

Artificial Intelligence Adoption and Organizational Decision-Making: A Literature Review

Dr Namara Asiimwe

Metropolitan International University

Abstract

This paper presents a literature review examining how organizations adopt and integrate artificial intelligence (AI) into managerial decision-making processes. Drawing on 24 peer-reviewed sources published primarily between 2013 and 2023, the review synthesizes findings across three themes: the theoretical foundations of technology adoption as applied to AI, the organizational and human factors that shape AI integration, and the documented impacts of AI on decision quality and speed. The review employs a systematic search and thematic synthesis approach informed by established methodological guidance. Findings indicate convergence around the view that AI adoption is less a discrete technology-implementation event than an ongoing sociotechnical process shaped by managerial trust, data infrastructure, and organizational readiness. The review identifies three persistent gaps: a shortage of longitudinal studies tracking decision outcomes after adoption, limited attention to small and mid-sized firms relative to large enterprises, and inconsistent operationalization of "AI adoption" as a construct across studies. The paper concludes by proposing a research agenda addressing these gaps and outlining implications for management practice.

Keywords: artificial intelligence, organizational decision-making, technology adoption, literature review, management

1.0 Introduction

Organizations across sectors are increasingly embedding artificial intelligence (AI) into functions that were historically the exclusive domain of human judgment, including resource allocation, forecasting, hiring, and strategic planning (Brynjolfsson & McAfee, 2017; Kolbjørnsrud, Amico, & Thomas, 2016). This shift has generated a rapidly expanding body of management literature addressing how, why, and with what consequences organizations adopt AI-based decision tools. Yet this literature remains fragmented across disciplinary silos — information systems, strategic management, and organizational behavior each frame the phenomenon differently, using inconsistent terminology and units of analysis (Duan, Edwards, & Dwivedi, 2019).

The purpose of this review is to synthesize this fragmented literature into a coherent account of what is known about AI adoption in organizational decision-making, to identify where empirical consensus exists and where it does not, and to propose a research agenda that addresses the field's most significant gaps. The review is organized around three guiding questions: (1) what theoretical frameworks have been used to explain AI adoption in organizational settings? (2) What organizational and human factors have been identified as enabling or constraining that adoption? (3) What outcomes, positive and negative, have been empirically associated with AI-supported decision-making?

The remainder of the paper proceeds as follows. Section 2 describes the search and selection methodology. Section 3 synthesizes the literature thematically. Section 4 offers a critical discussion of points of convergence and disagreement.

Section 5 identifies gaps in the current literature, and Section 6 concludes with implications for theory, practice, and future research.

2.0 Methodology

This review follows a hybrid narrative–systematic approach, combining the transparency of systematic search procedures (Kitchenham & Charters, 2007; Moher, Liberati, Tetzlaff, & Altman, 2009) with the interpretive synthesis characteristic of narrative reviews in management research (Torraco, 2016). This approach was selected because the phenomenon under review — AI adoption in decision-making — spans multiple literatures that use different terminology, making a purely systematic keyword search insufficient without an interpretive synthesis stage.

2.1 Search Strategy

Sources were identified through structured searches of Business Source Complete, Web of Science, and Google Scholar using combinations of the terms "artificial intelligence," "machine learning," "decision-making," "organizational adoption," and "management." The search was restricted to peer-reviewed journal articles and major practitioner outlets (e.g., Harvard Business Review) published between 2013 and 2023, reflecting the period of accelerated enterprise AI adoption following advances in machine learning.

2.2 Selection Criteria

Sources were included if they (a) addressed AI or machine learning explicitly, rather than information technology broadly; (b) examined organizational- or managerial-level decision-making rather than purely technical performance; and (c) were published in outlets with an editorial or peer-review process. An initial pool of sources was screened by title and abstract, followed by full-text review of the remaining set, using the method popularized by Webster and Watson (2002) for management literature reviews. The final set analyzed in this review comprises 24 sources, listed in the References section.

3.0 Thematic Synthesis

3.1 Theoretical Foundations

Much of the literature on AI adoption in organizations extends theoretical frameworks developed for earlier waves of information technology. The Technology Acceptance Model (Davis, 1989) and the broader Diffusion of Innovations framework (Rogers, 2003) remain frequently cited starting points, even though several authors argue these models understate the distinctive features of AI — namely its capacity to act autonomously and to improve its own performance over time (Von Krogh, 2018). The Technology-Organization-Environment framework (Tornatzky & Fleischer, 1990) has also been applied to explain firm-level AI readiness, particularly in studies examining resource and infrastructure prerequisites for adoption (Alsheibani, Cheung, & Messom, 2018). A smaller stream draws on dynamic capabilities theory (Teece, 2018) to frame AI adoption not as a one-time implementation but as an ongoing organizational capability that must be continuously reconfigured.

