

BEHAVIORAL OPERATIONS AND HUMAN-AI COLLABORATION:
EFFECTS OF ALGORITHMIC DECISION SUPPORT ON MANAGERIAL
JUDGMENT, EMPLOYEE TRUST, PRODUCTIVITY, AND
ORGANIZATIONAL PERFORMANCE

Edikan John^{*1}, Celestin Hakorimana²

^{*1,2}School of Collective Intelligence Mohammed VI Polytechnic University (UM6P), Morocco

¹edikan.john@um6p.ma, ²celestin.hakorimana@um6p.ma

DOI: <https://doi.org/10.5281/zenodo.22810975>

Keywords

behavioral operations; human-AI collaboration; algorithmic decision support; trust in automation; metaknowledge; delegation asymmetry; managerial judgment; organizational performance

Article History

Received: 01 June 2026

Accepted: 23 August 2026

Published: 17 September 2026

Copyright @Author

Corresponding Author: *

Edikan John

Abstract

The rapid penetration of artificial intelligence (AI) and machine learning into business processes has transformed the way managers make decisions, the way supply chains execute, and organizations design themselves. Indeed, early technology utopias promoted a fully automated “no-touch” style of environment, but what is becoming apparent is that value creation for organizations lies in the quality of the human-AI interaction as a socio-technical system not a product or service that can be easily be switched out of a solution stack. This review integrates behavioral operations research to explore the impact of algorithmic decision support on managerial judgment, employee trust, productivity, and organizational performance. Based on trust in automation theory, dual-process cognitive paradigms, and literature on algorithm aversion and appreciation, this paper provides a theoretical analysis on four collaboration modes (full automation, adjustable automation, human augmentation, and strategic delegation). Results demonstrate a strong delegation asymmetry: a high confidence accurate self-assessment allows AI systems to delegate efficiently, human managers, however, are metacognitive impaired, they hold on to tasks they are bad at while delegating tasks they are best at. Environmental boundary conditions add another layer of complexity: human overrides are found to improve accuracy in long-horizon, low-uncertainty contexts, but to impair accuracy in short-horizon, volatile contexts. Trust is identified as the dominant psychological process through which transparency, interpretability, and decision alignment influence planning effectiveness, with task complexity exerting a positive moderating influence on such relationship. The review also surfaces a blamemaintenance paradox in which managers offload ethically fraught decisions to algorithms while holding onto credit for positive outcomes, as well as productivity hazards from uncontrolled introduction. The article argues for context-sensitive override rules, explainability as the default, explicit delegation support, metaknowledge training, and institutional governance that maintain human moral authorship for sustainable performance.

1. INTRODUCTION

The fast-paced adoption of artificial intelligence (AI) and machine learning (ML) technologies into enterprise systems and workloads is transforming every aspect of traditional business processes, from managerial decision-making, to supply chain management and organizational design. The Day of the Decomposers Probes whose sponsors unfolded a scenario of big, complex systems recovery: the rectification of antiquated, deteriorated infrastructure management was object oriented and high-priority: structural, mathematical and technological enablers to increase efficiency. Early techno-narratives promoted completely automated facilities, or "no-touch planning," driven by fear of human decision-making's introduction of unacceptable levels of variability and noise into operational processes and of cognitive biases being included in the process (Singh, 2023).

However, enterprise deployments demonstrate that high levels of complexity do not necessarily lead to superior outcomes. Recent developments in the IS and behavioral operations management communities highlight that value creation at the organizational level through human-AI team interaction is better viewed as a socio-technical capability than a plug-and-play technology-based solution (Rane et al., 2024). The technical subsystem, consisting of algorithms, predictive models, and computational data pipelines, needs to be perfectly coordinated with the social subsystem, reflecting managerial judgment, psychological trust, cognitive metaknowledge, and organizational norms (Koushik, 2024).

