ISSN (Online) : 3139-3187
Journal of Business Practice and Academic Research (JBPAR)
https://jbpar.org

From Automation to Augmentation: How AI Adoption Influences Managerial Decision-Making and Organizational Performance

Mr Ravi Chandra Mohan Byri
Sr Analyst, Etiahad Water & Electricity
Dubai, UAE
rcmbyri9999@gmail.com

Abstract

Artificial intelligence (AI) is increasingly embedded in managerial work, yet its organisational value cannot be explained by adoption alone. AI can automate bounded tasks, augment managerial judgement, or combine both roles across different decision stages. This conceptual paper develops an integrative framework explaining how AI adoption influences managerial decision-making and organisational performance through human–AI collaboration and decision implementation. Drawing on the automation–augmentation paradox, sociotechnical systems thinking, decision-making theory, and dynamic capabilities, the paper argues that AI creates value when analytical capabilities complement managerial contextual knowledge and are embedded in accountable routines. The framework proposes that AI adoption influences decision quality through information processing, option generation, and decision support; decision quality contributes to performance when decisions are implemented effectively. Human–AI collaboration is positioned as a central mechanism, while task structuredness, uncertainty, managerial AI literacy, trust calibration, data quality, and governance are proposed as boundary conditions. Seven propositions guide empirical testing. The paper contributes by moving beyond a simple adoption–performance relationship and explaining mechanisms and conditions through which AI may support or undermine managerial judgement and organisational outcomes.

Keywords: Artificial intelligence; automation; augmentation; managerial decision-making; human–AI collaboration; organisational performance; AI governance

ISSN (Online) : 3139-3187
Journal of Business Practice and Academic Research (JBPAR)
https://jbpar.org

1. Introduction

1.1 Background of the Study

Artificial intelligence (AI) increasingly supports operational, tactical, and strategic managerial activities through automation, information analysis, forecasting, and decision support. However, its organisational value depends on how technologies interact with managerial expertise, organisational readiness, and governance. Automation delegates defined tasks to AI, whereas augmentation combines technological capabilities with human interpretation and contextual judgement. These modes can coexist within organisational processes rather than function as mutually exclusive alternatives (Raisch & Krakowski, 2021). Human–AI collaboration therefore requires attention to how managers interpret, challenge, implement, and review recommendations, particularly when decisions involve uncertainty and competing priorities (Jarrahi, 2018).

1.2 Problem Statement

AI adoption does not automatically improve managerial decision quality or organisational performance. Managers may struggle to assess analytical outputs, interpret their contextual relevance, or translate recommendations into coordinated action. Technological integration also differs from establishing decision authority and accountability (Baird & Maruping, 2021). Although existing scholarship addresses adoption, automation, augmentation, and collaboration, further conceptual integration is needed to explain their connections with decision quality, implementation, and performance. This study addresses that problem by examining these relationships alongside task characteristics, managerial AI literacy, calibrated trust, data quality, and governance as conditions that may strengthen or constrain outcomes.

1.3 Research Aim and Research Objectives

Research Aim

To develop an integrative conceptual framework explaining how AI adoption, through automation and augmentation, influences managerial decision-making and organisational performance.

Research Objectives

- **RO1:** To distinguish automation and augmentation as related modes of AI use and explain how they can be combined across managerial decision tasks.
- **RO2:** To explain how human–AI collaboration connects AI adoption with managerial decision quality.
- **RO3:** To examine how managerial decision quality and decision implementation connect AI use with organisational performance.
- **RO4:** To identify how task characteristics, managerial AI literacy, calibrated trust, data quality, and AI governance shape the proposed relationships.
- **RO5:** To develop a process-oriented conceptual framework and propositions integrating these relationships to guide future empirical research.

1.4 Research Questions

- **RQ1:** How do automation and augmentation differ, and how can they be combined across managerial decision tasks?
- **RQ2:** How does human–AI collaboration connect AI adoption with managerial decision quality?
- **RQ3:** How do managerial decision quality and decision implementation connect AI use with organisational performance?
- **RQ4:** How do task characteristics, managerial AI literacy, calibrated trust, data quality, and AI governance shape the proposed relationships?
- **RQ5:** How can these relationships be integrated into a process-oriented

conceptual framework and propositions that guide future empirical research?

