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Autonomy at the Crossroads: Knowledge Workers Teamed With Intelligent Machines a Qualitative Systematic Review

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ABSTRACT

Purpose – This study aims to identify risks in adopting artificial intelligence (AI) for organizational decision-making by examining empirical studies. AI is increasingly applied to automate tasks and decisions which were traditionally made by humans, posing challenges to sense of autonomy.
Design/methodology – A total of 28 empirical studies were selected using predefined inclusion and exclusion criteria. To this end, this research systematically explored the processes of inquiry, identification, selection, critical appraisal, and the synthesis of empirical studies. This study is undertaken to address the following primary inquiries: (1) What is the direction of the observed effect? (2) What is the magnitude of the effect within the inclusion criteria? (3) Does the effect exhibit a consistent pattern across the spectrum of studies encompassed in the analysis? (4) What is the level of evidentiary robustness underlying the discovered effect?
Findings – This content analysis interpretated within task-technology fit (TTF) model revealed that AI adoption represents a promising outlook for the future of human-AI teams. Anchoring on reliable data, this qualitative systematic review informs knowledge workers and leaders on adoption of AI systems and how it positively influences their working processes.
Contributions/value – This research conducted a structured analysis to reveal the gap between the collective perception of AI adoption and what leaders and knowledge workers have experienced in relying on AI systems. AI tools are becoming more autonomous therefore a true representation of human-AI team interaction must be displayed. By uncovering the diverse approaches of leaders and the reactions of knowledge workers to AI integration, this paper contributes to a deeper understanding of the evolving landscape of working in the age of AI. The provided insights can assist organizations in harnessing the potential of AI while maintaining a healthy balance of autonomy within their domain.

Keywords: Leadership, AI-driven decisions, Problem-solving, Digital autonomy, Hybrid intelligence, Human-machine teams, Qualitative systematic literature review

INTRODUCTION

This study investigates the balance of human-AI autonomy in leaders and knowledge workers, focusing on the impact of AI on critical thinking.

Through a qualitative systematic review of peer-reviewed literature, it examines concerns about AI integration into decision-making and problem-solving, emphasizing the need to understand its implications thoroughly.

BACKGROUND

The ever-accelerating pace of technological advancement has left organizational leaders in a state of bewilderment (Dencik et al., 2023) as they wrestle with the consequences of embracing AI. AI *is the system's ability to decode data, learn from, and use that learning to accomplish defined tasks* (Kaplan & Haenlein, 2019a). Various categories of AI, including neural networks, swarm intelligence, genetic algorithms, and fuzzy logic, are applicable in addressing diverse real-world problems (Autor, 2015).

On the one hand, AI systems are autonomously learning to improve processing data (Lange et al., 2012) and as they grow to become more autonomous, so is the gap in understanding how and where they are being used in driving organisational tasks and decisions (Booyse & Scheepers, 2023). On the other hand, freedom and autonomy are pillars of human's liberal democracy, values, ethics, and dignity (Prunkl, 2022; Raz, 1986; Roessler, 2021). Anderson and Honneth reconceptualize autonomy, underscoring that individuals' ability to live autonomously is influenced by their social interactions. They present a recognitional framework where autonomy arises from socially embedded capacities, emphasizing the significance of self-respect, self-trust, and self-esteem in enabling individuals to pursue fulfilling lives (Anderson & Honneth, 2005). To embark on an exploration of how leaders and knowledge workers engage with AI systems, it is imperative to comprehend the implications of their reliance on AI tools. To achieve this, task-technology fit (TTF) (Goodhue & Thompson, 1995) provides the capacity to recognize how elements weigh on adoption of AI technology. This theory provides a platform for conceptualizing the thematic findings of this review.

METHODS

Qualitative systematic reviews are conducted to detect, handpick, critically evaluate, and synthesize data from empirical studies, with the aim of addressing the following inquiries: "(1) What is the direction of the observed effect? (2) What is the magnitude of the effect within the inclusion criteria? (3) Does the effect exhibit a consistent pattern across the spectrum of studies encompassed in the analysis? (4) What is the level of evidentiary robustness underlying the discovered effect? (Higgins, 2008; Paré et al., 2015; Popay et al., 2006)" A typical technique for aggregating research findings within the framework of qualitative systematic reviews is narrative synthesis. Narrative synthesis applies a non-statistical narrative approach for summarizing the outcomes of studies during the synthesis process (Petticrew et al., 2009). Additionally PICO model (Population; Interest/Intervention; Comparison; Outcome) has exhibited utility in this investigation, not only as a search strategy tool but also in the formulation of search terms (Considine et al., 2017; Eriksen & Frandsen, 2018, p. 69). Within the scope of this investigation, the PICO framework has been defined as follows: (1) Population of leaders and knowledge workers, (2) Interest in adoption of AI systems (tasks/decisions); (3) Comparison of positive and negative impacts of relying on AI-driven tasks or decisions; and (4) Outcome of each individual record.

