humans, makes the decision or executes the decided action. The matrix developed in this study can serve as a basis for academics to uncover deeper and more complex relationships between technology and humans, as the relationship between AI and humans becomes increasingly important. Furthermore, this matrix can provide the basis for technology experts to consider human characteristics when modeling and programming AI by being aware of the different dimensions of technology.

In the following sections, we will examine some theoretical studies used to initiate the framework describing the four scenarios. The third section provides a detailed description of each collaboration mode. Ultimately, the discussion and conclusion close this manuscript.

Research Protocol Theoretical Background

In recent years, companies and organizations have used AI to create efficient and trustworthy workplaces, helping employees prioritize the selection between human or automated management agents (Höddinghaus et al., 2021). In this regard, based on Murray's study (Murray, Rhyme, & Sirmon, 2021), collaboration between humans and technology is categorized into four types of conjoined agency. Each type is based on a different combination of technology-human collaboration, considering who is involved in the "protocol development" and the "action selection". Moreover, each combination requires a specific set of technological functionalities. In this context, a conjoined agency refers to the shared capacity and capability of humans and non-humans (technology) to perform tasks more effectively to achieve specific organizational goals. In other words, the collaboration between humans and technology involves the ability to perform tasks with a specific intent, meaning that each has a role with defined purposes and goals in decision-making.

Table 1. The human-AI collaboration Matrix.

		Decision-making	
		Human	**AI**
		Legacy mode	**Compliance mode**
Decision Execution	**Human**	-Delegation of tasks to human agents for higher performance accuracy. -Algorithm aversion and trust in human actors. -Experience, flexibility, and Deep human thinking in handling cases with low frequency. -Desire for control and resistance to new technologies.	-Participative decision-making. -Impact on Job Satisfaction and Self-Efficacy. -Decision-making by AI based on predefined data and rules. -Collaboration between humans and AI reduces tedious tasks and improves overall performance.
		Augmentation mode	**Autonomous mode**
	AI	- The role of AI in decision execution and workload reduction. - The use of AI for delegation and recognition based on partners' suitability and uncertainty. - Meta-Knowledge's Impact on Delegation Decisions. - Inversion can drive for better performance.	-AI's unbiased, less self-interested, and less intentional nature. -AI perceives less intentional capacity and fewer perceived social risks. -Development of computational autonomy. - AI learns from large amounts of training instead of relying on defined rules.

Building on the conjoined agency framework proposed by Murray et al. (Murray, Rhyme, & Sirmon, 2021), we develop a conceptual model that focuses specifically on collaboration between AI and humans. We distinguish between decision-making processes and execution processes. After developing the initial framework, we reviewed the literature and selected studies that describe and analyze cases of each of the mentioned forms of collaboration between AI and humans. The framework was refined several times based on the analyzed literature, leading to the final version shown in Table 1.

Our framework identifies four modes of collaboration between AI and humans, depending on who is responsible for decision-making and who executes the actions. In legacy mode, organizations rely less on AI, with managers using their expertise and experience to make decisions and execute tasks. In contrast, in compliance mode, organizations rely heavily on AI to ensure accountability in decision-making. Augmentation mode is characterized by companies gradually anticipating operational changes, with AI increasingly taking the lead in executing tasks. Finally, autonomous mode requires ubiquitous connectivity, unlimited computing power, and big data, allowing AI to dominate both decision-making and execution, providing a competitive advantage.

The following section provides further details about each form of human-AI collab- oration supported by the selected literature.

The four Human-AI collaboration Modes

The collaboration between humans and AI substantially influences organizational processes. This complex collaboration requires specialized human expertise on the one hand and specific AI capabilities for data analysis on the other. The collaboration between humans and machine agents in the decision-making and executive processes creates a shared capacity called conjoined agency (Murray, Rhyme, & Sirmon, 2021). This study discusses four modes of conjoined agencies. The first mode assesses the human aspect, where managers are responsible for making decisions and executing the decided actions. In this scenario, managers are responsible for making and implementing decisions using their knowledge and expertise. In the second mode, managers are accountable for making organizational decisions, while AI is responsible for executing the actions. According to the third mode, AI is accountable for making final decisions. On the other hand, managers are responsible for executing the actions. In the fourth mode, AI is responsible for making decisions and executing the corresponding actions.

Legacy mode

Economic theory posits that the concept of risk aversion motivates investors to seek out the highest expected payoffs because of inherent risk. However, capital investors avoid doing so when they face unintentional outcomes stemming from the actions of third parties. Betrayal aversion will thus make people less willing to take risks when decision-making is delegated to the agent (Bohnet et al., 2008). In fact, human intention and betrayal aversion are crucial factors in the growing concern and avoidance of social risk. This social risk results in betrayal and untrustworthy conduct as a result of individuals' negative motivations and intentions (Butler & Miller, 2018). In this regard, social preferences, as a component of individual tendencies and attitudes, involve considering the benefits and advantages of others in decision-making processes (Bohnet et al., 2008). When making the decisions to delegate, it is important to consider all aspects related to cost-benefit analysis. However, the decision-making process is often suboptimal because this is not always the case (Bobadilla-Suarez et al., 2017). Studies indicate that individuals are less likely to entrust decision-making to another person, even if it means accepting lower expected payoffs (Dominguez-Martinez et al., 2014). There are multiple factors contributing to this behavior. Firstly, individuals are intentionally willing to incur significant financial expenses to retain authority over decision-making, a phenomenon referred to as premium control. This willingness affects not only individual choices but also the way economic and managerial behaviors are interpreted and analyzed (Owens et al., 2014). Consequently, people's desire for control appears to stem primarily from loss aversion, fear of others making mistakes and losing something, as well as irrational fear resulting from biased and false intentions (Dominguez-Martinez et al., 2014). These factors outweigh overconfidence and subjective beliefs (Owens et al., 2014). Many studies have explored humans' propensity to control decision-making from a psychological perspective (Benjamin et al., 2012), but the economic implications of this tendency have not received as much attention. Uncontrollable social risk is created by the desire to maintain control over decision-making even in the face of unknown or ambiguous situations (ambiguity aversion). This can be attributed to a variety of reasons, including the agent's inferior knowledge, inconsistent organizational priorities and objectives, conflict between personal interests and investor interests (self-interest) (Bobadilla-Suarez et al., 2017), and the human capacity for intentional action (Butler & Miller, 2018). Many investors engage in the micromanagement of their subordinates due to their inherent desire for self-reliance in decision-making, which prevents the development of employees and demotivates them, despite their high levels of expertise and skills (Owens et al., 2014).

The theory proposed by (Kőszegi & Rabin, 2006) posits that employees' irrational behavior and tendency to be loss-averse can result in managers losing control, even if such decisions lead to lower payoffs. The purpose of this is to exert managerial control and mitigate the risk of unforeseen losses or irrational conduct by employees. Social risk is another factor that discourages managers from handing over control. According to Butler & Miller (2018) Social risk does not arise from human actions but rather depends on the intentional ability of the counterparty. In other words, there will be an increased social risk premium when control is not delegated to an agent whose interest conflicts with the principal (Butler & Miller, 2018). Studies show that objectivity, being in control, and subjectivity, feeling in control, are two separate issues; this means that the desire to assign decision-making authority to others grows even though there is still a sense of control (Friedland et al., 1992). In other words, the subjective perception of control holds greater significance than the objective reality of decision-making authority. This sense of control diminishes uncertainty by relying on the decision-maker's past performance as well as intentions and motivations (Spreitzer & Mishra, 1999). The third factor contributing to the unwillingness to delegate decisions, which can result in reduced efficiency or negative consequences for the organization, is the inherent utility of authority (Bartling et al., 2013). Put differently, the authority and ability to make decisions create a sense of contentment and self-value in individuals (Benz et al., 2005). Power is one of the fundamental human needs, according to the motivation theory (McClelland, 2006). Additionally, the self-determination theory states that autonomy and freedom in decision-making promote psychological development, integrity, and well-being (Deci, 1985).

Research in the fields of psychology and organizational economics suggests that managers' strict control tendencies may cause behavioral biases among employees and decrease their willingness to cooperate (Dominguez-Martinez et al., 2014; Falk & Kosfeld, 2006). In this regard, apart from managers' desire for control despite its hidden expenses, centralization is another factor that diminishes employee motivation and undermines organizational efficiency (Dominguez-Martinez et al., 2014). Nonetheless, strategic ignorance—also referred to as real authority—is a fundamental component of assigning decision-making authority to subordinates. In other words, when managers in an organization possess excessive information and make decisions unilaterally, the employees will be less motivated to engage in the decision-making process (Aghion & Tirole, 1997). However, delegating tasks to employees results in job satisfaction and reveals the natural value of that job, which leads to a sense of accomplishment and responsibility, dedication to the organization's objectives, and ultimately, long-term organizational success (Hemmer et al., 2023). In this regard, Candrian & Scherer (2022) showed that users tend to delegate to AI agents when they face losses. In other words, managers employ AI to enhance security measures and achieve cost-efficiency. Operational transparency is another strategy that enhances the delegation of decision-making authority to human agents. Put differently, rather than prioritizing the explainability of AI, it is crucial to provide clear explanations for the actions and decisions made by human agents. This decision-making transparency can reduce social risk, uncertainty, and potentially malignant intentions (Candrian & Scherer, 2022).

AI exhibits higher levels of accuracy and efficiency as a result of its ability to leverage vast quantities of data. Nevertheless, it faces difficulties in areas characterized by random and uncertain scenarios (Guo & Wang, 2015). By contrast, managers possess side information and exhibit greater adaptability in challenging and unfamiliar situations, depending on their personal experiences and tacit knowledge. They excel at identifying uncommon or low-frequency cases and demonstrate superior performance with greater precision. Accordingly, they will generate novel ideas and enhance organizational growth (Hemmer et al., 2022; Lou & Wu, 2021). Therefore, humans' hesitance to utilize AI algorithms and predictions in decision-making stems from the superior adaptability and advancement of human progress in contrast to algorithms (Einhorn & Hogarth, 1975), as well as their lower tolerance for algorithmic errors (Dietvorst et al., 2014). In this regard, studies show that the collaboration between humans and AI has two main benefits. Firstly, it provides managers with access to internal data, which enhances their decision-making abilities (Kaplan & Haenlein, 2020; Sun et al., 2019). Secondly, AI contributes to the generation of diverse innovative ideas (Zhang et al., 2023). Conversely, the poor transparency of information caused by the intricacies of machine learning algorithms and the inadequate knowledge and expertise of employees due to insufficient training or the rapid advancement of technology reduces the trust in AI-made predictions (Lu & Zhang, 2024). Therefore, the challenges of cooperation between humans and AI that result in reduced performance and efficiency include human distrust of machines (Jacovi et al., 2021), over-reliance on machines (Fügener et al., 2021), over-cautiousness (Lu & Zhang, 2025), and hyper-focus on details (Wang et al., 2023). With the rapid development of technology, it has become essential for organizations to provide ongoing training and improve training procedures, even for experienced employees and managers. Therefore, managers need data literacy training programs and decision-making improvement loops to increase organizational productivity and efficiency (Hvalshagen et al., 2023).

Compliance mode

Modern organizations need to delegate tasks to subordinate decision-makers who have higher expertise and external commitment to the tasks to achieve higher efficiency (Sengul et al., 2012). Unlike delegating tasks, which involve transferring decision-making authorities to another person (Lupia, 2015), participatory decision-making involves the active involvement of two groups. Based on the agency theory, the principal delegates the responsibility of decision-making to a trusted individual known as the agent (Lupia, 2015). When delegating tasks to subordinates, two important factors should be taken into account. Firstly, the person should possess the necessary skills, knowledge, ability, competence, and high efficiency (Sengul et al., 2012). Secondly, there should be no conflict of interests or goals that would hinder progress in the same direction (Lupia, 2015). It is also noteworthy that managers' motivations in decision-making differ from those of shareholders and owners when they are given delegated authority. This is because managers are more committed to their decisions due to their access to more information and specific skills. As a result, they can engage in more effective interactions with competitors and enhance the overall performance of the organization (Sengul et al., 2012).

Managers refrain from delegating tasks to AI for various reasons, as indicated by research on organizational behavior. These reasons include the manager's aversion to taking risks (Di Vaio et al., 2022), inadequate understanding and familiarity with systems from a managerial standpoint (Hemmer et al., 2023), and distrust in AI designers' ability to handle additional responsibilities (Leana, 1986). Consequently, this leads to both intrinsic and extrinsic job dissatisfaction among employees (Hemmer et al., 2023). Self-efficacy is a crucial factor in understanding and explaining the impact of delegating tasks to AI on performance and job satisfaction. Self-efficacy, defined as the belief in one's ability to effectively accomplish a task, is a crucial factor in empowering and motivating employees (Bandura, 1977). Although a few studies have reported the positive effects of delegation on self-efficacy, its role in improving organizational performance has been proven (Lunenburg, 2011). In this regard, the employees' awareness of the fact that tasks are delegated by AI does not affect their job performance and satisfaction. In other words, awareness of delegation neither increases nor decreases the performance of human tasks (Hemmer et al., 2023).

Previous studies have not addressed the ability of humans and AI in situations where tasks are delegated to AI (Fügener et al., 2021; Bondi et al., 2022). (Hemmer et al., 2023) posits that the collaboration between AI and humans will result in enhanced team performance. AI will analyze and recognize human skills and expertise, and then offer them suitable opportunities, resulting in enhanced human task performance. Conversely, this collaboration reduces the repetitive and tedious tasks performed by humans. Although the delegation of tasks by AI enhances employee performance, humans often struggle to effectively delegate tasks due to their limited ability to recognize and comprehend complex tasks. Nonetheless, despite humans' poorer delegating performance, they are still willing to work with AI (Fügener et al., 2021). Due to the inability of humans to evaluate complex tasks and their incomplete understanding of AI's capabilities, humans entrust decisions to AI, which leads to false self-confidence and arbitrary and illogical decision-making (Fügener et al., 2021).

Because of technological advancements and the abundance of data, these systems have become more accurate, less explainable (Zhu et al., 2021; Huang et al., 2021), and capable of faster analysis and processing (Lu & Zhang, 2024). Since users typically prioritize accuracy over transparency, managers should focus on enhancing the efficiency and accuracy of AI systems while reducing the emphasis on procedural transparency. In fact, complex explanations regarding the internal functioning of systems are of little importance (Candrian & Scherer, 2022). Collaboration between humans and augmenting technology takes place when the technology analyzes vast quantities of data and subsequently offers humans the anticipated recommendations and suggestions to address the problem. In other words, humans are the ones who ultimately make decisions based on their expectations (Jordan & Mitchell, 2015). Machine learning algorithms have recently been employed in courts to forecast and furnish judges with information regarding various aspects of cases, such as the length of the sentence and the conditions of care for the defendants. Nevertheless, these predictions fail to account for all the details associated with the crime, rendering them unhelpful for judges who should not indiscriminately rely on these technologies without considering each case individually (Berk, 2019; Berk & Bleich, 1992). Other technologies, such as arresting technology, cannot establish their guidelines, norms, or protocols. However, it can choose actions automatically under specific conditions or based on predefined conditions without the need for human intervention, in contrast to other technologies. In other words, humans cannot change protocols and rules due to the limitations of this technology (Murray, Rhyme, & Sirmon, 2021). For example, blockchain-based smart contracts autonomously carry out actions upon fulfillment of predetermined conditions, resulting in higher levels of security, transparency, and changeability (Murray et al., 2019).

Augmentation mode

In recent years, AI models have outperformed human intelligence in some areas. For example, algorithmic management is a prominent characteristic of the platform economy, wherein it assumes the responsibility of transferring management tasks (Benlian et al., 2022). This concept involves the utilization of intelligent algorithms to play the role of both managers and employees, as opposed to traditional management methods (Zuboff, 1985). An important application of algorithmic management systems is in the gig economy; for example, online platforms such as Uber delegate tasks to these systems to make decisions in place of traditional managers (Benlian et al., 2022). Previous studies have examined algorithmic management from two contrasting perspectives. Algorithmic management methods have been highlighted for their ability to enhance decision-making accuracy, improve efficiency, and facilitate the scalability of business activities (Kellogg et al., 2020). In other words, delegating tasks to AI can lead to job satisfaction and self-efficacy, which is consistent with the findings of Hemmer et al. (2023). However, these systems present challenges such as distrust, dissatisfaction stemming from the absence of human interaction and automated decision- making, lack of transparency, and ongoing monitoring (Henfridsson, 2019). Nevertheless, predictive accuracy in high-risk fields like medicine is enhanced by human knowledge and experience, which is influenced by factors such as access to information and the patient's family history (Hemmer et al., 2023). AI models may have limited capacity to process and analyze data. Moreover, insufficient access to training data and exposure to outliers or unknown data can reduce decision-making accuracy and performance (Hemmer et al., 2023). From a humanistic perspective, AI technologies prioritize efficiency, effectiveness, and safety over spiritual aspects such as pleasure and a sense of usefulness (Kaasinen et al., 2015). On the other hand, enjoyable and spiritual work experience for people with higher values is not a way to avoid unpleasant work (Hassenzahl et al., 2013).