1.5 Research Gaps

- **AI Adoption Conceptualisation Gap:** Building on research on delegation and managing with AI, further integration is needed to connect adoption, collaboration, managerial decisions, and organisational performance (Baird & Maruping, 2021; Hillebrand et al., 2025).
- **Automation-to-Augmentation Gap:** Building on the interdependence of automation and augmentation, further explanation is needed of how their combination supports managerial judgement across decision tasks (Page & Kallapur, 2026; Raisch & Krakowski, 2021).
- **AI-to-Decision-Quality Gap:** Existing collaboration research provides a basis for further specifying how AI capabilities and human judgement jointly influence managerial decision quality (Jarrahi, 2018; Li & Tian, 2026).
- **Decision-Making-to-Performance Gap:** Research on complementary capabilities and organisational transformation motivates clearer explanation of how implementation translates improved decisions into organisational performance (Teece, 2007; Vial, 2019).
- **Contextual Conditions and Governance Gap:** Trust, interaction design, and algorithmic control research motivate integrating managerial capabilities, data quality, and governance into the proposed AI–decision–performance pathway (Amershi et al., 2019; Glikson & Woolley, 2020; Kellogg et al., 2020).

1.6 Significance of the Study

This study connects AI adoption, human–AI collaboration, managerial decision quality,

decision implementation, and organisational performance within an integrated conceptual framework. Its theoretical significance lies in combining sociotechnical systems thinking, decision-making theory, the automation–augmentation paradox, and dynamic capabilities to explain how organisational value may emerge. For managers, it highlights task allocation, human accountability, literacy, calibrated trust, data quality, and governance as considerations for responsible AI use. For researchers, the framework and seven propositions provide a foundation for empirical investigation while distinguishing proposed relationships from validated findings and recognising that improved decisions require effective implementation to support performance.

2. Literature Review

2.1 AI Adoption in Organisations

AI adoption involves integrating AI-enabled technologies into managerial tasks, routines, and decision processes. Davenport and Ronanki (2018) and Kaplan and Haenlein (2019) discuss business applications, while Baird and Maruping (2021) explain delegation between people and agentic information systems. Faraj et al. (2018) and Kellogg et al. (2020) show that algorithms interact with routines, expertise, and workplace relationships. Hillebrand et al. (2025) integrate human–AI collaboration and algorithmic management, providing a benchmark for examining managerial AI use. Adoption therefore cannot be equated with effective use or organisational value. Building on these perspectives, this paper connects adoption, collaboration, decision quality, implementation, and performance within a process-oriented framework. Its proposed contribution concerns the connections among these elements and their contextual conditions.

2.2 Automation and Augmentation

Automation delegates defined, repeatable tasks to AI, potentially improving processing speed, consistency, and scale. Augmentation uses AI to extend managerial analysis through pattern recognition, evidence synthesis, and alternative generation while

retaining human interpretation and accountability. Raisch and Krakowski (2021) explain that these modes are interdependent rather than mutually exclusive. Page and Kallapur (2026) further distinguish replacement, human–AI partnership, and disruptive AI-generated ideas. Their perspectives support allocating tasks according to decision requirements rather than assuming one mode is consistently superior. Structured activities may suit automation, whereas ambiguous decisions require greater contextual judgement. Both approaches nevertheless require verification and oversight. The proposed framework connects their allocation with collaboration, decision quality, implementation, and performance, recognising that benefits depend on how technological capabilities complement managerial work.