Table 1. Inclusion and exclusion criteria – (ProQuest and web of science).

Inclusion Criteria	Exclusion Criteria
(1) "Leader*" AND "Artificial Intelligence"; (2) "Manage*" AND "Artificial Intelligence"; (3) "Autonomy*" AND "Artificial Intelligence"; (4) "Choice*" AND "Artificial Intelligence"; (5) "Custom* Instruct*" AND "Artificial Intelligence".	Articles not responding to the research question. Journal article that does not relate to "Leadership", AND "Decision-Make*", AND "Decision Make*", OR "Problem Solve*", OR "Problem- Solve*", AND "Artificial Intelligence", OR "AI".
Academic Journals (Peer Reviewed), and Reviews	Book Papers, Conference papers, Thesis, dissertation, and non-academic material
English	Non-English Documents, and academic
Years 2017 – 2022	papers

A systematic database search was executed in ProQuest and Web of Science, adhering to the predefined criteria (see Figure 1). This analysis yielded meaningful insights about the phenomenon (Elo & Kyngäs, 2008) demonstrated in detail (see the Appendix).

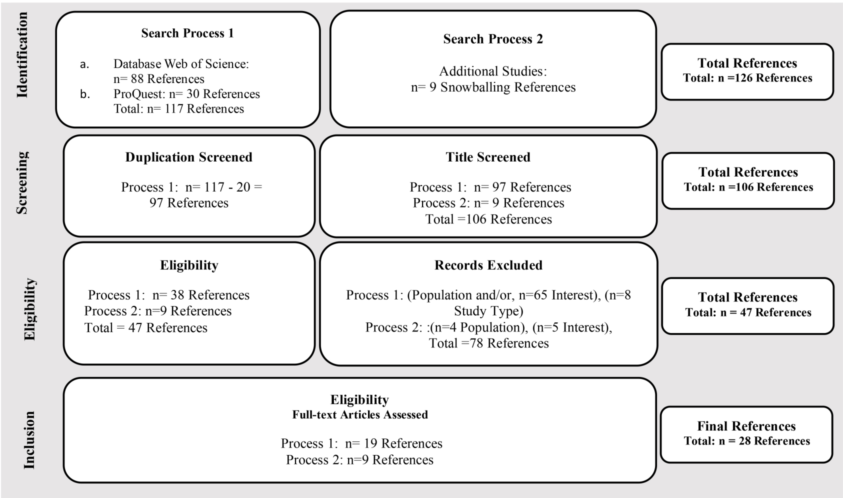

Figure 1: CCDAN PRISMA flowchart (Moher et al., 2009).

FINDINGS

This qualitative systematic review presents a positive overarching outcome with a magnitude weight of 68% from the total included studies. Records reporting a positive outlook shown as (PO) in the Appendix endorses a future where human-AI collaborations shape sustainable business models, mount hybrid intelligence, and optimize workflows. As reflected in Figure 2, Nineteen records recognised AI tools as a catalyst for organizational development, provoking sustainable business models, and transforming workflow and work engagement. AI-driven decision models emphasize pragmatic outcomes through predictive data-driven capabilities, transforming organizational landscapes and optimizing efficiency. Integration of AI systems enhances cognitive abilities of knowledge workers, promoting organizational skills (Hao et al., 2020).

Despite the predominantly positive findings regarding AI integration in this review, 11% of the records exhibited diverse impacts. Organizational AI adoption yielded mixed effects, as indicated in the records. These effects, categorized as Positive Outlook (PO) and Alarming Outlook (AO) in the appendix.