Complementary knowledge is a fundamental requirement for successful human-AI collaboration. A combination of humans and AI can outperform either of them alone in terms of efficiency or economy (Fügener et al., 2021). AI is beneficial in two ways. Firstly, it fosters innovation in problem-solving by effectively processing and analyzing vast and monotonous datasets. Secondly, it enhances job satisfaction in the workplace. Conversely, working in a dynamic and challenging environment motivates employees and increases job opportunities (Pink, 2011). Managers who have a wide range of experiences struggle to clearly articulate their decision-making rules, a phenomenon referred to as Polanyi's paradox, can greatly enhance organizational efficiency and productivity (Fügener et al., 2021). Managers who have access to abundant and detailed information, as well as algorithmic explanations (machine explanations), can actively evaluate decisions. This leads to enhancing the overall accuracy of decision-making and mitigating various biases, such as gender biases. In other words, these factors are the necessary prerequisites for active rethinking (Lu & Zhang, 2024). Managers may find the machine explanations to be inadequate and unhelpful during the rethinking process. Therefore, they employ relevant features to communicate with them (Lu & Zhang, 2024). As stated earlier, managers with different levels of experience and knowledge analyze the AI recommendations. Experienced managers may overlook machine recommendations, but even if they do not directly utilize them, these recommendations stimulate a process of rethinking that ultimately enhances organizational performance (Lu & Zhang, 2024). In these cases, humans and AI must understand and recognize each other's capabilities. For example, after evaluating and recognizing its own ability, AI delegates a task that requires human expertise and knowledge (Fügener et al., 2021). Metaknowledge is an essential tool for complement identification. This concept entails assessing the abilities and capabilities of each partner (AI or human) and recognizing when and how to delegate extremely important tasks. In other words, meta-knowledge allows individuals to recognize their abilities and effectively delegate tasks to humans or AI (Yzerbyt et al., 1998; Evans & J.G.F., 2011). An essential subject in metal knowledge pertains to individuals' capacity to effectively assess their knowledge and competencies in the face of intricate and challenging tasks. The lack of meta-knowledge can also lead to incorrect decisions about the difficulty of tasks, over- or under-confidence, and ineffective strategies (Russo & Schoemaker, 1992). An effective way to address the absence of meta-knowledge is formal education in schools and universities, which helps individuals identify their strengths and weaknesses and also encourages teamwork by acknowledging errors and ensuring logical and procedural coherence (Fügener et al., 2021).

Advisory algorithms are known as decision-support systems (Alter, 1977). These tools provide managers with the necessary information and suggestions for decision-making, which is called augmenting human decision-making. Nevertheless, the managers are responsible for the ultimate decision (Önkal et al., 2009). The utilization of advisory algorithms by investors has increased as a result of their superior decision-making capabilities (Cardillo & Chiappini, 2024). Advantages of these advisory systems include reduced biases, more timely financial forecasts, lower financial consulting costs, and increased productivity (Baker & Dellaert, 2017). Advisory algorithms are more accurate than managers in evidence-based prediction. This contradicts the decision-making literature known as algorithm aversion, which suggests that people tend to distrust algorithms (Dietvorst et al., 2014). Hence, the contrasting notions of human engagement with algorithms vary based on the circumstances and nature of the tasks at hand. (Dietvorst et al., 2018) asserts that although algorithms perform better and make fewer mistakes than humans, humans are more sensitive to algorithmic errors. In other words, the tendency of most individuals to react to algorithmic errors causes a loss of trust in algorithms, which is known as algorithm aversion. In contrast, (Logg et al., 2019) demonstrated that humans are more willing to utilize the capabilities and predictions of algorithms, a phenomenon referred to as algorithm appreciation.

Autonomous mode

In this case, these systems can process and analyze huge and varied data without human intervention. Moreover, they are constantly discovering and learning more optional methods through data analysis techniques and exposure to new data and modifications in the algorithmic framework. These technologies have minimized the need for human interventions because they are self-sufficient and independent in making decisions and implementing protocols (Murray, Rhyme, & Sirmon, 2021). For instance, unstructured machine learning programs, like videos and audio files, autonomously analyze data, establish rules, and subsequently execute them (Murray, Rhyme, & Sirmon, 2021). The rapid advancement in computational autonomy (Shrestha et al., 2019) and its ability to match or surpass human capabilities (ServiceNow, 2020) have made it a key focus in technology for gaining a competitive edge (Schrage, 2017). Some of the unique capabilities of these systems include fraud detection, traffic planning (Shrestha et al., 2019), and autonomous driving (Dowling et al., 2020). Other technologies, such as agent technologies, select rules and guidelines based on their capabilities in the development of protocols. In other words, these technologies restrict, enhance, or supplant human capabilities. The emergence of these technologies has caused a shift in the focus of agency from humans to AI and the collaboration between them (Murray, Rhyme, & Sirmon, 2021). The emergence of big data and data processing advancements has transformed AI into a superpower system with immense capabilities. Nevertheless, these advancements have resulted in a dearth of transparency, particularly in deep learning models, and the incomprehensibility of the decision-making procedure (Rai, 2020). The absence of transparency poses various problems, such as diminished user trust and substantial expenses associated with elucidating the underlying logic of algorithms (Candrian & Scherer, 2022). In a study conducted by Dietvorst et al. (2014), participants demonstrated a strong inclination to exclusively depend on their own decisions. Therefore, a subject recently analyzed by domain experts is the provision of clear and comprehensible explanations generated by machine learning models (Alufaisan et al., 2017). These techniques not only provide managers with AI recommendations understandably and reliably but also improve decision-making performance (Adadi & Berrada, 2020). In other words, the shortage of explanations provided by these models diminishes managers' confidence in them (Siau & Wang, 2018). In this way, providing managers with detailed information on AI-made decisions *(Lu et al., 2020)*, using post-hoc explanation methods, and limiting AI's role to a mere consultant (Dietvorst et al., 2018) all make these models work better and attract managers' trust (Mohseni et al., 2021). However, all aspects of explanations should be evaluated by AI. For example, unintuitive and unfamiliar explanations (Schmidt & Biessmann, 2020) or incomplete and biased information (Rudin, 2019) reduce managers' trust and cause the dissemination of false information.

Recent advancements in AI, particularly in deep neural networks (DNNs), have facilitated innovations in areas such as generic perception AI tasks and medicine (Kononenko, 2001; LeCun et al., 2015). The main objective of AI is to imitate human decision-making. However, limitations such as the lack of a comprehensive description of idiosyncratic decision-making rules and the existence of implicit and unconscious knowledge and abilities (known as Polanyi's paradox) restrict the application of AI technologies (Autor, 2014). Instead of relying on explicit human rules, DNNs use huge datasets to discover and extract data in order to overcome these limitations (Schmidhuber, 2015). According to the construal level theory (Trope & Liberman, 2010), humans believe that AI has both general and more realistic (specific) goals. The majority of people believe that, unlike humans, AI technologies such as robots or computer programs with predetermined thoughts or goals are incapable of performing intentional actions or voluntary tasks (Candrian & Scherer, 2022). In other words, AI agents lack self-driven goals (Kim & Duhachek, 2018), have less intentional capacity (Harbers et al., 2017), are less interested and less biased (Cardinaels et al., 2018; Fogg, 2009), and are less likely to perceive social risks (Candrian & Scherer, 2022). On the other hand, Gray et al. (2007) argue that humans are able to experience emotions such as pride, shame, fear, hunger, and desire, and possess capabilities such as reasoning, planning, and self-control. The theory of behavioral economics states that people's decisions are influenced by behavioral biases such as preference for certainty, social factors, and emotions that do not function rationally (Thaler, 2016). This is in contrast to the standard economic theory, which assumes that people's preferences are unchanging and unaffected by social values and emotional states (Dowling et al., 2020).

Discussion

Understanding how the relationship between technology and humans affects each other has always been one of the controversial topics of the scientific community. For this reason, it is necessary to examine a set of human-AI factors in more detail. In this context, we have summarized four forms of these factors in a matrix in which the relationship between humans and AI divides the ability for purposeful implementation differently. This matrix influences the scope and predictability of change and the interplay between the individual factors. There are contradictory findings about human collaboration with assistive technology, including cardiac surgery machines (Pisano, 2015), virtual collaboration tools (D'Adderio, 2001), and PowerPoint software (Kaplan, 2011). Assistive technologies have beneficial effects on organizational performance; for example, they provide previously unavailable information (Leonardi, 2013), prompt changes in consulting approaches to foster new collaborations (Leonardi, 2013) and facilitate organizational transformations and novel procedures (Desanctis & Scott, 2015). Conversely, the drawbacks of these technologies include the failure to adjust to the adopted emerging technologies and a reluctance to embrace them (Leonardi, 2013), as well as skepticism regarding the efficacy of utilizing such technologies (Lapointe & Rivard, 2005). Stimulating human deep thinking is one of the fundamental elements of promoting the benefits of collaboration between humans and AI. In other words, when collaborating with machines, humans can use deep thinking to make better decisions and improve their performance (Fügener et al., 2022). Researchers have examined dual-process theories of reasoning to accomplish these objectives. This theory encompasses two cognitive systems.

System 1 rapidly and instinctively processes information to arrive at a prompt decision, whereas System 2 requires logical reasoning and analysis (Kahneman, 2011). Two basic conditions must be provided to motivate individuals to use System 2 processing. The first condition states that tasks requiring critical thinking, problem-solving, and challenging situations (Amit & Shapiro, 2013) not only improve decision-making accuracy but also encourage cooperation and participation in decision-making (Oskamp, 1965). Useful cues are crucial in enhancing the decision-making process as part of the second requirement for promoting deep thinking. These cues necessitate a more thorough evaluation of decisions, which involves reexamining information and decisions, comparing decisions to the previous or traditional decision scheme to identify strengths and weaknesses, and coming up with original and creative solutions (Hollnagel, 1987).

Studies that have discussed the collaboration between humans and AI indicate that two groups of people resist the adoption and use of machines (Allen & Chen, 2022). The first group consists of people who use and act on AI advice but do not fully trust AI tools and technologies *(Tang et al., 2023;* Commerford et al., 2022). The second group comprises ordinary consumers who reject AI services for various reasons. For instance, consumers may refuse to accept services offered by chatbots because of their inadequate knowledge of these computer programs. Another reason for this resistance is the lack of empathy and the fact that chatbots are unable to fully comprehend and address consumers' needs and problems (Lou & Wu, 2021). In addition, consumers perceive AI robots as a threat to humans due to their superior performance in repetitive, low-skilled, and dangerous tasks, leading to the loss of many *jobs* (Autor & Dorn, 2013; *Lu et al., 2017).* The negative consequences of resistance to AI adoption can be mitigated by improving the knowledge, experience (Tong, 2021), and flexibility of managers and consumers, and encouraging them to adjust themselves to AI advice (Dietvorst et al., 2018; Tong, 2021). Overconfidence in AI has the potential to impair the capabilities of managers and impede the development of effective collaboration between managers and AI (Fügener et al., 2021). Despite the overall distrust in algorithms, algorithmic advising has gained popularity in recent years because it is less expensive than hiring human experts (Foltice & Ilcin, 2019). However, measuring algorithm appreciation and human decisions is a difficult task. For example, anticipating the outcomes of some decisions— such as how climate change and political events will turn out—years or even decades in advance is very hard (Logg et al., 2019). The advancement of AI has enabled managers to easily access various data and evaluate the effects of internal and external factors on corporate performance (Richtel, 2013). However, organizations would be deprived of the advantages of algorithmic advice if they solely focus on data collection and analysis (Logg et al., 2019).

To enhance their efficiency and organizational performance, organizations and expert managers need to delegate authority to AI (Schrage, 2017). AI agents can improve the speed and accuracy of decisions in high-risk investments by avoiding behavioral investments—*i.e.*, decisions based on emotions, instinctive behaviors, and prejudices—and improving the quality of decisions made during evaluations (Herrmann et al., 2015). On the other hand, training algorithms with a set of biased data (including prejudices and false preconceptions) poses serious challenges to the decision-making process (ServiceNow, 2020). Accordingly, overconfidence in AI in the decision-making process raises behavioral biases related to the quality of input data, decreases reliance on managers' knowledge and experience (Dowling et al., 2020), and increases the likelihood of accepting incorrect preferences and beliefs (Dowling et al., 2020). To avoid any conflict or interference, managers need to clearly define the authorities and duties of AI and humans. However, it can be very complicated and challenging to distinguish between human and AI authorities when making decisions (Schrage, 2017). Furthermore, AI systems continue to analyze data under human supervision using data provided by humans. Nevertheless, as technology advances, human supervision is becoming less stringent, making it harder for AI to detect biased data. Stated differently, for a successful implementation of AI, managers need to supervise and train AI algorithms to avoid various biases (ServiceNow, 2020).

Conclusion

The Conjoined Agency Framework aimed to develop a conceptual model that focuses on collaboration between AI and humans. We reviewed the literature to identify the individual dimensions of Cojoined Agency. We developed a framework that divides decision-making into two parts: the decision process and the decision execution. This framework identifies four modes of collaboration between AI and humans, each of which describes who is responsible and who executes the actions. In the next section, we provide the theoretical findings, practical implications, limitations, and future research directions.

Theoretical contributions

The first theoretical contribution concerns the proposed framework that extends the Conjoined Agency proposed by Ahmad Husairi & Rossi (2024), focusing on the decision-making process and considering a specific technology, Artificial Intelligence. Our goal is to contribute to the body of knowledge on human-AI collaboration by highlighting the wide range of detailed characteristics found in the literature, combining different theoretical perspectives, that allow us to better understand various nuances of the collaboration between humans and AI in decision-making processes and executions. For example, in economic theory, betrayal aversion makes people less willing to take risks when decision- making is delegated to the agent (Bohnet et al., 2008). In addition to economic theory, behavioral theory (Kőszegi & Rabin, 2006) states that the irrational behavior of employees and their tendency to avoid losses can cause managers to lose control, even if such decisions lead to lower profits. Likewise, motivation theory plays a crucial role in understanding human motivation in decision-making, where power is one of the basic human needs (McClelland, 2006). Again, self-determination theory notes that autonomy and freedom in decision-making promote psychological development, integrity, and well-being (Deci, 1985). Furthermore, Construal Agency helps organizations better understand the goals of humans and AI in the various forms of conjoined agency. According to this theory (Trope & Liberman, 2010), people believe that AI has both general and more realistic (specific) goals. The majority of people believe that AI technologies, such as robots or computer programs with predetermined thoughts or goals, are incapable of performing intentional actions or voluntary tasks, unlike humans (Candrian & Scherer, 2022). With the proposed framework, we seek to provide a holistic overview of the possible Human-AI collaboration forms concerning decision-making, providing a first attempt to combine different theoretical perspectives.

Practical implications

As can be seen from the conceptual framework, the collaboration between AI and decision-making is based on two dimensions, namely, the decision-making process and the execution process. In other words, as the results show, the collaboration between AI and humans can be categorized into different groups (*legacy mode, compliance mode, augmentation mode, and autonomous mode*). This framework can help managers select and implement the most appropriate form of human-AI collaboration to improve decision-making and task execution in their organization. It also provides managers with a better understanding of the different modes of human-AI collaboration.

One of the practical implications could relate to the area of managing business processes in an organization. Managers need to map business processes with the appropriate support or actions required for each process and identify the most efficient ways for AI and humans to work together. To improve collaboration, managers need to understand the role of AI within each business process. Managers could use the knowledge of AI to optimize each mode of work by analyzing the different business processes. In the area of algorithmic management, for example, platforms such as Uber show how managers can use chatbots to respond to customer requests. In this context, managers use the most effective methods of collaboration between humans and AI to solve customer problems (Benlian et al., 2022). On the other hand, in the field of product design, which requires human expertise and knowledge to create innovative designs, managers can optimize product design through human-AI collaboration (Das et al., 2023).

A second practical contribution is that, from a strategic perspective, managers need to carefully consider the opportunities and challenges associated with each mode of AI process. Depending on how managers decide which approach to take, this will shape the company's attitude towards the use of AI and emphasize the importance of investing in specific AI solutions according to one of the specific forms of human-AI collaboration. Managers who have doubts about adopting AI can focus on the training or augmentation mode and gradually use AI solutions in their operations in an automated or compliance mode to build long-term prospects. In industries such as self-driving cars, the transition from legacy to an automated mode depends on technological advances. Managers need to assess whether their approach is conservative or innovative. Another crucial point in the field of AI that needs to be carefully considered for appropriate investment decisions is the analysis of market needs. In this context, investment decisions should not only be based on personal or corporate experience but rather on the needs of the market, the decisions of competitors, and the expectations of customers. In other words, the selection of suitable modes should be based on a market analysis and the objectives of the stakeholders.

Limitations and Future Research Directions

The limitations we encounter in this study, by focusing exclusively on papers published in journals, are the possibility that valuable insights from other sources may be overlooked. Considering a broader range of literature could therefore improve the robustness of the conceptual framework.

Since our study is mainly theoretical, in a further step, we can investigate and refine the framework with some empirical studies. In this regard, researchers and managers can better understand how human-AI collaboration works and how it affects organizational decisions by comparing the perspectives presented in the theoretical literature and the workplace. In other words, can managers and employees with human expertise assess the capabilities of AI? Do managers improve their employees' job satisfaction when they delegate tasks to AI? Does collaboration between humans and AI lead to a reduction in repetitive and boring tasks and a reduction in gender bias? These and other questions can help determine the exact outcomes of human-AI collaboration in business decision-making. As decision-making is an interdisciplinary topic, future researchers should also consider the social, ethical, and cultural implications of human-AI collaboration to pave the way for future research.