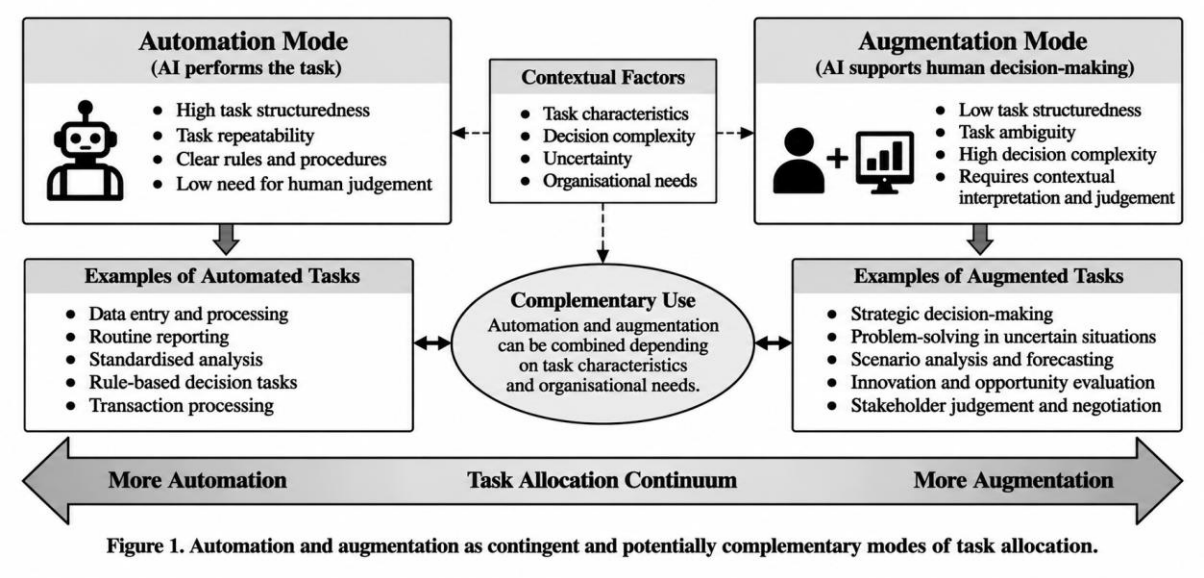


Figure 1. Automation and augmentation as contingent and potentially complementary modes of task allocation.

2.3 Managerial Decision-Making

Managerial decision-making involves defining problems, interpreting evidence, comparing alternatives, and selecting actions aligned with organisational objectives. AI can expand information processing and option generation, but decision quality also depends on contextual relevance and uncertainty. Jarrahi (2018) describes human–AI symbiosis as combining computational analysis with human judgement. Responses to algorithmic advice can reflect aversion or appreciation (Dietvorst et al., 2015; Logg et al., 2019). Glikson and Woolley (2020)

review determinants of trust in AI, supporting attention to appropriate reliance. Effective collaboration therefore requires calibrated trust, verification opportunities, and accountability. Li and Tian (2026) further examine AI–human decision configurations. The proposed framework positions collaboration as a mechanism linking adoption with decision quality, while recognising that organisational benefits require effective implementation.

2.4 Organisational Performance

Organisational performance encompasses operational efficiency, productivity, service quality, innovation, adaptability, customer outcomes, and financial results. AI may support these outcomes through faster processing, improved forecasting, resource allocation, and more consistent decisions. However, its contribution depends on complementary organisational changes rather than technological capability alone (Makridakis, 2017; Vial, 2019). Implementation costs, integration difficulties, employee learning, and oversight requirements can influence the timing and extent of benefits. Local improvements may also fail to generate wider value when they create bottlenecks or prioritise measures disconnected from strategic objectives. The framework therefore distinguishes managerial decision quality from organisational performance. Effective implementation, involving communication, coordination, resource allocation, and monitoring, provides the proposed connection between these outcomes. Performance improvements remain contingent expectations rather than automatic consequences of adoption.

2.5 The Automation–Augmentation Paradox

The automation–augmentation paradox challenges the assumption that organisations should permanently prioritise either technological substitution or human support. Raisch and Krakowski (2021) explain that these demands can coexist and influence one another. Automating predictable activities may release managerial attention for

interpretation, exception handling, and relationship-intensive work. However, excessive automation can weaken opportunities to maintain expertise, while extensive augmentation may create additional review demands. Appropriate allocation therefore depends on task characteristics and decision stages. Data extraction and routine checking may be automated, interpretation may be augmented, and consequential choices may require human deliberation. These arrangements should evolve alongside system capabilities and governance. The framework consequently treats automation and augmentation as contingent combinations whose value should be assessed through decision quality, accountability, implementation, and organisational outcomes.

3. Theoretical Foundation

3.1 Sociotechnical Systems Perspective

A sociotechnical perspective holds that organisational outcomes depend on the joint design of technological and social systems. AI is not simply inserted into an otherwise unchanged workplace. Its outputs interact with employee skills, task structure, incentives, authority, communication, and organisational culture. A technically capable system can fail if users do not understand its limits or if workflows prevent recommendations from being acted upon. Conversely, a modest system may create value when integrated into clear routines and supported by capable users. This perspective supports the emphasis on collaboration, work design, and governance as mechanisms connecting adoption with outcomes (Faraj et al., 2018; Kellogg et al., 2020).