3.2 Organizational and Human Factors

A consistent finding across the reviewed literature is that technical capability alone does not predict successful AI adoption; organizational and human factors are equally, if not more, consequential. Fountaine, McCarthy, and Saleh (2019) argue that the primary barriers to enterprise AI adoption are cultural and structural rather than technological, citing siloed data ownership and managerial resistance as recurring obstacles. Similarly, Jarrahi (2018) frames AI adoption as a question of human–AI complementarity, proposing that successful integration depends on managers appropriately delegating well-structured, data-rich decisions to AI while retaining ambiguous or high-stakes judgment calls for human deliberation. Wilson and Daugherty (2018) extend this argument empirically, reporting that organizations achieving the greatest performance gains treat AI as a collaborative partner rather than a replacement for managerial judgment.

Trust emerges as a recurring construct across this sub-literature. Several authors note that managerial trust in algorithmic outputs is not static but develops (or erodes) through repeated interaction with the system, and that transparency in how an AI system reaches its outputs is a significant predictor of continued use (Shrestha, Ben-Menahem, & Von Krogh, 2019).

3.3 Outcomes for Decision-Making

Empirical findings regarding the impact of AI on decision outcomes are more mixed than the practitioner literature often suggests. Mikalef and Gupta (2021) find a positive association between organizational AI capability and both creativity and firm performance, but note the relationship is moderated by complementary resources such as data governance maturity. Grover, Chiang, Liang, and Zhang (2018) similarly find that analytics-driven decision-making improves outcomes primarily when paired with organizational structures that allow decision rights to shift toward data-proximate actors. In contrast, Davenport and Ronanki (2018) caution that many organizations overestimate near-term gains from AI-supported decision-making, particularly where implementation outpaces the organization's capacity to interpret and act on algorithmic outputs. Dwivedi et al. (2021), synthesizing across disciplines, similarly conclude that documented outcomes vary substantially by sector, decision type, and time horizon, and caution against generalized claims of AI's impact on decision quality.

4.0 Critical Discussion

Read together, the reviewed literature reflects a shift in framing: earlier work (2013–2017) tends to treat AI as an extension of prior enterprise IT, evaluated through established technology-adoption lenses, while more recent work (2018–2023) increasingly treats AI adoption as a distinct organizational and even strategic phenomenon warranting its own theoretical apparatus. This shift parallels but has not fully resolved a tension in the literature between technologically deterministic accounts, which treat adoption outcomes as a function of system capability, and sociotechnical accounts, which treat outcomes as jointly produced by technology, organizational structure, and human interpretation (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013; Kaplan & Haenlein, 2019).

A second point of disagreement concerns measurement. Studies differ substantially in how they operationalize "AI adoption," ranging from binary presence/absence measures to multidimensional capability indices (Mikalef & Gupta,

2021). This inconsistency complicates cross-study comparison and may partly explain the mixed findings on decision-making outcomes described in Section 3.3.

5.0 Gaps in the Literature

Three gaps stand out from this synthesis. First, the literature is overwhelmingly cross-sectional; few studies track decision outcomes longitudinally following AI adoption, leaving open questions about whether observed benefits persist, diminish, or grow over time. Second, existing empirical work disproportionately samples large enterprises, particularly technology-sector firms, leaving the applicability of these findings to small and mid-sized organizations largely untested. Third, as noted in Section 4, the absence of a shared operational definition of AI adoption constrains the field's ability to accumulate comparable evidence across studies.

6.0 Conclusion

This review synthesizes a fragmented but rapidly growing literature on AI adoption in organizational decision-making, organized around theoretical foundations, organizational and human enabling factors, and empirical outcomes. While the literature converges on the view that successful adoption depends on organizational and human factors at least as much as technical capability, it diverges on the magnitude and consistency of AI's effect on decision quality. Addressing the identified gaps-particularly the need for longitudinal designs, broader firm-size sampling, and construct standardization represents a clear opportunity for future research to move the field from descriptive accounts toward cumulative, comparable evidence that can more confidently inform management practice.

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