As each specific AI category is expected to influence the AI-human relationship individually and affect each dimension of the matrix, it is suggested that future research explore the AI-human relationship based on different AI categories and their role in the four possible configurations of AI-human collaboration.

CHAPTER IV

Understanding Factors Influencing Employee Collaboration with AI in a Work-Related Context

Abstract. Artificial intelligence is becoming deeply embedded in organizational processes, reshaping how employees work and interact with technology. Our study aims to examine how various factors—including two types of trust beliefs, human-like and system-like—shape employees' interactions with AI, particularly in their collaboration with AI such as ChatGPT. We focus on factors influencing employee-AI collaboration, including AI delegation, perceived ease of use, perceived usefulness, and satisfaction. By analyzing 150 questionnaires from employees in French, Italian, UK, and US companies, we show that human-like trust is slightly more likely than system-like trust to lead to employees' willingness to delegate tasks to AI. Our findings also show a significant impact of the AI delegation variable on PEOU, PU, satisfaction, and employee engagement with AI. Our findings clarify the key factors that influence collaboration with AI, which can be highly important for AI-driven organizations.

Keywords: AI Delegation, Employee AI Collaboration, System Trust, Human Trust.

Introduction

Artificial intelligence (AI) is becoming deeply embedded in organizational processes, reshaping how employees work and interact with technology. Prior research consistently highlights the central role of trust in shaping technology adoption and collaboration (Chowdhury et al., 2022; Kong et al., 2023). Employees who perceive AI as trustworthy and beneficial tend to develop more positive attitudes toward AI-enabled work environments. Nevertheless, organizations continue to face hesitations regarding AI use, driven by concerns about privacy, job replacement, and uncertainty about employees' willingness to embrace AI systems (Dwivedi et al., 2023; Paluch & Wittkop, 2023). At the same time, studies show that when AI systems display human-like cues, they tend to evoke greater trust and cooperation from users (Song et al., 2023; Singh & Chandra, 2024). These contrasting dynamics underscore the growing need to understand what truly drives employees to collaborate with AI.

One area receiving increasing attention is human–AI collaboration, defined as the intentional interaction between employees and AI systems to enhance workplace performance (Kong et al., 2023; Pereira et al., 2023). A critical mechanism within this collaboration is task delegation, which refers to the extent to which individuals transfer responsibility or decision-making authority to AI (Freisinger & Schneider, 2024; Spitzer et al., 2025). As AI becomes more autonomous and capable of performing complex tasks, it can function not merely as a tool but as an agentic collaborator (Spitzer et al., 2025). This evolution raises essential questions about how employees choose to delegate tasks to AI—and whether such delegation strengthens or weakens their willingness to collaborate with AI systems.

Despite its relevance, existing research provides an incomplete understanding of the psychological mechanisms behind employees' decisions to collaborate with AI. First, studies have not jointly examined how two distinct forms of trust—human-like trust and system-like trust—influence AI delegation and, subsequently, collaboration. Prior literature emphasizes that trust may stem from either human-like quality (benevolence, competence, and integrity) (McKnight et al., 2002; Vance et al., 2008) or system-focused attributes (e.g., functionality, helpfulness, and reliability) (McKnight et al., 2011). Both forms of trust can shape employees' expectations, reduce uncertainty, and influence their behaviours toward AI (Lankton et al., 2015; Singh & Chandra, 2024). However, no study has assessed their distinct and joint impacts on delegation to AI and ultimately on employee collaboration with AI.

A second gap concerns the ambiguous role of AI delegation in shaping perceptions of usefulness, ease of use, satisfaction, and collaboration. While some studies argue that delegating tasks to AI can improve performance and satisfaction (Hemmer et al., 2025; Westphal et al., 2025), evidence remains mixed. In organizational contexts, delegating authority traditionally strengthens trust, cooperation, and performance when directed toward humans (Kærnested & Bragadóttir, 2012). Whether these benefits translate to delegating tasks to AI remains unresolved. Moreover, existing research has not clarified how delegation influences key technology-related perceptions—such as perceived usefulness (PU), perceived ease of use (PEOU), and satisfaction—which are known to shape individuals' attitudes and collaboration with technology (Davis, 1989).

To address these gaps, this study develops and empirically tests a research model that integrates trust beliefs (human-like and system-like), AI delegation, PEOU, PU, satisfaction, and employee–AI collaboration. We examine how different types of trust contribute to the decision to delegate tasks to AI and how this delegation, in turn, shapes core technology perceptions and collaboration between employees and

AI. Our findings reveal that both human-like and system-like trust significantly influence AI delegation. AI Delegation increases perceived usefulness, ease of use, and satisfaction. PU and satisfaction emerge as strong predictors of employee–AI collaboration, underscoring their importance for successful integration of AI in organizational contexts. PEOU has no impact on employee-AI collaboration.

By examining these mechanisms simultaneously, our study contributes to a more comprehensive understanding of what leads employees to collaborate with AI. The rest of the paper is organized as follows. Section 2 reviews the literature and presents the research model and our set of hypotheses. Section 3 introduces our methodology, while Section 4 presents the results. Section 5 discusses our findings, develops our contributions and research limitations, and offers suggestions for future research. Last, Section 6 concludes this paper.

Literature review and hypotheses development

Employee–AI collaboration refers to the joint behaviors through which employees and AI systems work together (Sowa et al., 2021). Sowa et al. (2021) identify four levels of human–AI proximity: working separately, supplementing one another, interdependence, and fully hybrid or fused collaboration between humans and AI. Recent studies, such as Li et al. (2025), show that employee-initiated collaboration with AI is becoming increasingly common in the workplace and significantly shapes employees' perceived usefulness of AI. In other words, the more employees trust these technologies, the more likely they are to engage in collaborative behaviors, which in turn reinforces their perception of AI's usefulness.

Such collaboration can generate outcomes that exceed what human workers can achieve alone, particularly when tasks require analytical or computational capabilities that surpass human limitations. In these settings, employees and AI systems jointly pursue shared goals and achieve collective intelligence (Kong et al., 2023). In digital organizations, human–AI collaboration has become a critical driver of productivity (Sowa et al., 2021; Marvi et al., 2025; Wang et al., 2024) and employee well-being (Kong et al., 2023). For example, Sowa et al. (2021) demonstrate through an experimental study involving a virtual assistant that effective collaboration with AI significantly increases the productivity of white-collar workers. More broadly, collaboration between humans and AI provides benefits such as effective and secure integration of employees and AI (Sowa et al., 2021), improved employee performance, and a competitive advantage for organizations (Chowdhury et al., 2022). It also supports the execution of more complex tasks and stimulates organizational innovation (Cabrera et al., 2023). For instance, AI-enabled systems can enhance production accuracy and improve the quality of decision-making (Wu et al., 2025).

Against this backdrop, the present study reviews the existing literature to examine how trust beliefs shape employee–AI collaboration. We develop a research model based on structural equation modelling to analyze these relationships directly and indirectly through the mediating variables of AI delegation, perceived ease of use (PEOU), perceived usefulness (PU), and satisfaction (see Figure 1). Delegating tasks to AI represents one important form of collaboration: when employees assign tasks to AI, their performance and job satisfaction may improve, which in turn reinforces more effective collaboration with AI. This collaborative dynamic is strengthened when employees hold higher levels of trust in AI.

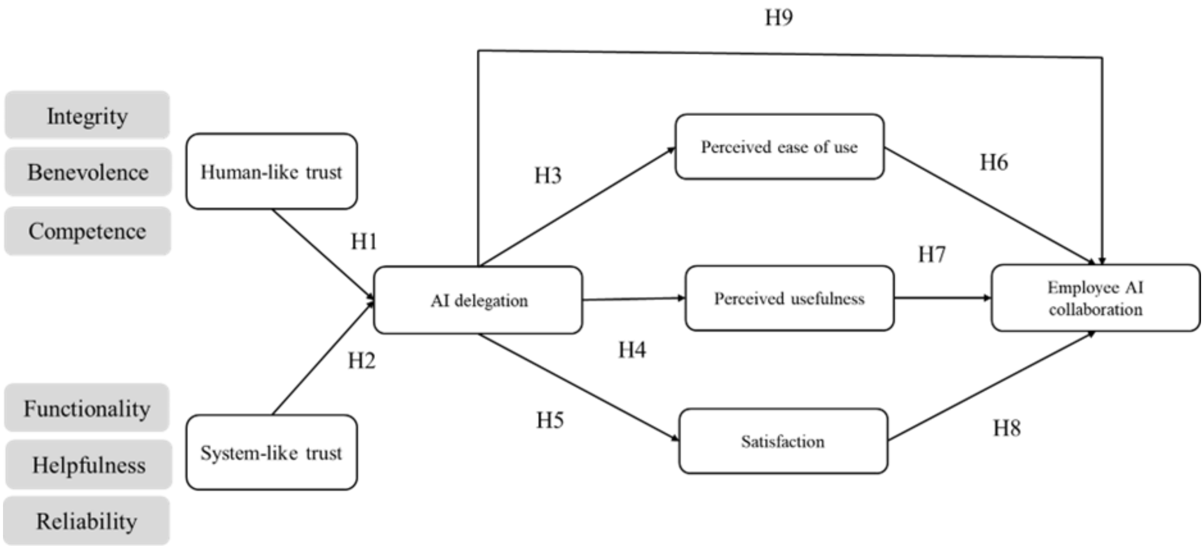

Figure 1.Research model.

Trust beliefs (Human-like and system-like trust)

Trust beliefs refer to individuals' willingness to rely on a technology based on their perceptions of its attributes. In the context of AI, these beliefs can be directed toward human-like characteristics or system-like qualities (Lankton et al., 2015). Human-like trust emerges when users attribute social or human characteristics to technological artifacts—for example, through features such as voice, animation, or interactive behaviours that make technologies appear more human (Lankton et al., 2015). In this study, human-like trust is operationalized through the beliefs of integrity, competence, and benevolence, which reflect the extent to which the AI is perceived as acting ethically, possessing adequate skills, and having positive intentions toward the user (McKnight et al., 2002).

System-like trust, in contrast, is based on perceptions of the technology's functional and performance-oriented attributes. To capture this form of trust, we rely on the beliefs of functionality, helpfulness, and reliability, which represent the extent to which AI is viewed as dependable, useful, and capable of performing tasks effectively (McKnight et al., 2011). Because AI systems often demonstrate high reliability, consistency, and transparency, they can strengthen employees' cognitive and emotional trust in their technical capabilities.

Prior research highlights that trust in AI is foundational to human–technology interactions, shaping employees' perceptions, behaviours, and openness to future engagement (Singh & Chandra, 2024; Campagna et al., 2022; Kong et al., 2023). When employees trust AI—whether due to its human-like qualities or its functional performance—they are more likely to hold positive attitudes toward it, engage collaboratively with AI, and respond more flexibly to evolving job requirements (Kong et al., 2023; Wohlgemuth et al., 2019). Trust, therefore, plays a central role in facilitating technology acceptance and collaboration in AI-driven work environments.

Building on this literature, we expect that both forms of trust influence employees' willingness to transfer responsibility or decision-making authority to AI systems. When employees perceive AI as socially trustworthy (human-like) or functionally competent (system-like), they are more likely to delegate tasks to it. Hence, we hypothesize the following:

H1: Human-like trust is positively related to AI delegation.

H2: System-like trust is positively related to AI delegation.

AI Delegation

AI delegation refers to situations in which specific task instances are assigned to an AI system rather than being completed by humans, to reduce human effort and improve overall performance (Hemmer et al., 2025; Westphal et al., 2025). Prior research shows that when AI selects or structures tasks for users, individuals often experience improved performance and higher task satisfaction, partly because delegated tasks tend to align more closely with their capabilities (Westphal et al., 2025). This improvement is explained by increases in self-efficacy, as individuals feel more capable and confident when they work on tasks that have been appropriately matched to their skill level (Hemmer et al., 2025; Westphal et al., 2025). Research in organizational behaviour highlights that effective delegation—when aligned with employee capability—supports satisfaction, motivation, and task mastery (Kærnested & Bragadóttir, 2012). Conversely, lack of confidence or inadequate assessment of one's own skills can create barriers to effective delegation and lead to poorer decisions (Kærnested & Bragadóttir, 2012; Fügener et al., 2022). Studies in human–AI collaboration further show that individuals who struggle to evaluate their own capabilities relative to AI tend to delegate poorly and produce suboptimal decisions (Fügener et al., 2022).

AI delegation has been shown to reduce human workload (Hemmer et al., 2025), increase perceived task suitability (Westphal et al., 2025), and enhance confidence in both personal and system capabilities (Spitzer et al., 2025). Taken together, this evidence suggests that delegation from humans to AI may influence how employees perceive the AI system. When AI takes responsibility for executing or selecting tasks, individuals may find the system easier to work with (higher perceived ease of use), more valuable (higher perceived usefulness), and more aligned with their expectations (higher satisfaction). Accordingly, we hypothesize the following:

H3: AI delegation is positively related to perceived ease of use.

H4: AI delegation is positively related to perceived usefulness.

H5: AI delegation is positively related to satisfaction.

Perceived Ease of Use and Perceived Usefulness

Perceived usefulness (PU) and perceived ease of use (PEOU) originate from the Technology Acceptance Model (TAM) (Davis, 1989) and are widely recognized as primary determinants of technology adoption in organizational settings. PU refers to employees' beliefs that using technology will enhance their job performance, while PEOU reflects their perception of how effortless the technology is to use. The more employees believe that a technological system can help them achieve higher-quality work, the more willing they are to adopt and engage in it.

Empirical studies support these associations in AI-related contexts. For instance, Mouakket (2015) found that employees who perceive AI technologies as useful demonstrate a stronger intention to use them. Similarly, Bilquise et al. (2024) show that perceived usefulness is positively correlated with individuals' intention to adopt AI tools. Building on this evidence, it is reasonable to expect that both PU and PEOU will enhance collaboration between employees and AI. We therefore propose the following hypotheses:

Accordingly, it is reasonable to posit that PEOU and PU will strengthen employee - AI collaboration. We hypothesize the following:

H6: PEOU increases employees' intention to collaborate with AI.

H7: PU increases employees' intention to collaborate with AI.

Satisfaction

As reported by Bhattacherjee (2001), satisfaction can be considered as an evaluation of an emotion (i.e., if the IS usage was as pleasurable as expected). Based on this statement, an individual could have a pleasant experience with the usage of a specific AI technology, but at the same time can feel dissatisfied if the experience is below expectations. In this way, satisfaction can be considered an effect (satisfied, dissatisfied, or neutral) feeling. This effect was deeply investigated in IS literature in the last 40 years, and it is considered an important predictor of intention concerning IS use, often related to the continuance intention to use (e.g., Davis et al. 1989; Karahanna et al. 1999; Taylor and Todd 1995; Carillo et al. 2017). In this paper, considering the anthropomorphism in AI-enabled technology (Li and Suh, 2022), we intend to investigate how a pleasant or unpleasant experience of a specific AI system can affect the intention to collaborate with it. Accordingly, we hypothesize the following:

H8: Satisfaction increases employees' intention to collaborate with AI.

Kærnested and Bragadóttir (2012) define delegation attitude as users' beliefs, perceptions, and emotional dispositions toward the act of assigning tasks to others. It captures how positively or negatively users view delegation, including whether they consider it useful, efficient, risky, or problematic. Delegation attitude reflects whether users perceive delegation as an opportunity for efficiency, teamwork, and professional role fulfilment or, conversely, as a source of risk, dissatisfaction, or loss of quality control. Recently, some studies investigated the effect of AI delegation on human-AI collaboration (Hemmer et al, 2023). Hence, following this stream of research, we hypothesize the following:

H9: AI delegation increases employees' intention to collaborate with AI.

Methodology

Sample and Data Collection

To construct our empirical dataset, we first designed a questionnaire and administered it through Qualtrics Inc. Before launching the full study, we conducted a pilot test with 15 individuals (approximately 15% of the target sample) using Google Forms. Based on their feedback, we made minor adjustments to improve clarity and reliability. The finalized questionnaire was then distributed in November 2025 via an online survey to participants from France, Italy, the United Kingdom, and the United States.

Data collection was carried out through Prolific, an online platform known for providing higher-quality participant responses than many other crowdsourcing alternatives (Albert & Smilek, 2023). We specified detailed sampling criteria (employment status is full-time or part-time) and set a target sample size of 150 respondents. To ensure data quality, we included an attention-check item to identify inattentive participants (select which response is not a month of the year).

The final sample consisted of 58.8% female and 40.5% male respondents, with 70.6% holding a college degree or equivalent. The average age was 43 years. Additional demographic details are reported in Table 1.

Table 1. Sample demographics.