3.2 Decision-Making and Bounded Rationality

Managerial decisions are constrained by limited time, attention, information, and cognitive capacity. Simon's (1955) behavioural account of rational choice provides a foundational basis for understanding these constraints. AI can extend analytical capacity by processing large datasets, identifying patterns, and

generating options. However, it does not remove bounded rationality; it changes the sources of constraint. Managers may face opaque recommendations, unreliable outputs, information overload, or difficulty distinguishing plausible language from valid evidence. AI-supported decisions therefore require a process that combines computational scale with human contextual interpretation and critical review (Shrestha et al., 2019).

3.3 Automation–Augmentation Paradox

The automation–augmentation paradox (Raisch & Krakowski, 2021) is useful because automation and augmentation can be contradictory yet interdependent demands. Organisations may seek efficiency through automation while needing human judgement for novelty, exception handling, accountability, and learning. Prioritising automation too strongly can erode human capability; prioritising augmentation without disciplined task allocation can create inefficient dependence on human review. The framework proposes contingent coexistence rather than a universal rule that augmentation is always preferable.

3.4 Dynamic Capabilities and Complementary Resources

The resource-based view explains differences in performance through valuable, rare, imperfectly imitable, and non-substitutable resources (Barney, 1991). Applied here, AI must be combined with complementary expertise, data, and routines rather than treated as a sufficient source of advantage. Dynamic capabilities explain how organisations sense changes, seize opportunities, and reconfigure resources (Teece, 2007). AI may support these activities through monitoring, prediction, and decision support, but benefits depend on governance, learning, and execution. This perspective connects technological use with organisational adaptation and implementation rather than assuming that technology ownership produces sustained performance improvements (Teece, 2007; Vial, 2019).

Together, these perspectives provide complementary explanations: the sociotechnical lens explains joint design; decision theory explains judgement under constraints; paradox theory explains the tension between automation and augmentation; and dynamic capabilities explain how AI-enabled decision processes may contribute to adaptation and performance.

4. Research Methodology

4.1 Research Design

The conceptual approach is appropriate because the primary objective is to integrate established theoretical perspectives and develop logically connected propositions rather than estimate statistical relationships using primary data. The framework is theory-building in orientation: it identifies the principal constructs, specifies the proposed relationships among them, and outlines the conditions under which these relationships may vary. The resulting propositions are theoretical expectations and should be evaluated through future empirical research rather than interpreted as confirmed causal effects.

4.2 Literature Selection

For analytical consistency, the selected literature was organised according to its relevance to the research questions and the explanatory role it played in the proposed framework. Foundational theoretical studies were used to establish the underlying perspectives, while research on AI adoption and human–AI collaboration informed the proposed mechanisms and relationships. The synthesis focused on conceptual alignment, differences in theoretical emphasis, and the connections among AI adoption, collaboration, decision quality, implementation, and organisational performance. Because a reproducible search and screening record was not maintained, this approach should be understood as a theory-led integrative synthesis rather than a comprehensive or systematic evidence review.

4.3 Thematic Synthesis and Framework Development

Framework development involved connecting the explanatory insights of these perspectives into a single proposed process model. The sociotechnical perspective informed the role of organisational and work-design conditions; bounded rationality informed the importance of managerial judgement and information-processing limitations; paradox theory informed the contingent relationship between automation and augmentation; and dynamic capabilities informed the connection between AI-enabled decision processes and organisational adaptation. These connections were then expressed through the proposed constructs and propositions (P1–P7). The resulting model represents a conceptual synthesis developed by the authors and remains subject to empirical validation.

Table 1. Research Methodology Overview

Component	Description	Purpose
Research design	Conceptual research using integrative synthesis	Develop a theory-driven explanation
Literature themes	AI adoption; automation/augmentation; decision-making; performance; governance	Clarify concepts and relationships
Analytical approach	Thematic comparison and conceptual integration	Identify mechanisms and research gaps
Theoretical lenses	Sociotechnical systems; bounded rationality; paradox theory; dynamic capabilities	Explain complementary mechanisms
Research output	Five research questions, five objectives, and seven propositions	Guide future empirical validation

5. Proposed Conceptual Framework

The proposed framework explains how AI adoption may contribute to managerial

decision-making and organisational performance through human–AI collaboration and effective implementation. It distinguishes the principal constructs and identifies conditions that shape their relationships.

5.1 Overview of the Proposed Conceptual Framework

The proposed conceptual framework connects AI adoption, human–AI collaboration, managerial decision quality, decision implementation, and organisational performance. Automation and augmentation represent complementary approaches whose suitability depends on managerial tasks and decision requirements. Human–AI collaboration combines analytical capabilities with contextual knowledge, supporting information processing, alternative evaluation, and judgement. However, improved decision quality does not automatically generate organisational benefits; implementation translates selected decisions into coordinated action. Task characteristics, managerial AI literacy, calibrated trust, data quality, and governance shape these relationships. Figure 2 presents the proposed pathway and its supporting conditions. These relationships remain conceptual expectations requiring empirical validation.

