Human-AI Interaction in Decision-Making: A Systematic Literature Review and Future Directions

HUMAN-AI INTERACTION IN DECISION-MAKING: A SYSTEMATIC LITERATURE REVIEW AND FUTURE DIRECTIONS

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ABSTRACT

AI helps organizations in decision-making by enhancing data analysis, predictive modelling, and providing insights. However, gaps remain in understanding the phenomenon from a socio-technical aspect. By systematically reviewing 77 articles, the study identifies 21 elements impacting decision-making across six dimensions and suggests future research on task complexity, culture, and ethical frameworks.

KEYWORDS

Artificial Intelligence, Human-AI Interaction, Decision-Making, Socio-Technical Systems, Systematic Literature Review

1. INTRODUCTION

The rapid development of artificial intelligence (AI) has revolutionized decision-making processes, especially within organizational settings (Raji & Buolamwini, 2019). By integrating AI technologies, enterprises are increasingly leveraging its potential to assist in data analysis, predictive modelling, and providing actionable insights to gain a competitive advantage (Steiner et al., 2018). However, despite these notable capabilities, successful and seamless integration of AI into decision-making processes remains challenging for many organizations (Steyvers, 2024). These challenges often result from a lack of understanding of effective human-AI interaction, as well as issues related to trust, transparency, and alignment of AI capabilities with human needs (Mahmud et al., 2022).

Current literature has largely focused on the technical attributes of AI, such as algorithmic improvements and data processing capabilities, while relatively little attention has been given to the broader socio-technical aspects (Steyvers, 2024). While substantial research exists on trust in AI, human-computer interaction, and AI-enabled collaboration, these studies often lack contextualization within organizational decision-making frameworks. This oversight creates a significant research gap in understanding the socio-technical factors that influence the effectiveness of human-AI interaction for decision-making (Puranam, 2021; Shrestha et al., 2019). Key factors include trust, transparency, and user involvement, alongside cultural and infrastructural elements that shape AI's integration into organizational processes (Wu et al., 2022) . Bridging this gap requires a holistic perspective that considers not just the technology but also the social, cultural, and organizational conditions that shape human-AI interaction.

This research aims to fill this gap through a socio-technical perspective by providing a comprehensive understanding of the key elements that influence human-AI decision-making. Specifically, we address the following research questions: (1) What are the key elements that influence the dynamics and effectiveness of human-AI interaction for decision-making? (2) How do technical capabilities and social dimensions interact to shape the outcomes of human-AI decision-making processes across organizational contexts? (3) What are the future directions in this field? To answer these questions, this study identifies and categorizes key elements under a socio-technical framework, exploring their interrelationships and the conditions under which they enhance or hinder decision-making. This framework aims to optimize human-AI interaction by fostering a balance between the technical and social dimensions of decision-making. Ultimately, this research provides

actionable insights to guide the integration of AI into decision-making processes, equipping organizations to navigate the complexities of human-AI collaboration effectively and ethically.

2. METHODOLOGY

We conducted a systematic literature review of 77 articles. These articles were identified through a structured process proposed by Madan and Ashok (2013) involving an initial search in major databases (i.e., World of Science, Scopus) with the particular Boolean search string ("machine learning" OR "AI" OR "artificial intelligence") AND ("HAI" OR "human-AI" OR "human-AI interaction") AND ("decision-making" OR "make decision" OR "algorithmic decision-making"), followed by screening for relevance and a detailed full-text review. Inclusion criteria were limited to journal articles or conference papers published in English after 2010 to ensure contemporaneity and rigor. Studies were excluded if they were unrelated to organizational contexts or lacked human involvement. This ensured the review remained relevant to understanding human-AI interaction in decision-making.

A comprehensive search initially identified 154 articles, supplemented by snowball sampling, which added 25 articles through reference examination, resulting in 179 unique studies after duplicate removal. A title and abstract review narrowed the pool to 117 articles. Finally, a thorough full-text review was deployed and 77 were selected for qualitative analysis and synthesis.

We applied the antecedents-phenomenon-consequences logic (Pereira, 2023) to thematically analyze the literature. In this framework, antecedents refer to the problems of AI integration in decision-making, phenomenon refers to the practice of human-AI interaction and its key features, and consequences capture the outcomes of this integration. This process allowed us to distinguish the key elements in decision-making, themes, and relationships under the 'antecedents-phenomenon-consequences' framework while highlighting gaps and opportunities for future research in this field.