Sample demographics (*n* =150)	**(%)**	**Sample demographics (*n* =150)**	**(%)**
Gender		**Task categories with AI use**	
Female	58.8	Planning and organizing	46
Male	40.5	Coordinating and supervising	06
Age (in years)	22-64	Information processing (e.g., recording, checking, reporting)	55
Education Level		Problem-solving and decision-making	50
Post-secondary non-tertiary education (Vocational/Technical training, Diploma)	27.9	Communication and interaction (e.g., meetings, emails, collaboration)	53
Bachelor's degree (BA, BSc, or equivalent)	46.1	Creative and idea generation	49
Master's degree (MA, MSc, MBA, or equivalent)	20.7	Learning and knowledge sharing	47
Doctoral degree (PhD, EdD, or equivalent)	.03.8	Physical or manual activities	05
Occupation		Supporting or assisting others	13.9
Self-employed / Entrepreneur	12.3	**Amount of time spent using AI tools/applications for professional activities (per day)**	
Employee – Entry level / Junior staff	17.5	- Less than 15 minutes	14

Employee – Professional / Specialist	29.8	- 15–30 minutes	18
Employee – Manager / Supervisor	37	- 30 minutes – 1 hour	21
Executive / Senior management (e.g., Director, CEO)	.03	- 1–2 hours	20.7
AI tools used		- 2–4 hours	17.5
ChatGPT (OpenAI)	96.7	- More than 4 hours	.05
Google Gemini (Bard)	55	- I do not use AI tools daily	.03
Microsoft Copilot (in Word, Excel, Teams, etc.)	60		
Claude (Anthropic)	17.5		
Perplexity AI	11		
MidJourney (image generation)	.05		
DALL·E (image generation)	10		
DeepSeek	16.8		

Measurement Model

The items used in this study for human-like trust and system-like trust were adapted from prior studies (McKnight, 2002; McKnight, 2012; Lankton, 2015). All items were measured on a 7-point Likert scale, where 1 indicates "strongly disagree," and 7 indicates "strongly agree." In this study, the 7-point Likert scale was chosen because it provides sufficient options and allows for finer distinctions between adjacent responses compared to a 5-point scale (Joshi et al., 2015). To measure AI delegation, we adapted items from Poteet (1984), which were later refined and validated by Kærnested and Bragadóttir (2012). These items are reverse-coded, as they measure employees' reluctance to delegate tasks to AI. Perceived ease of use (PEOU) and perceived usefulness (PU) were assessed using the original scales developed by Davis (1989). Satisfaction was measured using a validated scale from Bhattacherjee (2001), and employee–AI collaboration was captured using the scale developed and validated by Kong et al. (2023).

Results

Measurement model validity assessment

To conduct structural model analysis, we used partial least squares structural equation modelling (PLS-SEM) with SmartPLS 4.0 software in this study (Ringle 2024). This approach combines factor analysis and path analysis and is well-suited for examining relationships among multiple dependent variables (Hair et al., 2011). Furthermore, PLS-SEM does not require a specific data distribution, is not limited to a normal distribution, and is valid for small sample sizes and complex models (Hair et al., 2016).

Each measurement scale had both good Cronbach's alpha (Cronbach, 1951) and composite reliability (CR) measures. Cronbach's alpha coefficients ranged from 0.899 to 0.966, exceeding the recommended threshold of 0.70, indicating acceptable reliability (Nunnally, 1978). To assess the convergent validity of the constructs, we used the average variance extracted (AVE). As shown in Table 2, the AVE values for all constructs were greater than 0.5, confirming their convergent validity (Fornell & Larcker, 1981). The factor loadings for most variables were greater than 0.70, with only a few constructs having factor loadings between 0.40 and 0.70. However, the AVE values for all instruments were acceptable, indicating strong convergent reliability.

Table 2. Measurement and validity assessment.

Construct	**Cronbach's alpha**	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
AI Delegation	0.902	0.938	0.915	0.502
Employee AI collaboration	0.899	0.904	0.917	0.530
Human-Trust	0.951	0.961	0.958	0.677
PEOU	0.953	0.956	0.962	0.809
PU	0.946	0.954	0.961	0.862
Satisfaction	0.966	0.966	0.975	0.907
System-Trust	0.936	0.941	0.946	0.662

Discriminant validity assessment

We use the Fornell–Larcker criterion to assess the discriminant validity of the model constructs as part of the measurement model evaluation (Fornell & Larcker, 1981). Examining discriminant validity allows us to determine which constructs in the proposed model are conceptually distinct from each other. The correlations between variables were relatively strong, ranging from 0.218 to 0.953. According to the results in Table 3, the square root of the AVE for each variable was usually larger than its correlations with other constructs in the corresponding row and column. In this regard, according to the Fornell–Larcker criterion, discriminant validity was established. However, we observed that the correlation value between human-like trust and system-like trust (0.814) was larger than the square root of the AVE for human-like trust (0.823), indicating that discriminant validity was not established for these constructs. These results can be explained by the fact that system trust and human trust are conceptually related, as they represent two complementary facets of trust.

Table 3. Discriminate validity assessment.

	AI Delegation	Employee AI collaboration	Human-Trust	PEOU	PU	Satisfaction	System-Trust
AI Delegation	**0.708**						
Employee AI collaboration	-0.218	**0.728**					
Human-Trust	-0.522	0.489	**0.823**				
PEOU	-0.328	0.441	0.389	**0.899**			
PU	-0.454	0.596	0.590	0.497	**0.928**		
Satisfaction	-0.528	0.588	0.686	0.633	0.727	**0.953**	
System-Trust	-0.514	0.537	0.833	0.473	0.533	0.706	**0.814**

Structural model validity

First, we checked our inner model for multicollinearity. The results of this assessment, using the variance inflation factor (VIF), are presented in Table 4. According to Hair et al. (2011), the VIF value for each construct should be less than 5, and this condition was met for all our latent variables.

Table 4. Collinearity assessment (VIF).

	VIF
AI Delegation -> Employee AI collaboration	1.407
AI Delegation -> PEOU	1.000
AI Delegation -> PU	1.000
AI Delegation -> Satisfaction	1.000
Human-T -> AI Delegation	3.259
PEOU -> Employee AI collaboration	1.676
PU -> Employee AI collaboration	2.163
Satisfaction -> Employee AI collaboration	2.936
System-T -> AI Delegation	3.259

Second, in order to test the relationship between variables, we completed a Bootstrap analysis with 5,000 resamples through SmartPLS 4. The model explains the variance of the dependent variables at respectively R^2= 0.303 and R^2= 0.430 for AI delegation and Employee- AI collaboration, which demonstrates a moderate effect according to Hair et al. (2011).

Table 5 provides information about the path coefficients, sample mean, and t-statistics. Human-like trust has a stronger effect on AI delegation (β = -0.306, $p < 0.006$) compared to system-like trust (β = -0.259, $p < 0.032$). This indicates that the more employees trust AI systems, the more they are willing to delegate tasks to AI. AI delegation has a positive and significant effect on PU (β = -0.454, $p < 0.000$), PEOU (β = -0.328, $p < 0.000$), satisfaction (β = -0.528, $p < 0.000$), and employee-AI collaboration (β = -0.528, $p < 0.000$). There is also a significant relationship between PU and employee-AI collaboration (β = 0.159, $p < 0.042$) and satisfaction (β = 0.344, $p < 0.002$). In contrast, there is no significant relationship between PEOU and employee-AI collaboration (β = 0.091, $p < 0.345$). To summarize, H1, H2, H3, H4, H5, H7, H8, and H9 were supported at the $p < .05$ significance level, except for H6 related to PEOU, which is non-significant. The results of the PLS-SEM analysis are presented in Table 5 and can be visualized in Figure 2.

Table 5. Path coefficients and hypotheses assessments.

	Path	**Original sample (O)**	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	**Supported**
H1	Human-Trust -> AI Delegation	-0.306	-0.317	0.112	2.731	0.006	Yes
H2	System-Trust -> AI Delegation	-0.259	-0.261	0.121	2.144	0.032	Yes
H3	AI Delegation -> PEOU	-0.328	-0.334	0.086	3.807	0.000	Yes
H4	AI Delegation -> PU	-0.454	-0.463	0.061	7.448	0.000	Yes
H5	AI Delegation -> Satisfaction	-0.528	-0.538	0.055	9.601	0.000	Yes
H6	PEOU -> Employee AI collaboration	0.091	0.094	0.097	0.944	0.345	No
H7	PU -> Employee AI collaboration	0.374	0.375	0.111	3.378	0.001	Yes
H8	Satisfaction -> Employee AI collaboration	0.344	0.346	0.112	3.077	0.002	Yes
H9	AI Delegation -> Employee AI collaboration	0.164	0.159	0.081	2.029	0.042	Yes

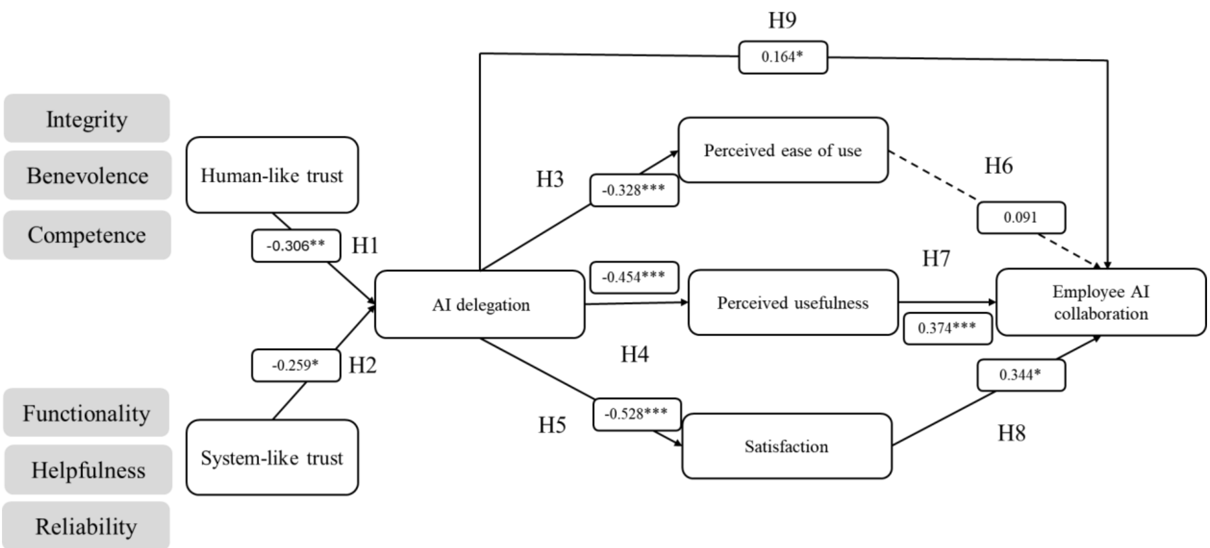

Figure 2. Assessment of the structural model.

Note: Dashed lines indicate non-significant paths. Standardized path coefficients. *p < 0.05, **p < 0.01, ***p < 0.001.

Discussion and Limitation

This research aimed at assessing the distinct and joint impacts of system and human trust on delegation to AI and ultimately on employee collaboration with AI. The results show that trust beliefs significantly affect task delegation to AI. Specifically, human-like trust indicates that the more employees trust AI with human-like characteristics, the more likely they are to delegate tasks to AI. Our findings are consistent with those of Kong et al. (2023), who found that the closer this trust is to human-like characteristics, the more willing employees are to delegate tasks to AI. When employees' trust in AI with system and functional characteristics increases, they are also willing to delegate tasks to AI. Furthermore, the results show a significant relationship between AI delegation and PEOU, PU, and satisfaction. Considering the β values obtained from these three variables, which are -0.328, -0.454, and -0.528, respectively (because AI delegation is reverse-coded), these findings indicate that as employees delegate more tasks to AI, their satisfaction, perceived usefulness, and perceived ease of use of AI increase.

Our findings align with those of Hemmer et al. (2025). Similarly, a study by Westphal et al. (2025) shows that delegating tasks to AI can increase task satisfaction and improve human performance by increasing self-efficacy. Another set of results shows no significant relationship between perceived ease of use and employee-AI collaboration. However, according to Table 5, the path coefficient is around 0.09, indicating that as perceived ease of use increases, employee collaboration with AI also increases. There is also a significant and positive relationship between perceived usefulness, satisfaction, and employee-AI collaboration. These findings indicate that greater ease of use and satisfaction with AI lead to increased employee collaboration with AI. Our findings are consistent with those of Bilquise et al. (2024) and Andreas Fügener et al. (2022), who state that the higher the perceived usefulness, the greater the employees' intention and willingness to use AI.

Based on these findings, this research leads to two main contributions: First, this study examines trust beliefs by focusing on human and system characteristics, AI delegation, PEOU, PU, and satisfaction, and their distinctive impacts on human-AI collaboration. This approach helps develop employees' understanding of AI in the context of their collaborative interactions with AI. As Pitts & Motamedi (2025) state, trust beliefs may lead to different results regarding the impact of trust on various factors due to measurement differences. In this context, employees in organizational work environments tend to prioritize human-like systems for delegating tasks because these systems exhibit human characteristics such as benevolence and integrity. This can reduce cognitive pressures on employees. Future research should examine other factors, including digital literacy, which is considered one of the most important elements for the formation of trust and cooperation with AI systems, across a wide range.

Second, although the path coefficient for PEOU (0.091) is positive and associated with employee-AI collaboration, this effect is not significant, and the hypothesis is not supported in this study. Chen et al. (2025) show that perceived ease of use positively affects behavioral intention. However, in our study, perceived ease of use was examined in relation to AI collaboration. Although the effect was in the expected direction, there is insufficient evidence to support it. One possible explanation is that employees' perceptions of the difficulty or ease of using AI systems are strongly influenced by their immediate emotional experiences—such as frustration, stress, or joy—during the interaction. These momentary emotional states may affect their willingness to collaborate with AI (Lan et al., 2025).

Moreover, this study has two main managerial implications: Our findings indicate that PEOU does not affect employees' collaboration with AI. However, it also shows that, on one hand, employees recognize the benefits and usefulness of PEOU, but on the other hand, some concerns or factors hinder this effect. This situation creates an opportunity for organizations to design and develop AI systems in a way that enhances employees' sense of ease and comfort, thereby promoting a better and more balanced human-AI interaction and collaboration.

Second, our findings provide valuable insights for employees working in organizations in France, Italy, the United Kingdom, and the United States. Research shows that PU and satisfaction are important factors in shaping employees' interactions with AI. This indicates that these factors serve as important motivational factors to encourage greater employee collaboration with AI. Therefore, organizations should continuously foster a positive attitude toward AI, as this positive perception leads to job satisfaction and perceived usefulness of AI systems. In this way, by providing better services, organizations can enhance employees' enjoyment of work and increase the likelihood that they will interact and collaborate with technologies, including AI, to perform their tasks.

Third, collaboration between humans and AI in organizations can occur through trust in AI. The more employees trust systems with human-like characteristics, the more effective and harmonious this collaboration becomes. Therefore, it is necessary for organizations to continuously incorporate digital skills, digital literacy, and training on working with AI systems into their educational programs.

This study also presents several limitations. First, although our sample was collected from multiple countries, including France, Italy, the UK, and the US, we still relied on a relatively small group of organizational employees. Therefore, future studies should increase sample sizes to obtain more robust, generalizable results. Second, our study did not account for other important factors, such as human laziness, which may moderate the relationships between certain constructs. Finally, since this study examined the effects of various factors on employee-AI collaboration specifically within organizational work environments, future researchers may explore human–AI collaboration in other domains—such as healthcare—where practitioners, like physicians, increasingly rely on AI systems to support accurate decision-making and prediction.

Conclusion

Artificial intelligence systems are considered among the most important tools for interacting with employees in organizational processes. Trust beliefs play a key role in delegating tasks to AI. Systems with human-like characteristics can foster greater employee trust, which may result in more employees assigning tasks to AI. This delegation of tasks can, in turn, lead to increased satisfaction, perceived usefulness, and perceived ease of use. Beyond having a positive and direct effect on these factors, task delegation can also directly influence employee-AI collaboration. Additionally, perceived usefulness and satisfaction can significantly affect employee collaboration with AI systems. However, perceived ease of use is not the only variable influencing collaboration with AI. By understanding the effects of these factors on employee collaboration with AI, this study offers a broader perspective on acceptance and collaboration, which can expand the research field and improve understanding of how organizational employees can achieve better collaboration with AI systems.

Concluding Insights on AI-Driven Decision-Making and Human–AI Collaboration

This thesis examined the role of AI in decision-making and collaboration with humans using various methodological approaches. More specifically, the results consistently indicate that, given the rapid growth and evolution of AI in organizations, these systems can be used to achieve diverse organizational goals and enhance managerial performance. Across the four studies, a central pattern emerges: from an organizational perspective, the more managers provide employees with the necessary training, the less resistance employees show toward adopting and using AI. As a result, human–AI collaboration becomes stronger and ultimately improves the efficiency and effectiveness of decision-making.

The first question was: How has academic discourse evolved in response to recent advancements in organizational activities and decision-making processes, and what key themes, concepts, and research gaps have emerged?

Based on the results obtained from this analysis, we found that the literature on AI has shown significant growth over the past five decades. This indicates a rising trend in publications on AI and decision-making across different sectors and domains. The adoption and implementation of AI applications in organizational processes—such as data analytics—has likely contributed to the considerable increase in the growth rate of publications since 2009. From an organizational standpoint, the less resistance employees show toward adopting and using AI, the stronger the collaboration between humans and AI becomes, ultimately improving the efficiency and effectiveness of decision-making.