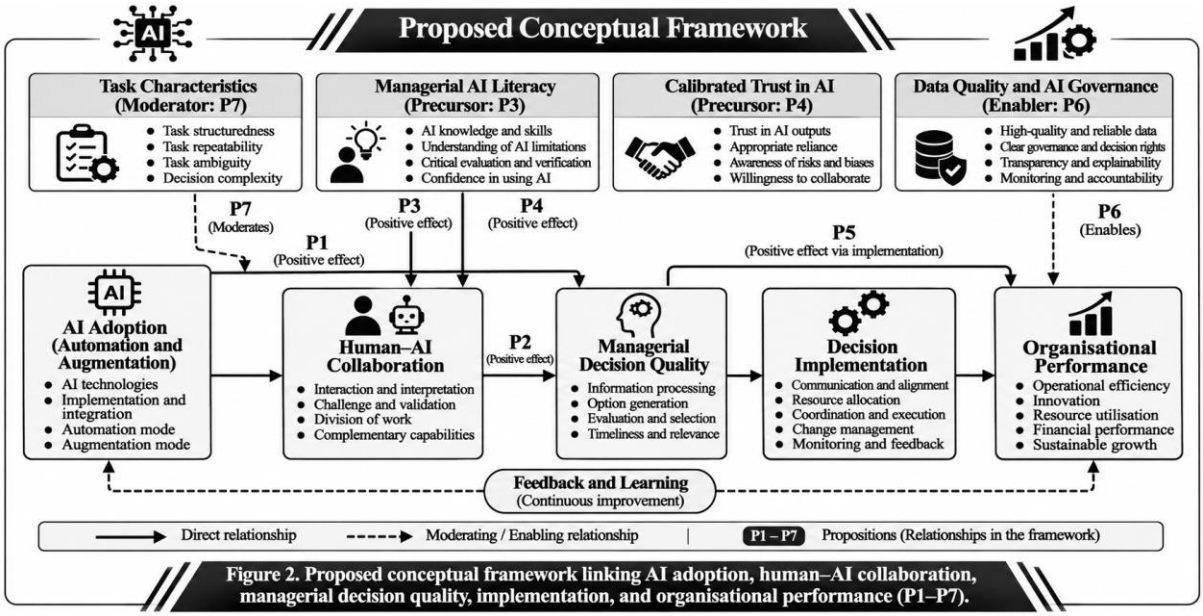


Figure 2. Proposed conceptual framework linking AI adoption, human–AI collaboration, managerial decision quality, implementation, and organisational performance (P1–P7).

ISSN (Online) : 3139-3187
Journal of Business Practice and Academic Research (JBPAR)
https://jbpar.org

5.2 AI Adoption: Automation and Augmentation Modes

AI adoption operates through automation and augmentation, with each mode serving different managerial requirements. Automation delegates structured, repetitive, and rule-based activities to AI, potentially improving speed, consistency, and efficiency. Augmentation supports managerial judgement through information analysis, pattern identification, scenario evaluation, and alternative generation. Organisations may combine these modes within the same decision process rather than adopt one universally. Predictable activities may suit automated execution, whereas ambiguous or uncertain decisions require greater human interpretation and oversight. Consequently, effective adoption depends on matching technological capabilities with task requirements. Table 2 distinguishes these modes from the framework's other constructs and explanatory roles.

Table 2. Core Constructs and Their Roles in the Conceptual Framework

Construct	Working definition or dimensions	Role in the framework
AI adoption	Introduction and assimilation of AI-enabled tools into managerial tasks	Starting condition; does not guarantee value
Automation and augmentation	AI task execution and AI-supported human judgement	Complementary modes of task allocation
Human–AI collaboration	Interaction, interpretation, challenge, and division of work	Proposed process mechanism
Managerial decision quality	Accuracy, relevance, timeliness, consistency, explainability, and contextual fit	Proximal decision outcome

Decision implementation	Coordinated action, execution, and resource allocation	Converts decisions into organisational action
Organisational performance	Efficiency, productivity, service quality, innovation, risk control, and longer-term effectiveness	Distal, multidimensional outcome
Contextual conditions	Task characteristics, AI literacy, calibrated trust, data quality, and governance	Shape the proposed relationships