3. RESULTS

This systematic literature review identifies twenty-one elements influencing decision-making, categorized into six socio-technical dimensions: people, goals, technology, processes, infrastructure, and culture (see Table 1). These dimensions are grounded in the socio-technical perspective, which emphasizes the interplay between human factors, organizational objectives, technological capabilities, and cultural contexts. The classification based on the socio-technical perspective highlights the interconnected nature of technical and social factors across all dimensions. For instance, the 'people' dimension focuses on trust, cognitive biases, and user involvement. Trust in AI exemplifies a socio-technical issue where transparency and explainability (technical) interact with user training and cultural attitudes (social) to shape its development. Similarly, the 'technology' dimension emphasizes features like explainable AI and adaptive systems, which require alignment with organizational and user needs to ensure effective integration. This classification enables a structured analysis of human-AI decision-making, capturing both technological advancements and the social considerations essential for success.

The *people* dimension is essential for understanding the dynamics of human-AI interaction, focusing on aspects such as trust in AI, cognitive biases, and user involvement. Trust in AI heavily shapes whether users accept or reject AI recommendations, influenced by factors such as system transparency, reliability, and fairness (Gomez et al., 2023). Ensuring users are aware of the AI system's capabilities and limitations is key to maintaining appropriate levels of trust, thereby preventing over-reliance or skepticism, both of which can hinder effective decision-making (Wu et al., 2022). Cognitive biases are another major challenge, with biases such as confirmation bias or overconfidence negatively impacting decision outcomes (Wilson et al., 2019). Addressing these biases through AI designs that prompt users to critically evaluate outputs can mitigate their adverse effects on decision quality. Additionally, direct user participation in AI processes, such as contributing to recommendations and providing feedback, fosters a sense of ownership and satisfaction, which ultimately improves decision outcomes (Gomez et al., 2023). Overall, building trust, minimizing biases, and involving users actively are all essential to creating effective, synergistic human-AI interactions.

Table 1. Key dimensions and elements influencing human-AI decision-making

Dimensions	Key elements	Representative examples
People	Trust in AI	Wu et al., 2022
	Cognitive bias	Wilson et al., 2019
	User involvement	Lin 2024
Goals	Improving decision-making	Steyvers, 2024
	Achieving complementarity	Morrison et al., 2024
	Bias reduction	Schoeffer et al., 2024
	Enhancing transparency and explainability	Shulner-Tal et al., 2024
Technology	AI Models and Tools	Zhou & Khatibi, 2024
	Anthropomorphism	Schelble et al., 2024
	Explainable AI	Shulner-Tal et al., 2024
	Adaptive Systems	Morrison et al., 2024
Processes	Decision Workflow	Lin 2024
	Interaction Pattern	Steyvers, 2024
	Feedback Loop	Shulner-Tal et al., 2024
	Stage of Decision-Making	Felin, 2024
Infrastructure	Data Architecture	Shrestha et al., 2021
	Integration of AI	Felin, 2024
	Scalability and Reliability	Felin, 2024
Culture	Cultural Attitude Towards AI	Shulner-Tal et al., 2024
	Organizational Culture	Wang et al., 2024
	Cross-Cultural Differences	Shulner-Tal et al., 2024

The *goals* dimension describes the broader objectives of human-AI interaction in decision-making, such as improving accuracy, achieving complementarity, reducing biases, and enhancing transparency. Improving decision accuracy is a key motivation for AI integration, as AI excels at processing large volumes of data and identifying patterns that enhance decision quality, particularly in complex situations where human judgment may fall short (Wilson et al., 2019). Achieving complementarity between human intuition and AI capabilities enables the combination of AI's analytical strengths with human contextual insights to optimize decision-making (Felin, 2024). Bias reduction is also an ethical goal for effective human-AI interaction, with AI models designed to recognize and mitigate biases in data or user assumptions, thereby promoting fairness (Schoeffer et al., 2024). Transparency and explainability are equally fundamental to fostering trust and collaboration, as explainable AI (XAI) helps users understand not only the outputs but also the rationale behind AI recommendations, which is vital for confidence in AI-assisted decision-making (Bucinca, 2024). Collectively, these goals support the optimization of human-AI collaboration for improved decision-making in organizational contexts.

The *technology* dimension emphasizes the tools and techniques that enable effective AI-driven decision-making, including AI models and tools, anthropomorphism, explainable AI, and adaptive systems. AI models and tools are vital for enhancing decision-making, providing the computational power and sophisticated algorithms needed to analyze complex datasets (Zhou & Khatibi, 2024). By identifying patterns and generating insights often beyond human capability, AI models significantly improve decision efficiency. Anthropomorphism is another important element, involving the assignment of human-like qualities to AI systems to enhance user engagement (Schelble et al., 2024). However, it must be managed carefully to avoid creating unrealistic expectations. XAI supports transparency by making AI decisions interpretable, which is critical for fostering trust and collaboration (Shulner-Tal et al., 2024). Finally, adaptive systems, as discussed by Morrison et al., (2024), adjust their behaviors to user needs and decision contexts, making them highly effective in dynamic environments by responding to users' actions in real-time.