Beyond organizational contexts, AI has also achieved remarkable progress in healthcare. Our review of studies revealed that AI systems have secured a significant position in diagnosing and recommending more effective treatments. In summary, the development and expansion of AI have led many researchers to investigate the relationship between AI and decision-making from multiple dimensions. Ultimately, for proper adoption and implementation of AI systems in organizations, managers must provide adequate training, encourage employees to utilize these systems, and reduce issues related to biases in AI-generated outcomes.

The second question was: Which AI factors do managers and organizations use (under certain *conditions and circumstances) in their decision-making processes, and how do these factors affect optimal decision-making?" "Under what conditions are Challenges Driven by AI (e.g., human resources, organizational goals, and ethics) likely to have a negative impact on individuals and organizations"?*

After examining the role of AI in the decision-making process from a bibliometric perspective, we used the meta-synthesis method to obtain a more accurate and comprehensive estimation of the effects of AI-related factors on decision-making. In this method, we analyzed the multidimensional aspects and factors shaping the relationship between AI and decision-making. In other words, as the results indicate, AI-based decision-making can be categorized into several groups, including the value of information in decision-making, the enhancement of skills and capabilities, the scope of decision-making, challenges arising from AI, and the improvement of organizational performance.

Based on the findings, we concluded that AI serves as powerful tools for achieving greater accuracy and speed in decision-making. Therefore, managers need to ensure that employees receive the necessary training to effectively implement AI. Moreover, organizations aiming for successful AI adoption require access to large amounts of data, as such access can create competitive advantages. Additionally, for the successful adoption of AI, managers must be aware of organizational rules and regulations and adhere to quality control procedures (Yang et al., 2024), because a lack of awareness of the legal and regulatory environment—as well as unsupervised managerial practices—can lead to negative and ethical consequences for employees, including job loss and diminished control (Boyes & Schippers, 2024).

Furthermore, organizations face challenges in adopting AI, such as limited resources, resistance to change, and job security risks. To overcome these barriers, organizations need to provide proper training for employees, develop creative talent, and foster an innovative-oriented workplace culture. This is important because even with new regulations, there is no guarantee that AI will always act accurately or responsibly. Therefore, it is emphasized that meaningful interaction between employees and AI occurs only when adequate training, time, and resources are provided to ensure full understanding and integration of AI. Such interaction leads to optimized organizational performance and more effective collaboration between AI systems and human decision-makers. Training programs can update employees' understanding of the capabilities and limitations of AI—such as potential biases and lack of transparency in their work contexts—and help minimize misconceptions that hinder AI adoption. Moreover, increasing transparency in AI-generated decisions through the use of explainable AI tools enables employees to develop a better understanding of the technology and make decisions with greater confidence and certainty.

The third question was: Academic discourse on technological advancements has expanded the collaboration between humans and AI in the workplace. What themes related to modes of conjoined agency and what research gaps have emerged in this context?

After conducting a meta-synthesis and identifying the factors influencing how AI affects decision-making and the elements that contribute to human-AI collaboration in this process, we sought to determine how the roles of humans and AI operate within different frameworks of AI system use, and to specify the responsibilities of each. Therefore, we developed a co-joined agency framework. By creating this framework, we aimed to examine in which modes humans take on the roles of control, supervision, and execution, and in which modes they take responsibility for decision-making—and vice versa for AI. The purpose of the "co-joined agency" framework was to develop a conceptual model focusing on collaboration between AI and humans.

We adopted the "co-joined agency", encompasses various forms of collaboration (Murray, Rhyme, & Sirmon, 2021). We created a framework that divides decision-making into two parts: the decision-making process and the implementation of the decision. This framework identifies four modes of collaboration between AI and humans, each describing who is responsible and who performs the actions.

As the findings show, collaboration between AI and humans can be classified into four categories: Legacy Mode, Compliance Mode, Augmented Mode, and Autonomous Mode. This framework can help managers choose and implement the most appropriate form of human–AI collaboration to improve decision-making and task execution within their organizations. It also provides managers with a better understanding of the different modes of human–AI interaction.

In Legacy Mode, organizations rely minimally on AI, and managers depend on their own expertise and experience for decision-making and task execution. In contrast, in Compliance Mode, organizations heavily rely on AI to ensure responsiveness and support in decision-making. The Augmented Mode is characterized by companies gradually anticipating operational changes, with AI increasingly taking the lead in task execution. Finally, the Autonomous Mode requires pervasive connectivity, unlimited computational power, and big data, enabling AI to dominate both decision-making and execution, thereby creating competitive advantage.

In the domain of business process management, managers need to understand and identify the role of AI within each business process and propose the most efficient approaches for human–AI collaboration. From a strategic perspective, managers must offer specific solutions to the organization based on the opportunities and challenges associated with each mode. Managers may initially use the Legacy Mode to train their employees and gradually move toward the Autonomous Mode, depending on market needs, competitor strategies, and customer expectations.

The fourth question was: *How do different types of trust contribute to the decision to delegate tasks to AI, and how does this delegation, in turn, shape core technology perceptions and collaboration between employees and AI?*

After thoroughly and comprehensively examining the factors influencing AI in decision-making and developing a framework to conceptualize the initial foundations of human–AI collaboration, we needed to reach an empirical conclusion using the data collected through a questionnaire. To achieve this, we gathered data from a survey administered to employees of French, Italian, UK, and US companies through Prolific and analyzed the data using PLS software.

This study aimed to assess the distinct and shared effects of system-like trust and human-like trust on delegation to AI and, ultimately, on employees' collaboration with AI. The results show that trust beliefs significantly influence the delegation of tasks to AI. Specifically, human-like trust indicates that the more employees trust AI with human characteristics, the more likely they are to delegate tasks to it. Furthermore, the results reveal a significant relationship between AI delegation and PEOU (Perceived Ease of Use), PU (Perceived Usefulness), and satisfaction. Based on the β values obtained for these three variables (-0.328, -0.454, and -0.528, respectively, since AI delegation was reverse-coded), these findings indicate that as employees delegate more tasks to AI, their satisfaction, perceived usefulness, and perceived ease of use of AI increase.

Another set of findings shows no significant relationship between perceived ease of use and employee–AI collaboration. However, according to Table 5, the path coefficient is approximately 0.09, suggesting that as perceived ease of use increases, employee collaboration with AI also increases. Additionally, there is a significant and positive relationship between perceived usefulness, satisfaction, and employee–AI collaboration. These findings suggest that greater ease of use and higher satisfaction with AI lead to increased employee collaboration with AI. Research shows that PU and satisfaction are important factors in shaping employees' interactions with AI. This indicates that these factors serve as important motivational factors to encourage greater employee collaboration with AI. Therefore, organizations should continuously foster a positive attitude toward AI, as this positive perception leads to job satisfaction and perceived usefulness of AI systems. Moreover, employees in organizational work environments tend to prioritize human-like systems for delegating tasks because these systems exhibit human characteristics such as benevolence and integrity. This can reduce cognitive pressures on employees. Future research should examine other factors, including digital literacy, which is considered one of the most important elements for the formation of trust and cooperation with AI systems, across a wide range.

This thesis aims to enhance the understanding of the impact of AI on decision-making process and human–AI collaboration using various methods. Previous studies have addressed certain specific aspects of this topic; however, the research appears fragmented and not well integrated. To address this gap, this thesis brings together three theoretical studies that collectively examine the trends, key themes, and factors and modes related to the impact of AI on decision-making and collaboration with humans. Figure 1 presents a summary of these studies. This thesis is structured around four complementary studies. The first study examines the theoretical foundations of the impact of AI on decision-making processes using a bibliometric method. Based on the results, it can be stated that keywords and major themes are mainly related to AI, decision making, decision support systems, human–machine interaction, data analytics, innovation, big data, automation, explainable AI, and trust. Building on these insights and the key themes identified, the second study theoretically examines the relationship between AI and decision-making processes from another perspective—namely the positive and negative factors influencing this relationship—using a meta-synthesis method. In this study, the factors and codes extracted from the literature address topics such as Improvement of Organizational Performance, Enhancement of Capabilities and Skills, The Value of Information in

Decision-Making, Challenges Driven by AI, and Decision Scop. In the third Study, considering the main factors and codes identified in the previous studies, we directed our research toward the topic of human–AI collaboration. One of the key advantages of collaboration between humans and AI is the improvement of human decision-making, increased human productivity in performing tasks, and more effective processing of big data, which is often impossible for humans to analyze on their own. This complex collaboration, on the one hand, requires human expertise, and on the other hand, it depends on the specific analytical capabilities of AI for data processing. Collaboration between humans and machine agents in decision-making and execution processes creates a shared capacity known as Conjoined agency (Murray, Rhyme, & Sirmon, 2021). Initially, we theoretically identified, evaluated, and discussed four modes of Conjoined agency, which include Legacy mode, Compliance mode, Augmentation mode, and Autonomous mode. Finally, based on the theoretical insights obtained from the first three studies, we were able to achieve a broader understanding of human–AI collaboration by collecting data through a questionnaire. In this study, considering the key factors and concepts identified earlier, we examined variables such as AI Delegation, Employee–AI Collaboration, System-like Trust, Human-like Trust, Perceived Ease of Use (PEOU), Perceived Usefulness (PU), and Satisfaction. An important point is that these four theoretical and empirical studies are designed to build upon one another and collectively address the main research question of this thesis. The first study identifies the major trends, concepts, and keywords that guide the subsequent empirical research. The second study examines the fundamental positive and negative factors influencing the impact of AI on decision-making and provides theoretical insights into this relationship. By identifying these factors, which relate to human–AI collaboration, the third study shifts its focus toward human–AI collaboration and examines the different modes of this collaboration. Finally, the last study expands this framework using real-world data collected through questionnaire surveys from employees in organizations. Taken together, these studies provide a coherent and progressive contribution to the literature on AI, decision-making, and human–AI collaboration.

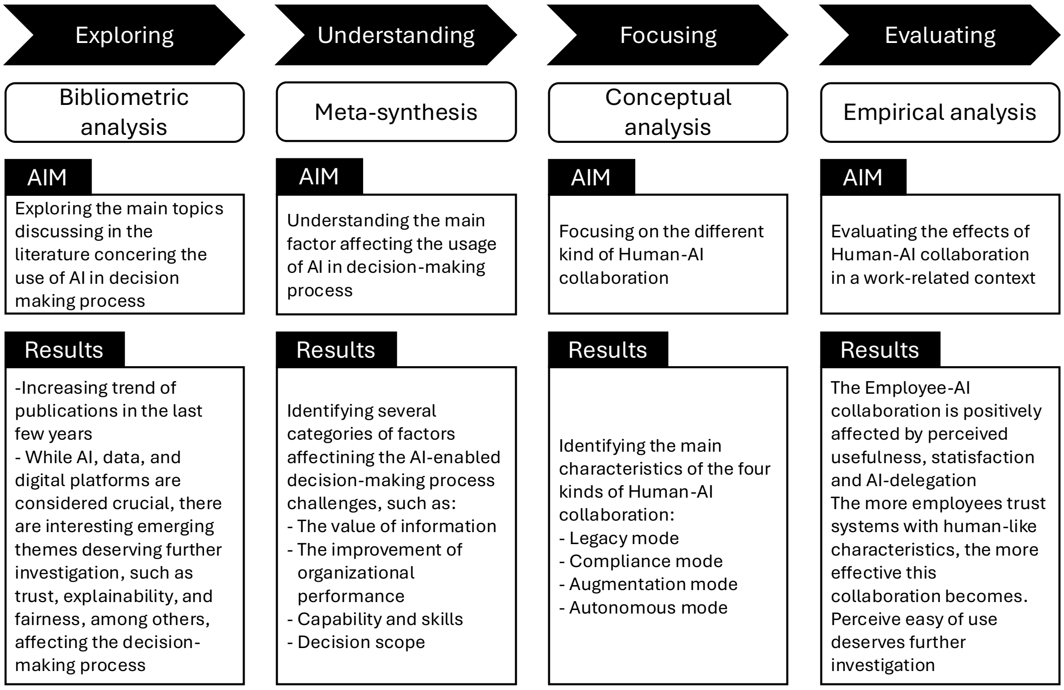

Figure 1. Overall Conceptual Framework of the Dissertation

References

A. Jacovi, A. Marasović T, Miller Y, G.: Formalizing trust in artificial intelligence: Prerequisites, causes and goals of human trust in AI. Proc. 2021 ACM Conf. fairness, accountability, transparency, 624–635 (2021).

Adadi, A., Berrada, M.: Peeking inside the black box: A survey on Explainable Artificial Intelligence (XAI). IEEE Access. PP, 1 (2020).

Adadi, A., Lahmer, M., & Nasiri, S. (2022). Artificial Intelligence and COVID-19: A Systematic umbrella review and roads ahead. *Journal of King Saud University. Computer and Information Sciences/Mağalaï Ğam'aï Al-malīk Saud: Ùlm Al-ḥasib Wa Al-ma'lumat*, *34*(8), 5898–5920.

Adi AmitLilach, S.S.: The role of epistemic motivation in individuals' response to decision complexity. Organ. Behav. Hum. Decis. Process. 121(1)104–117. (2013).

Aghion, P., Tirole, J.: Formal and Real Authority in Organizations. Author (s): Philippe Aghion and Jean Tirole. Source: Journal of Political Economy, Vol. 105, No. 1 (Feb 1997).

Ahmad Husairi, M., Rossi, P.: Delegation of purchasing tasks to AI: The role of perceived choice and decision autonomy. Decis. Support Syst. 179, 114166 (2024).

Akgun, S., & Greenhow, C. (2021). Artificial intelligence in education: Addressing ethical challenges in K-12 settings. *AI And Ethics*, *2*(3), 431–440. https://doi.org/10.1007/s43681-021-00096-7

Albert Bandura: Self-efficacy: toward a unifying theory of behavioral change. Psychol. Rev. 84, 2 (1977), 191–215. (1977).

Albert, D. A., & Smilek, D. (2023). Comparing attentional disengagement between Prolific and MTurk samples. *Scientific Reports*, *13*(1), 20574.

Ali, O., Abdelbaki, W., Shrestha, A., Elbaşi, E., Alryalat, M. a. A., & Dwivedi, Y. K. (2023). A systematic literature review of artificial intelligence in the healthcare sector: Benefits, challenges, methodologies, and functionalities. *Journal of Innovation & Knowledge*, *8*(1), 100333.

Alter, S.: A taxonomy of decision support systems. Sloan Manag. Rev. 19 (1), 39 (1977).

Alufaisan, Y., Marusich, L.R., Bakdash, J.Z., Zhou, Y.: Does Explainable Artificial Intelligence Improve Human Decision-Making? (2017).

Aria, M., & Cuccurullo, C. (2017). Bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics*, *11*(4), 959–975. https://doi.org/10.1016/j.joi.2017.08.007

Aria, M., Misuraca, M., & Spano, M. (2020). Mapping the evolution of social research and data science over 30 years of social indicators research. *Social Indicators Research*, *149*(3), 803–831.

Atrill, P. (2019). Financial management for decision makers. Pearson Higher Ed.

Atrill, P., & McLaney, E. J. (2008). *Financial accounting for decision makers.* Pearson Education.

Autor DH: Polanyi's paradox and the shape of employment growth. Proc. Fed. Reserv. Bank Kansas

City—Jackson Hole Econ. Policy Symp. 129–179. (2014).

Autor, D. H., & Dorn, D.: How technology wrecks the middle class. The New York Times, 24(2013), 1279-1333 (2013).

Azadeh, A., Yazdanparast, R., Zadeh, S. A., & Keramati, A. (2018). An intelligent algorithm for optimizing emergency department jobs and patient satisfaction. *International Journal of Health Care Quality Assurance*, *31*(5), 374–390. https://doi.org/10.1108/ijhcqa-06-2016-0086

Baker, T., & Dellaert, B.: Regulating robo advice across the financial services industry. Iowa L. Rev., 103, 713 (2017).

Baporikar, N. (2014). Technology is imperative in managerial Decision-Making. In *Advances in Human Resources Management and Organizational Development book series* (pp. 158–176). https://doi.org/10.4018/978-1-4666-4478-6.ch009

Barile, D., Secundo, G., & Del Vecchio, P. (2025). An artificial intelligence-based innovation ecosystem enabling open innovation and sustainable growth: evidence from a case study. *Innovation*, 1-23.

Bartling, B., Fehr, E., Herz, H.: The Intrinsic Value of Decision Rights. SSRN Electron. J (2013).

Becker, F., Skirzyński, J., Van Opheusden, B., & Lieder, F. (2022). Boosting Human Decision-making with AI-Generated Decision Aids. Computational Brain & Behavior, 5(4), 467–490.

Benjamin P. Commerford, Sean A. Dennis, Jennifer R. Joe, J.W.U.: Man versus machine: Complex estimates and auditor reliance on artificial intelligence. J. Account. Res. 60(1)171–201. (2022).

Benjamin, D.J., Heffetz, O., Kimball, M.S., Rees-Jones, A.: What do you think would make you happier? What do you think you would choose? Am. Econ. Rev. 102, 2083– 2110 (2012).

Benlian, A., Wiener, M., Cram, W.A., Krasnova, H., Maedche, A., Möhlmann, M., Recker, J., Remus, U.: Algorithmic Management: Bright and Dark Sides, Practical Implications, and Research Opportunities. Bus. Inf. Syst. Eng. 64, 825–839 (2022).