5.3 Human–AI Collaboration and Managerial Decision Quality

Human–AI collaboration connects technological capabilities with managerial knowledge through interpretation, evaluation, challenge, and application of AI-generated recommendations. AI may improve information processing, identify relevant patterns, and generate alternatives, while managers assess contextual relevance, organisational priorities, and potential consequences. Managerial AI literacy supports understanding of system capabilities and limitations, enabling more informed evaluation of outputs. Drawing on trust research (Glikson & Woolley, 2020), calibrated trust is understood here as reliance proportionate to system reliability rather than unquestioning acceptance or unnecessary rejection. Together, these capabilities may strengthen the accuracy, relevance, consistency, and timeliness of decisions. The framework therefore positions effective collaboration as an important mechanism through which AI adoption may support managerial decision quality.

5.4 Decision Implementation and Organisational Performance

Decision implementation provides the connection between managerial decision quality and organisational performance. Accurate and relevant decisions create organisational value when translated into communication, resource allocation, coordination, execution, and monitoring. Effective implementation may support productivity, operational efficiency, innovation, and improved resource utilisation. However, limited resources, employee resistance, inadequate coordination, or unclear responsibilities can constrain these benefits. The framework therefore separates decision-level improvements from wider organisational outcomes and recognises execution capacity as essential to their connection. Figure 3 illustrates how review and implementation are followed by outcome monitoring and learning. This feedback supports adjustments to subsequent decisions, managerial routines, and AI-supported work.

5.5 Contextual Conditions and Responsible AI Governance

The framework recognises that AI-supported decision outcomes depend on contextual conditions. Task structuredness, repeatability, ambiguity, and complexity influence the suitability of automation and augmentation. Managerial AI literacy and calibrated trust shape how recommendations are interpreted, checked, and applied. Data quality supports reliable analysis, while responsible governance establishes decision rights, accountability, human oversight, monitoring, and explainability. These arrangements help managers identify limitations, address exceptions, and review consequential recommendations. Their effectiveness may strengthen or constrain the relationships among adoption, collaboration, decision quality, implementation, and performance. Accordingly, organisational value depends on the alignment of task requirements, managerial capabilities, reliable information, and accountable governance practices.

6. Conceptual Propositions

P1: Higher levels of AI adoption through automation and augmentation are positively associated with improved managerial decision quality.

P2: More effective Human–AI Collaboration is positively associated with higher managerial decision quality.

P3: Higher managerial AI literacy is positively associated with more effective Human–AI Collaboration.

P4: Higher levels of calibrated trust in AI are positively associated with more effective Human–AI Collaboration.

P5: Higher managerial decision quality is positively associated with improved organisational performance when decisions are implemented effectively.

P6: Stronger AI governance and higher data quality are positively associated with improved organisational performance through more reliable, transparent, and accountable AI-supported decisions.

P7: Task characteristics, including task structuredness, repeatability, and uncertainty, moderate the relationships between AI adoption modes and managerial decision quality, such that the effectiveness of automation and augmentation varies across decision contexts.

7. Discussion and Implications

7.1 Theoretical Contributions

The framework connects AI adoption with performance through collaboration, decision quality, and implementation as distinct conceptual links. It builds on Raisch and Krakowski's (2021) contingent view of automation and augmentation. Hillebrand et al. (2025) integrate collaboration and algorithmic management; the present framework focuses specifically on how decisions translate into organisational outcomes through implementation. Its contribution lies in connecting task allocation with this process and distinguishing improved decisions from realised performance. AI literacy, calibrated trust,

data quality, and governance shape the proposed pathway. The framework integrates established explanations rather than claiming these elements are new, and its relationships require empirical validation.

7.2 Managerial Implications

Managers should evaluate decision tasks before selecting AI applications, distinguishing activities suitable for automation from those requiring augmented judgement. Routine processing may be automated when outputs can be checked, while ambiguous decisions require contextual interpretation and human accountability. Organisations should establish verification procedures, override authority, and training covering system limitations, bias, data protection, and unreliable outputs. Performance assessment should examine decision accuracy, timeliness, implementation success, customer outcomes, employee capability, and total cost. Tracking these indicators before and after implementation can support evaluation. Effective adoption therefore requires attention to task allocation, managerial competence, and the capacity to translate decisions into coordinated action.