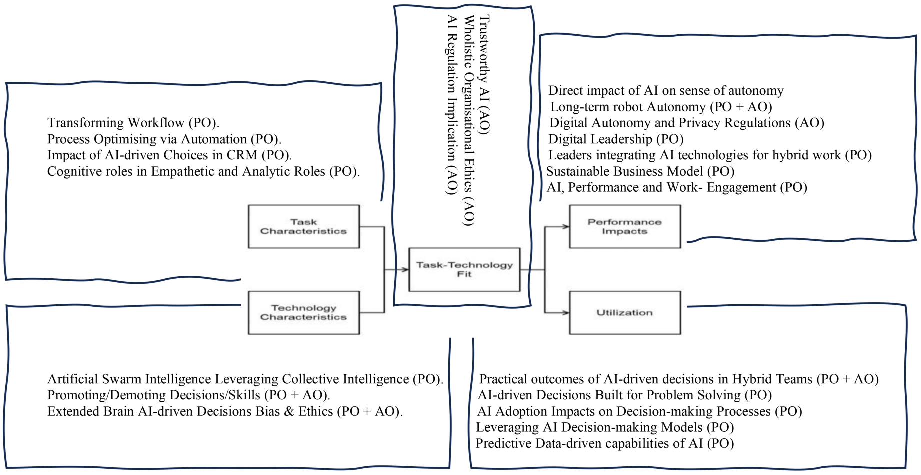

Figure 2: Qualitative content analysis categorisation integrated with "task-technology-fit approach (Goodhue and Thompson, 1995, p. 220)".

Despite the predominantly positive findings regarding AI integration in this review, 11% of the records exhibited diverse impacts. Organizational AI adoption yielded mixed effects, as indicated in the records. These effects, categorized as Positive Outlook (PO) and Alarming Outlook (AO) in the Appendix, highlighted themes suggesting that AI usage may lead to less authentic decision-making (Hao et al., 2020), where others such as Wang (2021) positively defined AI-driven decisions as an extension to brain. These studies emphasize the crucial need for organizations to maintain a balance between skill promotion and demotion. These findings underscore the emergence of a bidirectional human-AI autonomy interface, where AI systems can learn from human feedback and vice versa.

Floridi and Cowls (2019) link autonomy to humans' inclination to delegate decisions to AI, while Wang (2021) explores how human moral judgment can enhance AI-assisted decision-making. Recognizing the significance of human-machine interdependence offers insights into decision-making AI systems, revealing critical challenges and opportunities. Independent analysis of records and exploration of emerging themes reveal discernible patterns, as depicted in Figure 2.

Remainder records, comprising 21% of reviewed studies, highlight structural deficiencies in organizational AI adoption. These studies scrutinize ethical regulations and autonomy balancing, emphasizing the intricate boundaries of AI adoption within organizational contexts. Negative impacts of AI adoption involves various dimensions, particularly concerning fear, trust, and communication within human-machine teams (Abbass, 2019; Baum, 2020). Establishing trustworthy AI is crucial for achieving sustainable autonomy balance (Jones, 2018). Organizational ethics regulations are pivotal in safeguarding digital autonomy and privacy (Baum, 2020; Dobbe et al., 2021). In the absence of regulated guidelines for digital autonomy, human privacy may be compromised (Jarrahi, 2018; Laacke et al., 2021).

DISCUSSION

Exploiting the depth of each study within the task-technology fit (TTF) model several themes were identified. Evidence is provided on the extent to which the observed magnitudes have continued through the scope of this review and beyond.

This narrative synthesis provides several key insights: first, leaders and knowledge workers exhibited predominantly positive workflow transformation and task optimization experiences. An imperative discovery was made that AI integration leads to an increase in workforce demand, as when it is utilized in original contributions it results in increased efficiency (i.e., speed and quality of task completion) Das and Granados (2022). Additionally, Hao's research exhibited that Authentic leadership displays as an effective facilitator in progressing technological capabilities of followers (Hao et al., 2020). Change leadership played a positive moderating role in the relationship between AI adoption and employee work engagement (Wijayati et al., 2022).

Second prospect in the context of educational leadership was using AI systems as an extended brain during decision-making processes Wang (2021). However, according to (Jarrahi, 2018) if AI is to benefit humanity, it needs to respect human autonomy (Jarrahi, 2018). Furthermore, explains the effects of digital experiences on human autonomy are complex and inconsistent, leading to our third insight.

Advancements in replication of human cognitive abilities is continuing to enable autonomous agents to intercommunicate and exchange knowledge following certain protocols (Gonzalez-Rodriguez & Hernandez-Carrion, 2018). An imperative discovery that AI integration leads to an increase in workforce demand, as when it is utilized in original contributions, it results in increased efficiency (i.e., speed and quality of task completion) (Das et al., 2022).