Benz, M., Frey, B.S., Stutzer, A.A.S.: Introducing Procedural Utility: Not Only What, But Also How Matters. SSRN Electron. J. 1–29 (2005).

Berk, R.: Machine learning risk assessments in criminal justice settings. New York, NY: Springer (2019).

Bertsimas, D., & Kallus, N. (2020). From predictive to prescriptive analytics. *Management Science*, *66*(3), 1025–1044. https://doi.org/10.1287/mnsc.2018.3253

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*, 351-370.

Bilquise, G., Ibrahim, S., & Salhieh, S. E. M. (2024). Investigating student acceptance of an academic advising chatbot in higher education institutions. *Education and Information Technologies*, *29*(5), 6357-6382.

Bischof-dos-Santos, C., Takahashi, A. R. W., Giacomini, M. M., Rocha, C. F., Da Veiga, C. P., &

Duclós, L. C. (2017). New causal model for Brazilian private higher education institutions: A dynamic capability perspective. *Information Resources Management Journal (IRMJ)*, *30*(1), 15-29.

Bobadilla-Suarez, S., Sunstein, C.R., Sharot, T.: The intrinsic value of choice: The propensity to under-delegate in the face of potential gains and losses. J. Risk Uncertain. 54, 187–202 (2017).

Bohnet, I., Greig, F., Herrmann, B., & Zeckhauser, R. Betrayal aversion: Evidence from Brazil, China, Oman, Switzerland, Turkey, and the United States. American Economic Review, 98(1), 294-310 (2008).

Bolton, R. (2018). *The Future of HR 2019: In the Know or the No.* KPMG International. 1– 24.

Bondi, E., Koster, R., Sheahan, H., Chadwick, M., Bachrach, Y., Cemgil, T., Paquet, U., Dvijotham, K.: Role of Human-AI Interaction in Selective Prediction. Proc. 36th AAAI Conf. Artif. Intell. AAAI 2022. 36, 5286–5294 (2022).

Booyse, D., & Scheepers, C. B. (2024). Barriers to adopting automated organisational decision-making through the use of artificial intelligence. *Management Research Review*, *47*(1), 64-85.

Braun, H., & Chandler, J. S. (1987). Predicting Stock Market Behavior Through Rule Induction: An Application of the Learning-From-Example Approach. *Decision Sciences*, *18*(3), 415–429.

Brynjolfsson, E., McAfee, A.: The second machine age: Work, progress, and prosperity in a time of brilliant technologies (2014).

Butler J. Miller J: Social risk and the dimensionality of intentions. Manager. Sci. 64, 2787– 2796 (2018).

Cabrera, Á. A., Perer, A., & Hong, J. I. (2023). Improving human-AI collaboration with descriptions of AI behavior. *Proceedings of the ACM on Human-Computer Interaction*, *7*(CSCW1), 1-21.

Cabrerizo, F. J., Ureña, R., Pedrycz, W., & Herrera-Viedma, E. (2014). Building consensus in group decision-making with an allocation of information granularity. *Fuzzy Sets and Systems*, *255*, 115–127. https://doi.org/10.1016/j.fss.2014.03.016

Çalışkan, A., Bryson, J. J., & Narayanan, A. (2017). Semantics derived automatically from language corpora contain human-like biases. *Science*, *356*(6334), 183–186. https://doi.org/10.1126/science.aal4230

Campagna, R. L., Mislin, A. A., Dirks, K. T., & Elfenbein, H. A. (2022). The (mostly) robust influence of initial trustworthiness beliefs on subsequent behaviors and perceptions. *Human Relations*, *75*(7), 1383-1411.

Candrian, C., Scherer, A.: Rise of the machines: Delegating decisions to autonomous AI. Comput. Human Behav. 134, 107308 (2022).

Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. Technovation, 106, 102312.

Caputo, F., Papa, A., Cillo, V., & Del Giudice, M. (2019). Technology readiness for education 4.0: barriers and opportunities in the digital world. In *Opening up education for inclusivity across digital economies and societies* (pp. 277-296). IGI Global.

Cardillo, G., Chiappini, H.: Robo-advisors: A systematic literature review. Financ. Res. Lett. 62, 105119 (2024).

Cardinaels, E., Hollander, S., White, B.J.: Automatic summaries of earnings releases: Attributes and effects on investors' Automatic summaries of earnings releases: Attributes and effects on investors' judgments. (2018).

Carrie R Leana. Predictors and consequences of delegation. Acad. Manag. J. 29, 4 (1986), 754–774. (1986).

Chatterjee, S., Chaudhuri, R., & Vrontis, D. (2021). Does a data-driven culture impact the innovation and performance of a firm? An empirical examination. *Annals of Operations Research*, *333*(2–3), 601–626.

Chen, N., Liu, W., Bai, R., & Chen, A. (2017). Application of computational intelligence technologies in emergency management: a literature review. *Artificial Intelligence Review*, *52*(3), 2131–2168.

Chen, X., Jiang, L., Zhou, Z., & Li, D. (2025). Impact of perceived ease of use and perceived usefulness of humanoid robots on students' intention to use. *Acta Psychologica*, *258*, 105217.

Chernov, A., Chernova, V. A., & Komarova, T. (2020). The Usage of Artificial Intelligence in Strategic Decision Making in Terms of the Fourth Industrial Revolution. *Proceedings of the 1st International Conference on Emerging Trends and Challenges in Management Theory and Practice (ETCMTP 2019)*.

Chien, C., Dauzère-Pérès, S., Huh, W. T., Jang, Y. J., & Morrison, J. R. (2020). Artificial intelligence in manufacturing and logistics systems: algorithms, applications, and case studies. International Journal of Production Research, 58(9), 2730–2731.

Chowdhury, S., Budhwar, P., Dey, P. K., Joel-Edgar, S., & Abadie, A. (2022). AI-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems, and organisational socialisation framework. *Journal of Business Research*, *144*, 31-49.

Cobo, M. J., Jürgens, B., Herrero-Solana, V., Martínez, M. a. A., & Herrera-Viedma, E. (2018). Industry 4.0: a perspective based on bibliometric analysis. *Procedia Computer Science*, *139*, 364–371.

Cobo, M. J., López-Herrera, A. G., Liu, X., & Herrera, F. (2011). An approach for detecting, quantifying, and visualizing the evolution of a research field: A practical application to the Fuzzy Sets Theory field. *Journal of Informetrics*, *5*(1), 146–166. https://doi.org/10.1016/j.joi.2010.10.002

Condé, L., & Münch, C. (2025). Resilient by Design: Exploring the Social Abilities and Actor-Network Roles of Artificial Intelligence in Supply Chain Management. *Journal of Business Logistics*, *46*(4), e70032.

Critical Appraisal Skills Programme (2018). CASP (Systematic Reviews) Checklist. https://casp-uk.net/casp-tools-checklists/

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *psychometrika*, *16*(3), 297-334.

Crowston, K., Bolici, F.: Impacts of machine learning on work. Proc. Annu. Hawaii Int. Conf. Syst. Sci. 2019-January, 5961–5970 (2019).

D'Adderio, L.: Crafting the virtual prototype: How firms integrate knowledge and capabilities across organizational boundaries. Res. Policy, 30 1409–1424 (2001).

D'Allura, G. M., Mariasole, B., & Filippi, E. (2025). Innovating with heart: family firms' decision to automate with emotional responsibility. *Journal of Family Business Management*, *15*(4), 1070-1086.

Daly, S. J., Wiewiora, A., & Hearn, G. (2025). Shifting attitudes and trust in AI: Influences on organizational AI adoption. *Technological Forecasting and Social Change*, *215*, 124108.

Das, A. C., Phalin, G., Patidar, I. L., Gomes, M., Sawhney, R., & Thomas, R.: The next frontier of customer engagement: AI-enabled customer service. McKinsey's Operations Practice (2023).

Das, R., & Ranasinghe, A. (2025, February). *A qualitative study: Can AI make management decisions? International Journal of Science Academic Research, 6*(2), 9340–9346.

Davenport, T. H., & Harris, J. G. (2005). Automated decision making comes of age. *MIT Sloan Management Review*, *46*(4), 83.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, *96*(1), 108-116.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319-340.

Dawes, R.M.: The robust beauty of improper linear models. Am. Psychol. 34, 571–582 (1979).

Deci, E.L.: Intrinsic Motivation and Self-Determination in Human Behavior. (1985).

Desanctis, G., Scott, M.: Capturing Complexity in Advanced Technology Use: Adaptive Structuration Theory. 5, 121–147 (2015).

Desiere, S., & Struyven, L. (2020). Using Artificial Intelligence to Classify Jobseekers: The Accuracy-Equity Trade-off. *Journal of Social Policy*, *50*(2), 367–385. https://doi.org/10.1017/s0047279420000203

Devarajan, J. P., Manimuthu, A., & Sreedharan, V. R. (2023). Healthcare Operations and Black Swan Event for COVID-19 Pandemic: A Predictive Analytics. *IEEE Transactions on Engineering Management*, *70*(9), 3229–3243.https://doi.org/10.1109/tem.2021.3076603

Di Vaio A., Hassan R., Alavoine C: Data intelligence and analytics: A bibliometric analysis of human-Artificial intelligence in public sector decision-making effectiveness. Technological Forecasting

& Social Change, 174, 121201 (2022).

Dietvorst, B.J., Simmons, J.P., Massey, C.: Algorithm Aversion: People Erroneously Avoid Algorithms after Seeing Them Err. SSRN Electron. J. 143, 1–13 (2014).

Dietvorst, B.J., Simmons, J.P., Massey, C.: Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. Manager. Sci. 64, 1155– 1170 (2018).

Dixon-Woods, M., Booth, A., & Sutton, A. J. (2007). Synthesizing qualitative research: a review of published reports. Qualitative Research, 7(3), 375–422.

Dominguez-Martinez, S., Sloof, R., Von Siemens, F.A.: Monitored by your friends, not your foes: Strategic ignorance and the delegation of real authority. Games Econ. Behav. 85, 289–305 (2014).

Dowling, K., Guhl, D., Klapper, D., Spann, M., Stich, L., Yegoryan, N.: Behavioral biases in marketing. J. Acad. Mark. Sci. 48, 449–477 (2020).

Duan, N., Liu, L., Yu, X., Li, Q., & Yeh, S. (2019). Classification of multichannel surface electromyography signals based on convolutional neural networks. *Journal of Industrial Information Integration*, *15*, 201–206. https://doi.org/10.1016/j.jii.2018.09.001

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice, and policy. *International Journal of Information Management*, *57*, 101994.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., . . . Wright, R. (2023). Opinion Paper: “So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges, and implications of generative conversational AI for research, practice, and policy. *International Journal of Information Management*, *71*, 102642.

Edwards, J. S., Duan, Y., & Robins, P. C. (2000). An analysis of expert systems for business decision making at different levels and in different roles. European Journal of Information Systems, 9(1), 36–46.

Einhorn, Hillel J. Hogarth, R.M.: Unit weighting schemes for decision making. Organ. Behav. Hum. Performance, 13(2), 171–192. (1975).

Elgendy, N., & Elragal, A. (2014). Big data analytics: a literature review paper. In *Advances in Data Mining. Applications and Theoretical Aspects: 14th Industrial Conference, ICDM 2014, St. Petersburg, Russia, July 16-20, 2014. Proceedings 14* (pp. 214-227). Springer International Publishing.

Ellegaard, O., & Wallin, J. A. (2015). The bibliometric analysis of scholarly production: How great is the impact? *Scientometrics*, 105, 1809-1831.

Elo, S., & Kyngäs, H. (2008). The qualitative content analysis process. Journal of Advanced Nursing, 62(1), 107–115. https://doi.org/10.1111/j.1365-2648.2007.04569.x

Fabregat-Aibar, L., Barberà-Mariné, M. G., Terceño, A., & Pié, L. (2019). A bibliometric and visualization analysis of socially responsible funds. *Sustainability*, *11*(9), 2526. https://doi.org/10.3390/su11092526

Falk, A., Kosfeld, M.: The hidden costs of control. Am. Econ. Rev. 96, 1611–1630 (2006).

Fernandes, F., Santos, P., Sá, L., & Neves, J. (2023). Contributions of Artificial Intelligence to Decision Making in Nursing: A Scoping Review Protocol. Nursing Reports, 13(1), 67–72.

Fogel, L. J., Owens, A., & Walsh, M. J. (1965). Intelligent decision-making through a simulation of evolution. *Simulation*, *5*(4), 267–279. https://doi.org/10.1177/003754976500500413

Fogg, B.: A behavior model for persuasive design. ACM Int. Conf. Proceeding Ser. 350. (2009).

Foltice, B., & Ilcin, P.: The Influences of Locus of Control, Debt, and Framing on Retirement Contributions. Journal of Advanced Studies in Finance, 10(1 19), 34-44. (2019).

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50.

Fred C Lunenburg: Self-efficacy in the workplace: implications for motivation and performance. Int. J. Manag. Business, Adm. 14, 1, 1–6 (2011).

Friedland, N., Keinan, G., & Regev, Y.: Controlling the uncontrollable: Effects of stress on illusory perceptions of controllability. J. Personal. Soc. Psychol. 63(6), 923. (1992).

Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2022). Cognitive challenges in human–artificial intelligence collaboration: Investigating the path toward productive delegation. *Information Systems Research*, *33*(2), 678-696.

Fügener, Andreas, Grahl, Jörn, Gupta, Alok, Ketter, W.: Cognitive Challenges in Human– Artificial Intelligence Collaboration: Investigating the Path Toward Productive Delegation. Inf. Syst. Res. 33, 678–696 (2022).

Fügener, Andreas, Jörn Grahl, Alok Gupta, W.K.: Will humans-in-the-loop become borgs? merits and pitfalls of working with ai. Manag. Inf. Syst. Q. (MISQ)-Vol 45. (2021).

Gati, I., & Kulcsar, V. (2021). Making better career decisions: From challenges to opportunities. *Journal of Vocational Behavior*, *126*, 103545.

Gezdur, A., Bhattacharjya, J., & Panagiotelis, A. (2024). Improving the forecasting approach for crude oil sourcing at an oil refining firm: a decision theory perspective. *Production Planning & Control*, 1-18.

Glazer, S., & Karpati, T. (2014). The role of culture in decision making. *Cutter IT Journal*, 27(9), 23-

29.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627-660.

Govindan, K., & Sivakumar, R. (2015). Green supplier selection and order allocation in a low-carbon paper industry: integrated multi-criteria heterogeneous decision-making and multi-objective linear programming approaches. *Annals of Operation Research/Annals of Operations Research*, *238*(1–2), 243–276.

Gray, H.M., Gray, K., Wegner, D.M.: Dimensions of mind perception. Science (80-.). 315, 619 (2007).

Greenhow, C., Galvin, S. M., Brandon, D. L., & Askari, E. (2020). A Decade of Research on K–12 Teaching and Teacher Learning with Social Media: Insights on the State of the Field. *Teachers College Record*, *122*(6), 1–72. https://doi.org/10.1177/016146812012200602

Guo, H., Wang, W.: An active learning-based SVM multi-class classification model. Pattern Recognit. 48, 1577–1597 (2015).

Guo, Y., Hao, Z., Zhao, S., Gong, J., & Yang, F. (2020). Artificial intelligence in health Care: Bibliometric analysis. *Journal of Medical Internet Research*, *22*(7), e18228. https://doi.org/10.2196/18228

Gupta, S., Leszkiewicz, A., Kumar, V., Bijmolt, T., & Potapov, D. (2020). Digital Analytics: modeling for insights and new methods. *Journal of Interactive Marketing*, *51*, 26–43.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed, a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139-152.

Hair, J.F.; Hult, G.T.M.; Ringle, C.; Sarstedt, M. (2016). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*; Sage Publications: Thousand Oaks, CA, USA.

Harbers, M., Peeters, M.M.M., Neerincx, M.A.: Perceived autonomy of robots: Effects of appearance and context. Intell. Syst. Control Autom. Sci. Eng. 84, 19–33 (2017).

Hassenzahl, M., Eckoldt, K., Diefenbach, S., Laschke, M., Lenz, E., Kim, J.: Designing moments of meaning and pleasure. Experience design and happiness. Int. J. Des. 7, 21–31 (2013).

Hemmer, P., Schemmer, M., Kühl, N., Vössing, M., & Satzger, G. (2025). Complementarity in human-AI collaboration: Concept, sources, and evidence. *European Journal of Information Systems*, 1-24.

Hemmer, P., Schemmer, M., Kühl, N., Vössing, M., Satzger, G.: On the Effect of Information Asymmetry in Human-AI Teams (2022).

Hemmer, P., Westphal, M., Schemmer, M., Vetter, S., Vössing, M., Satzger, G.: Human- AI Collaboration: The Effect of AI Delegation on Human Task Performance and Task Satisfaction. Int. Conf. Intell. User Interfaces, Proc. IUI. 453–463 (2023).

Henfridsson, O.: What People Hate About Being Managed by Algorithms, according to a Study of Uber

Drivers (2019).

Heradio, R., Fernández-Amorós, D., Cerrada, C., & Cobo, M. J. (2020). Group Decision- Making Based on Artificial Intelligence: A Bibliometric Analysis. *Mathematics*, *8*(9), 1566.