ISSN (Online) : 3139-3187
Journal of Business Practice and Academic Research (JBPAR)
https://jbpar.org

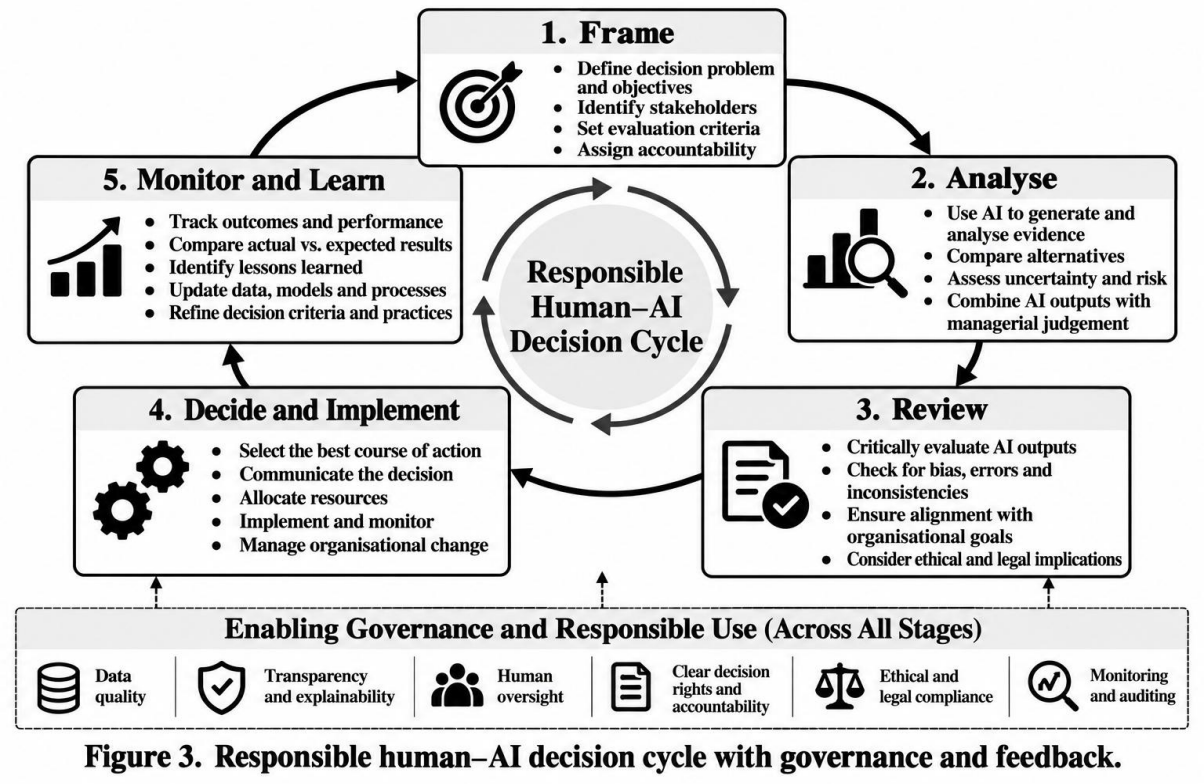


Figure 3. Responsible human–AI decision cycle with governance and feedback.

7.3 Governance and Responsible Use

AI governance should reflect the consequences of the decision being supported. Routine internal activities may require lighter controls, whereas consequential decisions require stronger documentation, review, and escalation. Responsibility should remain clear even when AI supplies recommendations. Meaningful oversight requires reviewers with appropriate expertise, sufficient time, access to evidence, and authority to challenge outputs. Transparency and explainability should support contextual understanding rather than be assumed to improve outcomes automatically (Amershi et al., 2019; Siau & Wang, 2020; Sullivan & Weger, 2025). These arrangements can strengthen accountability while supporting proportionate, informed reliance on AI throughout managerial decision processes.

7.4 Organisational Learning and Continuous Improvement

Organisational learning connects AI-supported decisions with continuing adaptation and improvement. Organisations

should monitor implementation outcomes, identify errors, and compare results with expectations to inform subsequent decisions. Feedback from managers and employees can reveal system limitations, implementation difficulties, and opportunities to improve task allocation between automation and augmentation. As illustrated in Figure 3, monitoring and learning form an ongoing part of the responsible human–AI decision cycle. Regular review can help refine decision criteria, update data and models, strengthen oversight, and adjust organisational routines. These activities support learning about when AI contributes value without assuming that every observed improvement results from AI adoption.