Fourth, a five-year analysis of scientific advancements elucidates the absence of trust in the Human-AI relationship by comparing the interactions between human and artificial cognitive intelligence (Abbass, 2019). Baum (2020) confirms Abbass's outcomes by adding three decision-making challenges in the design of AI systems based on social choice facets: 1) determining whose ethical views are included; 2) how to identify and measure these views; and 3) how to aggregate individual perspectives into a cohesive view that pilots AI conduct.

Our findings have implications for the following domains. Within the scope of this review, leaders and knowledge workers are faced with ongoing effects of AI adoption experiences. These experiences have complex and inconsistent impacts on their sense of autonomy (Jarrahi, 2018). Laacke et al. (2021), for instance, showcased the use of AI depression detectors (AIDDs) that can analyze data from social media to detect signs of mental disorders like depression. AIDDs can identify individuals who may be at risk of depression before they seek professional help. The ethical considerations of applying AIDDs on personal data of users posed challenges in extending this concept due to a breach of digital autonomy.

Overall, AI integrations have a predominantly positive impact on choices and workflow transformation. Concerns about AI's effect on choice authenticity are countered by its efficiency gains and the synergy between human and AI decision-making capabilities. This synergy, termed "hybrid decision-making," demonstrates the effective fusion of AI capabilities with human critical thinking, as evidenced by compelling cases. Hybrid decision-making, emphasized for its significance in achieving long-term autonomy balance, entails the integration of AI planning for task sequencing, daily task generation, and action prioritization (Kunze et al., 2018). Baum (2020) underscores the necessity for meticulous organizational decision-making during AI design, as delegating such decisions solely to AI is impractical.

APPENDIX

Content Assessment

No.	Study	Content Validation
1	(Abbass, 2019) Qualitative Australia	Human-Machine teams & Trustworthy AI AO
2	(Baum, 2020) Qualitative UK	Wholistic Organizational Ethics Regulation AO
3	(Bilan et al., 2022) Mixed Methods Lithuania	AI and Organizational Change PO
4	(Das et al., 2022) Quantitative India	Impact of AI driven choices in CRM PO

No.	Study	Content Validation
5	(Dobbe et al., 2021) The Netherlands-USA	Ethics Implication AO
6	(Bankins & Formosa, 2021) Qualitative Australia	Promote/Demote /Decisions/Skills PO & AO
7	(Fedorets et al., 2022) Germany	Direct impact of AI on Autonomy PO
8	(Hao et al., 2020) Quantitative Phuket	AI adoption and Performance: Individuals vs Team PO & AO Individuals –PO Teams– AO
9	(Jones, 2018) Qualitative USA	Long Term Autonomy Balance AO
10	(Kunze et al., 2018) Quantitative	Long-term robot Autonomy PO
11	(Sebastian Laacke et al., 2021) Quantitative USA	Digital autonomy and Privacy regulations AO
12	(Lawless et al., 2019) Quantitative USA	Human Machine teams PO
13	(Lin & Zhu, 2021) Qualitative China	Leveraging AI decision-making models PO
14	(Pescetelli, 2021) Qualitative USA	Bias-proved Hybrid Intelligence PO
15	(Ploug et al., 2021) Mixed Methods Denmark	Outcomes of AI-driven decisions in hybrid teams PO
16	(Smith & Green, 2018) Qualitative USA	Digital Leadership PO
17	(Unhelkar & Gonsalves, 2020) Qualitative USA	Predictive Data-driven capabilities of AI PO
18	(Yinying Wang, 2021) Qualitative USA	(Extended Brain) AI driven Decisions biases & Ethics PO & AO
19	(Wijayati et al., 2022) Quantitative Indonesia	AI, Performance & Work Engagement PO
20	(Di Vaio et al., 2020) Malaysia	Sustainable Business model PO
21	(Metcalf et al., 2019) Qualitative USA	Artificial swarm intelligence leveraging collective intelligence PO
22	(Barro & Davenport, 2019) Qualitative UK	Transforming Workflow PO
23	(Huang et al., 2019) Qualitative USA	Changing roles in Empathetic and Analytic roles PO
24	(Kaplan & Haenlein, 2019b) Qualitative USA	Leaders integrating AI technologies for hybrid work PO
25	(Haseeb et al., 2019) Quantitative Thailand	Process Optimising via Automation PO

No.	Study	Content Validation
26	(Duan et al., 2019) Qualitative UK	Problem Solving use of AI- Decision making systems PO
27	(Schneider & Leyer, 2019) Quantitative Germany	AI Adoption Impacting Decision-making Processes PO
28	(Jarrahi, 2018) Qualitative USA	Autonomy in digital environments AO

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