Höddinghaus, M.; Sondern, D.; Hertel, G.: The automation of leadership functions: Would people trust decision algorithms? Comput. Hum. Behav., 116, 106635. (2021).

Hollnagel, E.: Information and reasoning in intelligent decision support systems. International Journal of Man-Machine Studies, 27(5-6), 665-678(1987).

Howard, J. (2013). The business impact of deep learning. *Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*.

Huang, J.-H., Duan, X.-Y., He, F.-F., Wang, G.-J., Hu, X.-Y: A historical review andBibliometric analysis of research on Weak measurement research over the past decades based on Biblioshiny. 1–19 (2021).

Hvalshagen, M., Lukyanenko, R., Samuel, B.M.: Empowering Users with Narratives: Examining the Efficacy of Narratives for Understanding Data-Oriented Conceptual Models. Inf. Syst. Res. 34, 89–909 (2023).

Ikeuchi, K. (Ed.). (2021). *Computer vision: A reference guide*. Cham: Springer International Publishing.

intelligence, robotics, advanced technologies, and human resource management: a systematic review. *International Journal of Human Resource Management*, *33*(6), 1237–1266.

J. Edward RussoPaul SchoemakerPaul Schoemaker: Managing Overconfidence. (1992).

Jahan, R., & Tripathi, M. M. (2021, June). Brain tumor detection using machine learning in MR images. In *2021 10th IEEE International Conference on Communication Systems and Network Technologies (CSNT)* (pp. 664-668). IEEE.

James A Evans, J.G.F.: Metaknowledge. Sci. 331(6018) 721–725. (2011).

Janssen, M., Hartog, M. H. D., Matheus, R., Ding, A. Y., & Kuk, G. (2020). Will algorithms blind people? The effect of Explainable AI and Decision-Makers' experience on AI- supported Decision-Making in Government. *Social Science Computer Review*, *40*(2), 478–493.

Jillahi, K. B., & Iorliam, A. (2024). A Scoping Literature Review of Artificial Intelligence in Epidemiology: Uses, Applications, Challenges, and Future Trends. *Journal of Computing Theories and Applications*, *1*(4), 421-445.

Jimma, B. L. (2023). Artificial intelligence in healthcare: A bibliometric analysis. *Telematics and Informatics Reports*, *9*, 100041. https://doi.org/10.1016/j.teler.2023.100041

Joshi, A., Kale, S., Chandel, S., & Pal, D. K. (2015). Likert scale: Explored and explained. *British journal of applied science & technology*, *7*(4), 396.

Jussupow, E., Spohrer, K., Heinzl, A., & Gawlitza, J. (2021). Augmenting medical diagnosis decisions? An investigation into physicians' decision-making process with artificial intelligence. *Information Systems Research*, *32*(3), 713-735.

Kaasinen, E., Roto, V., Hakulinen, J., Heimonen, T., Jokinen, J.P., Karvonen, H., Tuuli Keskinen, H.K., Lu, Y., Saariluoma, P., Al, E.: Defining user experience goals to guide the design of industrial systems. Behav. Inf. Technol. 34, 10 (2015), 976–991. (2015).

Kærnested, B., & Bragadóttir, H. (2012). Delegation of registered nurses revisited: Attitudes towards delegation and preparedness to delegate effectively. *Vård i Norden*, *32*(1), 10-15.

Kahneman, D.: Thinking, fast and slow. Farrar, Straus and Giroux (2011).

Kaplan, A., & Haenlein, M.: Rulers of the world, unite! The challenges and opportunities of artificial intelligence. Business Horizons, 63(1), 37-50 (2020).

Kaplan, S.: Strategy and PowerPoint: An inquiry into the epistemic culture and machinery of strategy making. Organ. Sci. 22 320–346. (2011).

Katherine C KelloggMelissa A. ValentineAngele Christin: Algorithms at work: the new contested terrain of control. Acad Manag Ann 14(1)366–410. (2020).

Kaushal, N., Kaurav, R. P. S., Sivathanu, B., & Kaushik, N. (2021). Artificial intelligence and HRM: identifying future research Agenda using systematic literature review and bibliometric analysis. *Management Review Quarterly*, *73*(2), 455–493. https://doi.org/10.1007/s11301-021-00249-2

Kim, T.W.W., Duhachek, A.: The Impact of Artificial Agents on Persuasion: a Construal Level Account. AP-Asia-Pacific Adv. Consum. Res. 12, 53–53 (2018).

Kim, Y. J., Chun, J. U., & Song, J. (2009). Investigating the role of attitude in technology acceptance from an attitude strength perspective. *International Journal of Information Management*, *29*(1), 67-77.

Kleinberg, J., Lakkaraju, H., Leskovec, J., Ludwig, J., & Mullainathan, S. (2017). Human Decisions and Machine Predictions. *NBER Working Paper No. 23180*. https://doi.org/10.3386/w23180

Kleinberg, J., Lakkaraju, H., Leskovec, J., Ludwig, J., & Mullainathan, S. (2018). Human decisions and machine predictions. *The Quarterly Journal of Economics*. https://doi.org/10.1093/qje/qjx032

Kleinmuntz B: Why we still use our heads instead of formulas: Toward an integrative approach. Psych. Bull. 107(3):296–310. (1990).

Kolbjørnsrud, V., Amico, R., & Thomas, R. J. (2017). Partnering with AI: How organizations can win over skeptical managers. Strategy and Leadership, 45(1), 37–43.

Kong, H., Yin, Z., Baruch, Y., & Yuan, Y. (2023). The impact of trust in AI on career sustainability: The role of employee–AI collaboration and protean career orientation. *Journal of Vocational Behavior*, *146*, 103928.

Kononenko I: Machine learning for medical diagnosis: History, state of the art, and perspective. Artif. Intell. Med. 23(1)89–109. (2001).

Kőszegi, B., & Rabin, M.: A model of reference-dependent preferences. The Quarterly Journal of

Economics, 121(4), 1133-1165 (2006).
Kwon, H., Roh, J. J., & Miceli, N. (2016). Better practice prediction using neural networks: an application to the smartphone industry. *Benchmarking*, *23*(3), 519–539. https://doi.org/10.1108/bij-08-2013-0080
Lan, Y., Liu, S., Chen, H., & Xia, L. (2025). Mindfulness and AI adoption: extending the technology acceptance model for Chinese media students. *Frontiers in Psychology*, *16*, 1637502.
Lankton, N. K., McKnight, D. H., & Tripp, J. (2015). Technology, humanness, and trust: Rethinking trust in technology. *Journal of the association for information systems*, *16*(10), 1.
Lapointe, L., & Rivard, S.: A multilevel model of resistance to information technology implementation. MIS Quarterly, 461-491 (2005).
Lawrence, T. B. (1991). Impacts of artificial intelligence on organizational decision making. *Journal of Behavioral Decision Making*, *4*(3), 195–214. https://doi.org/10.1002/bdm.3960040306
Lecun, Y., Bengio, Y., Hinton, G.: Deep learning. Nature. 521, 436–444 (2015).
Lehner, O. M., Ittonen, K., Silvola, H., Ström, E., & Wührleitner, A. (2022). Artificial intelligence-based decision-making in accounting and auditing: ethical challenges and normative thinking. *Accounting Auditing & Accountability*, *35*(9), 109–135. https://doi.org/10.1108/aaaj-09-2020-4934
Leonardi, P.M.: When does technology use enable network change in organizations? A comparative study of feature use and shared affordances. Manag. Inf. Syst. Quarterly, 37 749–775. (2013).
Li, B., Zhang, X., Hong, N., & Hussain, A. (2022). A bibliometric study and science mapping research on intelligent decision-making. *Cognitive Computation*, *14*(3), 989–1008. https://doi.org/10.1007/s12559-022-09993-3
Li, J. M., Wu, H. Y., Zhang, R. X., & Wu, T. J. (2025). How does employee-generative AI collaboration affect employees' work and family outcomes? The relationship instrumentality perspective. *The International Journal of Human Resource Management*, 1-27.
Logg, J.M., Minson, J.A., Moore, D.A.: Algorithm appreciation: People prefer algorithmic to human judgment. Organ. Behav. Hum. Decis. Process. 151, 90–103 (2019).
Lou, B., & Wu, L.: AI on drugs: Can artificial intelligence accelerate drug development? Evidence from a large-scale examination of bio-pharma firms. Evidence from a Large- scale Examination of Bio-pharma Firms (March 15, 2021). MISQ Forthcoming (2021).
Lu, J., Lee, D.D.K., Kim, T., Danks, D.: Good Explanation for Algorithmic Transparency Good Explanation for Algorithmic Transparency (2020).
Lu, N. J., Liu, N. J., Couzin, I. D., & Levin, S. A. (2008). Emerging collective behaviors of animal groups. *2008 7th World Congress on Intelligent Control and Automation*. https://doi.org/10.1109/wcica.2008.4593068

Lu, T., Zhang, Y.: 1 + 1 > 2? Information, Humans, and Machines. Inf. Syst. Res (2024).

Lu, Tian, and Yingjie Zhang. "1+ 1> 2? Information, humans, and machines." Information Systems Research 36.1 (2025).

Luan, H., Geczy, P., Lai, H., Gobert, J., Yang, S. J., Ogata, H., Baltes, J., Guerra, R., Li, P., & Tsai, C. C. (2020). Challenges and future directions of big data and artificial intelligence in education. *Frontiers in Psychology*, *11*. https://doi.org/10.3389/fpsyg.2020.580820

Lupia, A.: Delegation of power: Agency theory. Int. Encycl. Soc. Behav. Sci. (2nd ed., pp. 58–60) (2015).

M. I. Jordan, Mitchell, T.M.: Machine learning: Trends, perspectives, and prospects. Sci. 349 255–260. (2015).

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, *120*, 262–273. https://doi.org/10.1016/j.jbusres.2020.07.045

Maphosa, V., & Maphosa, M. (2022). Artificial Intelligence in Project Management Research: A Bibliometric Analysis. *Zenodo (CERN European Organization for Nuclear Research)*.

Maphosa, V., & Maphosa, M. (2023). Artificial intelligence in higher education: a bibliometric analysis and topic modeling approach. *Applied Artificial Intelligence*, *37*(1).

Marvi, R., Foroudi, P., & AmirDadbar, N. (2025). Dynamics of user engagement: AI mastery goal and the paradox mindset in AI–employee collaboration. *International Journal of Information Management*, *83*, 102908.

McCelland, D.C.: Power: The Inner Experience. Irvington, NY: Halsted Press. 2006, 2036.

McKnight, D. H., Carter, M., Thatcher, J. B., & Clay, P. F. (2011). Trust in a specific technology: An investigation of its components and measures. *ACM Transactions on Management Information Systems (TMIS)*, *2*(2), 1-25.

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information systems research*, *13*(3), 334-359.

Meng Xiaocheng TangSiyuan Xia, et al: Algorithm aversion: Evidence from ridesharing drivers. Manag. Sci. (2023).

Meskó, B., Hetényi, G., & Győrffy, Z. (2018). Will artificial intelligence solve the human resource crisis in healthcare? *BMC Health Services Research*, *18*(1). https://doi.org/10.1186/s12913-018-3359-4

Metcalf, L., Askay, D. A., & Rosenberg, L. B. (2019). Keeping Humans in the Loop: Pooling Knowledge through Artificial Swarm Intelligence to Improve Business Decision Making. California Management Review, 61(4), 84–109.

Mintzberg, H. (1975). *Impediments to the use of management information: A Study Carried Out on*

Behalf of the National Association of Accountants, New York, N.Y., and the Society of Industrial Accountants of Canada, Hamilton, Ontario, Canada. New York: National Association of Accountants; Hamilton, Ont.: Society of Industrial Accountants of Canada.

Mohiuddin Babu, M., Akter, S., Rahman, M., Billah, M., & Hack-Polay, D. (2024). The role of artificial intelligence in shaping the future of the Agile fashion industry. *Production Planning & Control*, *35*(15), 2084-2098.

Mohseni, S., Yang, F., Pentyala, S., Du, M., Liu, Y., Lupfer, N., Hu, X., Ji, S., Ragan, E.: Machine Learning Explanations to Prevent Overtrust in Fake News Detection (2021).

Moriuchi, E., Landers, V. M., Colton, D., & Hair, N. (2020b). Engagement with chatbots versus augmented reality interactive technology in e-commerce. *Journal of Strategic Marketing*, *29*(5), 375–389.

Mouakket, S. (2015). Factors influencing continuance intention to use social network sites: The Facebook case. *Computers in Human Behavior*, *53*, 102-110.

Murray, A., Kuban, S., Josefy, M.: Contracting in the Smart Era: The Implications of Blockchain and Decentralized Autonomous Organizations for Contracting and Corporate Governance (2019).

Murray, A., Rhyme, J., Sirmon, D.G.: Humans and technology: Forms of conjoined agency in organizations. Acad. Manag. Rev. 46, 552–571 (2021).

Murray, A., Rhymer, J. E. N., & Sirmon, D. G. (2021). Humans and technology: Forms of conjoined agency in organizations. *Academy of Management Review*, *46*(3), 552-571.

Nalini, R. (2024). The transformative power of artificial Intelligence in Decision-Making, automation, and customer engagement. In Advances in Logistics, Operations, and Management Science book series (pp. 189–208).

Negash, S., Gundlack, J., Buch, C., Apfelbacher, T., Schildmann, J., Frese, T., ... & Mikolajczyk, R. T. (2025). Physicians' Attitudes and Acceptance towards Artificial Intelligence in Medical Care: A Qualitative Study in Germany. *Frontiers in Digital Health*, *7*, 1616827.

Nikoi, E. (Ed.). (2013). Collaborative communication processes and decision-making in organizations. In the Advances in Human Resources Management and Organizational Development book series.

Noblit GW.; Hare RD. Meta-ethnography: Synthesizing qualitative studies. sage; 1988

Nouis, S. C., Uren, V., & Jariwala, S. (2025). Evaluating accountability, transparency, and bias in AI-assisted healthcare decision-making: a qualitative study of healthcare professionals' perspectives in the UK. *BMC Medical Ethics*, *26*(1), 89.

Nunnally, J. C. (1978). An overview of psychological measurement. *Clinical diagnosis of mental disorders: A handbook*, 97-146.

Nwogugu, M. (2005). Towards multi-factor models of decision making and risk. *The Journal of Risk Finance*, *6*(2), 150–162. https://doi.org/10.1108/15265940510585815

Önkal, D., Goodwin, P., Thomson, M., Gönül, S., & Pollock, A.: The relative influence of advice from human experts and statistical methods on forecast adjustments. Journal of Behavioral Decision Making, 22(4), 390-409 (2009).

Oskamp, S. Overconfidence in case-study judgments. Journal of Consulting Psychology, 29(3), 261 (1965).

Owens, D., Grossman, Z., Fackler, R.: The control premium: A preference for payoff autonomy. Am. Econ. J. Microeconomics. 6, 138–161 (2014).

Palos-Sánchez, P. R., Baena-Luna, P., Badicu, A., & Moro, J. C. I. (2022). Artificial Intelligence and Human Resources Management: A Bibliometric Analysis. *Applied Artificial Intelligence*, *36*(1). https://doi.org/10.1080/08839514.2022.2145631

Paluch, S., & Wittkop, T. (2023). Role of Risk on Employees' Willingness to Collaborate with Artificial Intelligence and Its Impact on Wellbeing. In *Springer eBooks* (pp. 281–302).

Pan, Y., Froese, F., Liu, N., Hu, Y., & Ye, M. (2021). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. *International Journal of Human Resource Management*, *33*(6), 1125–1147. https://doi.org/10.1080/09585192.2021.1879206

Papagiannidis, E., Mikalef, P., Conboy, K., & Van de Wetering, R. (2023). Uncovering the dark side of AI-based decision-making: A case study in a B2B context. *Industrial Marketing Management*, *115*, 253-265.

Pereira, V., Hadjielias, E., Christofi, M., & Vrontis, D. (2023). A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective. *Human Resource Management Review*, *33*(1), 100857.

Pesapane, F., Volonté, C., Codari, M., & Sardanelli, F. (2018). Artificial intelligence as a medical device in radiology: ethical and regulatory issues in Europe and the United States. Insights Into Imaging, 9(5), 745–753.

Philipp N.: Herrmann, Dennis O. Kundisch, M.S.R.: Beating irrationality: Does delegating to IT alleviate the sunk cost effect? Manag. Sci. 61(4), 831–850. (2015).

Philipp Schmidt, F. Biessmann, T.T.: Transparency and trust in artificial intelligence systems. J. Decis. Syst. 29(4)260–278. (2020).

Pink, D. H. (2011). *Drive: The Surprising Truth About What Motivates Us*. Penguin.

Pink, D.: Drive: The Surprising Truth About What Motivates Us, 1st paperback ed. (Riverhead Books, New York) (2011).

Pisano, G.P.: Disrupted Routines: Team Learning and New Technology Implementation in Hospitals (2015).

Pitts, G., & Motamedi, S. (2025). Understanding human-ai trust in education. *arXiv preprint arXiv:2506.09160*.

Porter, M.E., & Heppelmann, J.E. (2015). How Smart, Connected Products Are Transforming Companies. *Harvard Business Review, 93, 1-37*

Poteet, G. W. (1984). Delegation strategies a must for the nurse executive. *JONA: The Journal of Nursing Administration*, *14*(9), 18-21.