8. Limitations and Future Research

This study has several limitations that provide opportunities for future research. First, the paper is conceptual and does not empirically validate the proposed relationships. Therefore, the seven propositions require testing through quantitative, qualitative, or mixed-method approaches. Second, the literature synthesis is theory-led and integrative rather than a systematic review with reproducible database searches and formal screening. Third, AI technologies, including predictive models, recommendation systems, process automation, and generative AI, differ in their capabilities and risks. Their effects may vary across industries, organisational sizes, decision levels, and regulatory environments. Furthermore, organisational performance is multidimensional and influenced by factors beyond AI-supported decision-making. Future research should examine how automation and augmentation influence managerial decision quality across different task contexts. Longitudinal studies and field experiments could investigate human–AI collaboration, managerial AI literacy, calibrated trust, data quality, and governance. Researchers should also explore how effective decision implementation translates improved decision quality into organisational performance. Such investigations would help validate and extend the proposed framework.

9. Conclusion

AI adoption creates opportunities to automate routine work and augment managerial judgement, but it does not guarantee better decisions or stronger organisational performance. Value depends on how tasks are allocated, how human and machine capabilities are combined, and whether recommendations are translated into effective action. This paper develops a conceptual framework linking AI adoption with human–AI collaboration, managerial decision quality, decision implementation, and organisational performance. It proposes that task characteristics, managerial AI literacy, calibrated trust, data quality, and governance shape the strength of these relationships. The framework advances a contingent view of automation and augmentation and offers seven propositions for empirical testing. Its central implication is that organisations should evaluate AI not only by technical capability or adoption rates, but by the quality, accountability, and consequences of the decisions it supports.

References

1. Amershi, S., Weld, D., Vorvoreanu, M., Fourney, A., Nushi, B., Collisson, P., Suh, J., Iqbal, S., Bennett, P. N., Inkpen, K., Teevan, J., Kikin-Gil, R., & Horvitz, E. (2019). Guidelines for human-AI interaction. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3290605.3300233
2. Baird, A., & Maruping, L. M. (2021). The next generation of research on IS use: A theoretical framework of delegation to and from agentic IS artifacts. *MIS Quarterly, 45*(1), 315–341. https://doi.org/10.25300/MISQ/2021/15882
3. Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120. https://doi.org/10.1177/014920639101700108

4. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108–116. https://hbr.org/2018/01/artificial-intelligence-for-the-real-world
5. Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General, 144*(1), 114–126. https://doi.org/10.1037/xge0000033
6. Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and Organization, 28*(1), 62–70. https://doi.org/10.1016/j.infoandorg.2018.02.005
7. Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals, 14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057
8. Hillebrand, L., Raisch, S., & Schad, J. (2025). Managing with artificial intelligence: An integrative framework. *Academy of Management Annals, 19*(1), 343–375. https://doi.org/10.5465/annals.2022.0072
9. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons, 61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007
10. Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons, 62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004
11. Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174

12. Li, H., & Tian, F. (2026). Advancing decision-making through AI-human collaboration: A systematic review and conceptual framework. *Group Decision and Negotiation, 35*, Article 26. https://doi.org/10.1007/s10726-026-09980-1
13. Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes, 151*, 90–103. https://doi.org/10.1016/j.obhdp.2018.12.005
14. Makridakis, S. (2017). The forthcoming artificial intelligence (AI) revolution: Its impact on society and firms. *Futures, 90*, 46–60. https://doi.org/10.1016/j.futures.2017.03.006
15. Page, S. E., & Kallapur, A. (2026). Replace, augment, disrupt: AI & organizational decision-making. *Journal of Organization Design, 15*, 19–26. https://doi.org/10.1007/s41469-025-00194-4
16. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072
17. 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. https://doi.org/10.1177/0008125619862257
18. Siau, K., & Wang, W. (2020). Artificial intelligence (AI) ethics: Ethics of AI and ethical AI. *Journal of Database Management, 31*(2), 74–87. https://doi.org/10.4018/JDM.2020040105
19. Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics, 69*(1), 99–118. https://doi.org/10.2307/1884852
20. Sullivan, V., & Weger, K. (2025). Transparency and explainability in AI-assisted decision making: Effects on trust, perceived reliability, confidence, and ease of

understanding. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 69*(1). https://doi.org/10.1177/10711813251369473

21. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and micro foundations of (sustainable) enterprise performance. *Strategic Management Journal, 28*(13), 1319–1350. https://doi.org/10.1002/smj.640
22. Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems, 28*(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003