The key components of the *processes* dimension include decision workflows, interaction patterns, feedback loops, and decision stages. Effective workflows are necessary for smoothly integrating AI into decision processes. Waqar (2024) and Lin (2024) emphasize designing workflows that clearly define when and how AI recommendations should be incorporated, ensuring efficient collaboration between humans and AI. Interaction patterns are also integral to shaping productive human-AI relationships. Structured interaction patterns, as highlighted by Vereschak et al., (2024) and Wang et al., (2024), help foster clear communication and support users in effectively interpreting AI inputs. Feedback loops play an important role in refining AI systems over

time. Integrating user feedback allows these systems to continuously adapt and improve, aligning their outputs with human expectations (Waqar, 2024). AI systems should also provide targeted support at different stages of decision-making, from initial data gathering to final recommendations (Felin, 2024).

The *infrastructure* dimension highlights the organizational and technical support needed for effective human-AI integration. Robust data architecture is essential for ensuring AI systems receive reliable and high-quality data (Shrestha et al., 2021). Integrating AI into existing organizational processes requires both technical and cultural readiness (Salimzadeh & Gadiraju, 2024). Organizations must develop the necessary infrastructure to effectively accommodate AI, while ensuring that their workforce is prepared for this transition. Scalability and reliability are also important considerations. AI systems must be designed to scale across diverse contexts while maintaining consistent performance (Zhou & Khatibi, 2024). Scalability enables these systems to handle increasing data loads, whereas reliability ensures effectiveness even under challenging conditions.

The *culture* dimension addresses the social and organizational factors influencing AI adoption. Cultural attitudes towards AI play a significant role in determining user acceptance (Shulner-Tal et al., 2024). Adaptable AI systems that respect local cultural norms are more likely to be trusted and adopted. Similarly, organizational culture has a strong impact on the successful implementation of AI; open, innovation-driven environments are more conducive to effective AI adoption (Wu et al., 2022). Finally, addressing cross-cultural differences is key for AI systems deployed globally—adaptable systems that respect cultural diversity foster greater acceptance and encourage effective human-AI collaboration (Vereschak et al., 2024).

4. FUTURE DIRECTIONS

Several key avenues for future research emerge. First, further exploration is needed to understand how evolving tasks, from routine to complex, affect human-AI collaboration and decision quality. Additionally, more research should focus on how cultural differences, both at the organizational and societal levels, influence trust in AI and the design of culturally sensitive AI systems. New metrics for evaluating AI systems should go beyond accuracy and transparency to include contributions to human creativity and collaborative problem-solving. Furthermore, the role of continuous feedback loops and adaptive learning in AI systems requires deeper examination, as these features can significantly enhance long-term system performance. Finally, research should focus on developing comprehensive ethical governance frameworks to ensure that AI systems operate transparently, accountably, and in alignment with human values, supporting responsible AI integration in decision-making.

5. CONCLUSION

The integration of AI into organizational decision-making offers significant potential but demands careful attention to the factors influencing human-AI collaboration. This study outlines key elements critical to fostering effective collaboration between humans and AI systems. Organizations that consider these elements can maximize the benefits of AI, ensuring that decision-making processes remain aligned with ethical standards and human values, leading to a more effective and supportive decision-making environment.

This study makes a critical theoretical contribution by providing a comprehensive literature review on human-AI decision-making through a socio-technical lens. By synthesizing insights from diverse studies, this review contributes to theoretical development by offering a structured framework that captures the complexity of human-AI collaboration. The findings of this study advance the understanding of human-AI decision-making by shifting the focus from a predominantly technological lens to a holistic socio-technical perspective. By identifying and categorizing key elements across interconnected dimensions, this study provides an organizing framework that captures the interplay between human, organizational, and technological factors. Furthermore, the research highlights how socio-technical factors interact with technological advancements like explainable AI, offering deeper insights into their interdependencies.

Practically, the framework serves as a diagnostic tool for organizations to assess and enhance their human-AI decision-making processes. By identifying potential issues like trust deficits or insufficient user involvement, managers can implement targeted interventions, such as deploying explainable AI or refining

feedback systems. This application ensures that decision-making processes remain adaptive and aligned with organizational objectives and ethical standards.

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