Rahal, A., & Zainuba, M. (2019). The rating dilemma of academic management journals: Attuning the perceptions of peer rating. *Advances in Business Research, 9, 26–45.*

Rai, A.: Explainable AI: from black box to glass box. J. Acad. Mark. Sci. 48, 137–141 (2020).

Rajagopal, N. K., Khan, N. I., Durga, S., Ramírez-Asís, E., Huerta-Soto, R., Gupta, S. K., & Deepak, S. (2022). Future of Business Culture: An Artificial Intelligence-Driven Digital Framework for Organization Decision-Making Process. *Complexity*, *2022*, 1–14. https://doi.org/10.1155/2022/7796507

Randerson, K., & Radu-Lefebvre, M. (2021). Managing ambivalent emotions in family businesses: governance mechanisms for the family, business, and ownership systems. *Entrepreneurship Research Journal*, *11*(3), 159-176.

Ribbens, A., Hermans, J., Maes, F., Vandermeulen, D., & Suetens, P. (2013). Unsupervised segmentation, clustering, and groupwise registration of heterogeneous populations of brain MR images. IEEE Transactions on Medical Imaging, 33(2), 201–224.

Richard A. BerkJustin Bleich: Forecasts of violence to inform sentencing decisions. J. Quant. Criminology, 30 79–96. (1992).

Richtel, M.: How big data is playing recruiter for specialized workers. New York Times, 27 (2013).

Ringle, C. M., Wende, S., & Becker, J.-M. (2024). *SmartPLS 4* [Computer software]. SmartPLS. https://www.smartpls.com

Rothman, N. B., Pratt, M. G., Rees, L., & Vogus, T. J. (2017). Understanding the dual nature of ambivalence: Why and when ambivalence leads to good and bad outcomes. *Academy of Management Annals*, *11*(1), 33-72.

Roumbanis, L. (2025). On the present-future impact of AI technologies on personnel selection and the exponential increase in meta-algorithmic judgments. *Futures*, *166*, 103538.

Rout, J. K., Choo, K. R., Dash, A. K., Bakshi, S., Jena, S. K., & Williams, K. L. (2017). A model for sentiment and emotion analysis of unstructured social media text. *Electronic Commerce Research*, *18*(1), 181–199. https://doi.org/10.1007/s10660-017-9257-8

Rudin C: Stop explaining black box machine learning models for high-stakes decisions and use interpretable models instead. Nat. Mach. Intell. 1(5)206–215. (2019).

Ryan T. Allen, P.C.: Algorithm-augmented work and domain experience: The countervailing forces of ability and aversion. Organ. Sci. 33(1)149–169. (2022).

Saaty, T. L. (2013). The modern science of multicriteria decision making and its practical applications:

the AHP/ANP approach. *Operations Research*, *61*(5), 1101–1118. https://doi.org/10.1287/opre.2013.1197

Sadeghian, S., & Hassenzahl, M. (2022, March). The" artificial" colleague: evaluation of work satisfaction in collaboration with non-human coworkers. In *proceedings of the 27th international conference on intelligent user interfaces* (pp. 27-35)

Sahoh, B., & Choksuriwong, A. (2023). The role of explainable Artificial Intelligence in high-stakes decision-making systems: a systematic review. *Journal of Ambient Intelligence and Humanized Computing*, *14*(6), 7827–7843.

Sandelowski, M., & Barroso, J. (2007). Handbook for Synthesizing Qualitative Research. Springer Publishing Company.

Sandstedt, M., Henriksson, L., Janzon, M., Nyberg, G., Engvall, J., De Geer, J., Alfredsson, J., & Persson, A. (2019). Evaluation of an AI-based, automatic coronary artery calcium scoring software. *European Radiology*, *30*(3), 1671–1678. https://doi.org/10.1007/s00330-019-06489-x

Sanín, C., Mancilla-Amaya, L., Haoxi, Z., & Szczerbicki, E. (2012). DECISIONAL DNA: THE CONCEPT AND ITS IMPLEMENTATION PLATFORMS. *Cybernetics and Systems*, *43*(2), 67–80. https://doi.org/10.1080/01969722.2012.654069

Schmidhuber, J.: Deep Learning in neural networks: An overview. Neural Networks. 61, 85–117 (2015).

Schrage, M.: 4 Models for using AI to make decisions. Harvard Bus. Rev. (2017).

Sengul, M., Gimeno, J., Dial, J.: Strategic delegation: A review, theoretical integration, and research agenda. J. Manage. 38, 375–414 (2012).

ServiceNow.Autonomous AI: How powerful new Networks will drive more businesses (2020).

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies*, *146*, 102551. https://doi.org/10.1016/j.ijhcs.2020.102551

Shrestha, Y. R., Ben-Menahem, S. M., & Von Krogh, G. (2019). Organizational Decision- Making structures in the Age of Artificial Intelligence. *California Management Review*, *61*(4), 66–83.

Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G.: Organizational Decision-Making Structures in the Age of Artificial Intelligence. In California Management Review (Vol. 61, Issue 4, pp. 66–83). SAGE Publications (2019).

Siau, K., Wang, W.: Building Trust in Artificial Intelligence, Machine Learning, and Robotics (2018).

Sim, J., & Mengshoel, A. M. (2022). Meta-synthesis: issues of empirical and theoretical context. Quality & Quantity, 57(4), 3339–3361.

Singh, D., & Chandra, S. (2024). Mitigating Uncertainty and Enhancing Trust in AI: Harmonizing Human-Like, System-Like Features with Innovative Organizational Culture.

Sofo, F., Colapinto, C., Sofo, M., & Ammirato, S. (2013). Adaptive decision-making and intellectual styles. In *SpringerBriefs in Psychology*. https://doi.org/10.1007/978-1- 4614-6708-3

Song, Y., Tao, D., & Luximon, Y. (2023). In robot we trust. The effect of emotional expressions and contextual cues on anthropomorphic trustworthiness. *Applied Ergonomics*, *109*, 103967.

Soni, N., Sharma, E.K., Singh, N., Kapoor, A.: Artificial Intelligence in Business: From Research and Innovation to Market Deployment. Procedia Comput. Sci. 167, 2200–2210 (2020).

Sowa, K., Przegalinska, A., & Ciechanowski, L. (2021). Cobots in knowledge work: Human–AI collaboration in managerial professions. *Journal of Business Research*, *125*, 135-142.

Spreitzer, G.M., Mishra, A.K.: Giving up Control Without Losing Control: Trust and Its Substitutes' Effects on Managers' Involving Employees in Decision Making. Gr. Organ. Manag. 24, 155–187 (1999).

Strauss A.; Corbin J. Basics of qualitative research. Newbury Park, CA: Sage; 1990.

Sun, J., Zhang, D., Hu, H., Van Mieghem, J.A.: Predicting Human Discretion to Adjust Algorithmic Prescription: A Large-Scale Field Experiment in Warehouse Operations. SSRN Electron. J. 1–41 (2019).

Susan F. Lu, Huaxia Rui, A.S.: Does Technology Substitute for Nurses? Staffing Decisions in Nursing Homes: Does Technology Substitute for Nurses? Staffing Decisions in Nursing Homes. (2017).

Tangiuchi, T., Mochihashi, D., Nagai, T., Uchida, S., Inoue, N., Kobayashi, I., Nagaoka, T., Hagiwara, Y., Iwahashi, N., & Inamura, T. (2019). Survey on frontiers of language and robotics. *Advanced Robotics*, *33*(15–16), 700–730.

Thaler, R.H.: Behavioral Economics: Past, Present, and Future. Am. Econ. Rev. 106, 1577– 1600. (2016).

Tilmes, N. (2022). Disability, fairness, and algorithmic bias in AI recruitment. *Ethics and Information Technology*, *24*(2).

Tong, S.: The Janus face of artificial intelligence feedback: Deployment versus disclosure effects on employee performance. 1600–1631 (2021).

Trope Y., & Limberman, N.: construal-level theory of psychological distance. Psychological Review (2010).

Trunk, A., Birkel, H., & Hartmann, E. (2020). On the current state of combining human and artificial intelligence for strategic organizational decision-making. *BuR – Business, Research*, *13*(3), 875–919. https://doi.org/10.1007/s40685-020-00133-x

Trunk, A., Birkel, H., & Hartmann, E. (2020). On the current state of combining human and artificial intelligence for strategic organizational decision-making. BuR - Business Research, 13(3), 875–919.

Tuncalp, D. (2025). Directing the future: artificial intelligence integration in family businesses. *Journal of Family Business Management*, *15*(2), 254-277.

Van Raan, A. F. J. (1999). Advanced bibliometric methods for the evaluation of universities. *Scientometrics*, *45*(3), 417–423. https://doi.org/10.1007/bf02457601 Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2021). Artificial

Vance, A., Elie-Dit-Cosaque, C., & Straub, D. W. (2008). Examining trust in information technology artifacts: the effects of system quality and culture. *Journal of Management Information Systems*, *24*(4), 73-100.

Vasconcelos, H., Jörke, M., Grunde-McLaughlin, M., Gerstenberg, T., Bernstein, M. S., & Krishna, R. (2023). Explanations can reduce overreliance on AI systems during Decision-Making. Proceedings of the ACM on Human-Computer Interaction, 7(CSCW1), 1–38.

Wang, D., Churchill, E., Maes, P., Fan, X., Shneiderman, B., Shi, Y., & Wang, Q. (2020, April). From human-human collaboration to Human-AI collaboration: Designing AI systems that can work together with people. In *Extended abstracts of the 2020 CHI conference on human factors in computing systems* (pp. 1-6).

Wang, J., Zhao, Y., Balamurugan, P., & Selvaraj, P. (2022). Managerial decision support system using an integrated model of AI and big data analytics. *Annals of Operations Research*, 1-18.

Wang, L., Chen, Y., Yu, H., Wu, L., You, A., Zheng, X., & Zhang, Y. (2024). The experiences of newly qualified nurses in the intensive care unit: a qualitative meta-synthesis. Frontiers in Medicine, 11.

Wang, W., Liu, X., Zhang, X., & Hong, Y. Knowledge trap: Human experts are distracted by details when teaming with AI. University of Miami Business School Research Paper, (4395858) (2023).

Westphal, M., Hemmer, P., Vössing, M., Schemmer, M., Vetter, S., & Satzger, G. (2025). Towards Understanding AI Delegation: The Role of Self-Efficacy and Visual Processing Ability. *ACM Transactions on Interactive Intelligent Systems*, *15*(1), 1-24.

Wohlgemuth, V., Wenzel, M., Berger, E. S., & Eisend, M. (2019). Dynamic capabilities and employee participation: The role of trust and informal control. *European Management Journal*, *37*(6), 760-771.

Wu, T. J., Zhang, R. X., & Zhang, Z. (2025). Navigating the human-artificial intelligence collaboration landscape: Impact on quality of work life and work engagement. *Journal of Hospitality and Tourism Management*, *62*, 276-283.

Yan, L., Liu, L., Wang, F., Zhao, F., & Hu, X. (2024). Barriers and facilitators to feeling safe for inpatients: a model based on a qualitative meta-synthesis. Frontiers in Public Health, 12.

Yang, J., Blount, Y., & Amrollahi, A. (2024). Artificial intelligence adoption in a professional service industry: A multiple case study. *Technological Forecasting and Social Change*, *201*, 123251.

Yang, Y., Gai, T., Cao, M., Zhang, Z., Zhang, H., & Wu, J. (2023). Application of group decision making in Shipping Industry 4.0: Bibliometric analysis, trends, and future directions. *Systems*, *11*(2), 69. https://doi.org/10.3390/systems11020069

Young, E., Wajcman, J., & Sprejer, L. (2023). Mind the gender gap: Inequalities in the emergent professions of artificial intelligence (AI) and data science. *New Technology Work and Employment*, *38*(3), 391–414. https://doi.org/10.1111/ntwe.12278

Young, J., Lloyd, A., & Haraldsdottir, E. (2024). A qualitative meta-synthesis of studies of patients' experience of exercise interventions in advanced cancer. Frontiers in Rehabilitation Sciences, 4.

Yu, L., & Li, Y. (2022). Artificial intelligence Decision-Making transparency, and employees' trust: The parallel multiple mediating effects of effectiveness and discomfort. *Behavioral Sciences*, *12*(5), 127. https://doi.org/10.3390/bs12050127

Yuan, Y., Tan, G. W., & Ooi, K. (2024). Does the COVID-19 pandemic motivate privacy self-disclosure in mobile fintech transactions? A Privacy-Calculus-Based Dual-Stage SEM- ANN analysis. *IEEE Transactions on Engineering Management*, *71*, 2986–3000. https://doi.org/10.1109/tem.2022.3204285

Yzerbyt, Vincent Y., Lories, Guy Dardenne, B.: From social cognition to metacognition. Yzerbyt VY, Lories G, Dardenne B, eds. Meta-cognition Cogn. Soc. Dimens. (Sage Publ. London), 1–15. (1998).

Za, S., & Braccini, A. M. (2017). Tracing the roots of the organizational benefits of IT services. In *Exploring Services Science: 8th International Conference, IESS 2017, Rome, Italy, May 24-26, 2017, Proceedings 8* (pp. 3-11). Springer International Publishing.

Za, S., & Spagnoletti, P. (2013). Knowledge creation processes in information systems and management: Lessons from simulation studies. *Organizational Change and Information Systems: Working and Living Together in New Ways*, 191-204.

Zeng, Z., Chen, P., & Lew, A. A. (2020). From high-touch to high-tech: COVID-19 drives robotics adoption. *Tourism Geographies*, *22*(3), 724–734. https://doi.org/10.1080/14616688.2020.1762118

Zhang MSun TLuo LGolden J: Consumer and AI Co-creation: When and Why Nudging Human Participation Improves AI Creation. Conf. Inf. Syst. Technol. Work. Inf. Syst. Econ. INFORMS Mark. Sci. Conf (2023).

Zhang, X., Qian, J., Wang, B., Jin, Z., Wang, J., & Wang, Y. (2017). Leaders' behaviors matter: The role of delegation in promoting employees' feedback-seeking behavior. *Frontiers in Psychology*, *8*, 920.

Zhou, G., Zhang, C., Li, Z., Ding, K., & Wang, C. (2019). Knowledge-driven digital twin manufacturing cells towards intelligent manufacturing. *International Journal of Production Research*, *58*(4), 1034–1051. https://doi.org/10.1080/00207543.2019.1607978.

Zhu, Y.Q., Corbett, J. Ueline, Chiu, Y. Te: Understanding employees' responses to artificial intelligence. Organ. Dyn. 50, 100786 (2021).

Zuboff S: Automate/informate: the two faces of intelligent technology. Org Dyn 14(2)5–18. (1985).

Appendix A: List of studies and source codes

Source code	Author(s)	Year	Article title	Journal
S1	Dawid Booyse & Caren Brenda Scheepers	2024	Barriers to adopting automated organizational decision-making through the use of artificial intelligence.	Management Research Review
S2	Deniz Tuncalp	2024	Directing the future: artificial intelligence integration in family businesses.	Journal of Family Business Management
S3	Giorgia Maria D'Allura, et al	2024	Innovating with heart: family firms' decision to automate with emotional responsibility.	Journal of Family Business Management
S4	Ekaterin Jussupow et al	2021	Augmenting medical diagnosis decisions: an investigation into physicians' decision-making process with artificial intelligence	Information Systems Research
S5	Arda Gezdur et al	2024	Improving the forecasting approach for crude oil sourcing at an oil refining firm: a decision theory perspective.	Production Planning & Control
S6	Domenica Barile et al	2025	An artificial intelligence-based innovation ecosystem enabling open innovation and sustainable growth: evidence from a case study	Innovation Organization & Management
S7	Lansiné Condé & Christopher Münch	2025	Resilient by Design: Exploring the Social Abilities and Actor-Network Roles of Artificial Intelligence in Supply Chain Management	Journal of Business Logistics
S8	Mujahid Mohiuddin Babu et al	2022	The role of artificial intelligence in shaping the future of the Agile fashion industry	Production Planning & Control
S9	Lambros Roumbanis	2025	On the present-future impact of AI technologies on personnel selection and the exponential increase in meta-algorithmic judgments	Futures
S10	Emmanouil Papagiannidis et al	2023	Uncovering the dark side of AI-based decision-making: A case study in a B2B context	Industrial Marketing Management
S11	Jiaqi Yang et al	2024	Artificial intelligence adoption in a professional service industry: A multiple case study	Technological Forecasting & Social Change
S12	Sarah J. Daly et al	2025	Shifting attitudes and trust in AI: Influences on organizational AI adoption	Technological Forecasting & Social Change
S13	Saoudi CE Nouis et al	2025	Evaluating accountability, transparency, and bias in AI-assisted healthcare decision-	BMC Medical Ethics

			making: a qualitative study of healthcare professionals' perspectives in the UK	
S14	Ripan Das and & Aruna Ranasinghe	2025	A qualitative study: Can artificial intelligence take management decisions?	International Journal of Science Academic Research
S15	Sarah Negash et al	2025	Physicians' attitudes and acceptance towards artificial intelligence in medical care: a qualitative study in Germany	Frontiers in Digital Health