When algorithmic systems are introduced without attention to human behavioral factors, the result is severe operational friction for the entity involved. This tension leads to irrational overrides of correct algorithmic predictions, to systemic underuse of decision support systems, or to unthinking overuse that magnifies decision errors throughout the organization (Edisen, 2026). Achieving high operational effectiveness requires

understanding the psychological and behavioral mechanisms that govern how human decision-makers interact with, interpret, and act upon algorithmic outputs. The operational decision-making pipeline is driven by an underlying interaction where algorithmic architectures feed directly into cognitive mechanisms, which are heavily conditioned by contextual task characteristics before translating into overall decision quality (Patel et al., 2025).

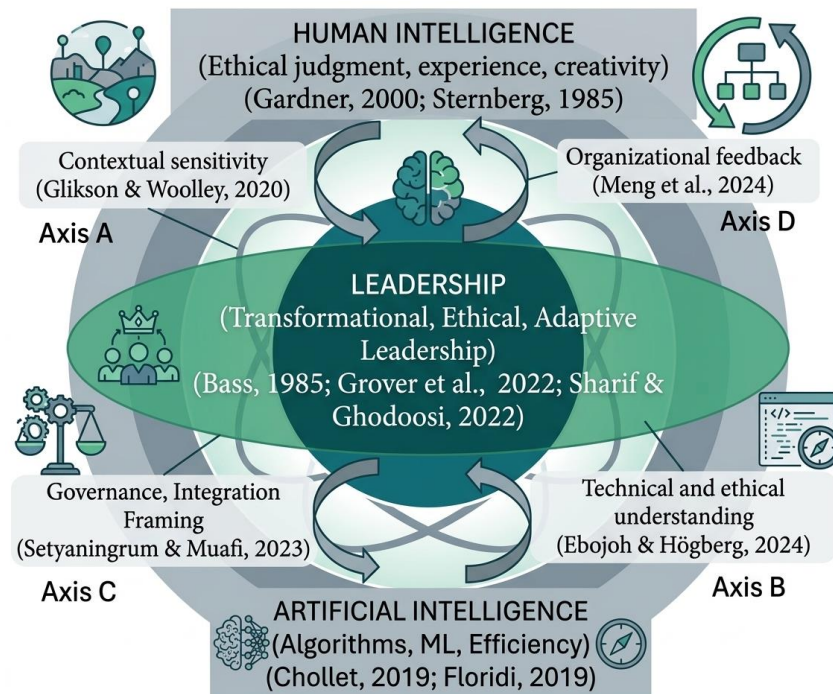
1.1 Defining Behavioral Operations in the AI Era

Behavioral operations management studies the effects of human cognition, psychological biases, emotion, and social interactions on decisions and processes within operations. In particular, with respect to AI-assisted contexts, behavioral operations extends its lens to study how algorithmic recommendations shape human judgement, how decision-makers divide tasks between themselves and machines, and how trust mediates performance outcomes (Lee, 25).

The new reality is one of high decision complexity, rapidly changing data, and ambiguous tasks in the modern operational environment. Quantitative algorithms, while very good at analyzing high-volume structured data, discerning complex statistical patterns, and operating in a rule-based fashion, are limited by the lack of common sense, qualitative domain knowledge, and ethical judgements. On the other hand, human managers have important contextualization abilities, such as the ability to make sense of tacit knowledge, respond to unforeseen structural breaks, and consider the moral aspects of a situation and so forth, but their rationality is bounded and they are subject to cognitive biases (Zhang et al., 2025). As a result the focus of behavioural operations research is shifting from substituting human managers to augmenting human-AI hybrids. This science explores where on the continuum human agency optimizes or diminishes algorithmic intelligence, to define a dynamic balance of

computational power and managerial intuition (Nunes & Park, 2020).

Figure 1: Multi-Axial Framework of Human-AI Collaboration and Leadership Dynamics



2. Theoretical Foundations of Human-AI Collaboration

2.1 From Automation to Augmentation: Collaboration Modalities

To study human-AI teaming in depth, the decision architecture of human-AI operations are dissected into different modes of operation along three dimensions (Fügner et al., 2026): locus of authority, decision velocity, and intervention rate. In fully automated environments, also known as no-touch operations, the algorithmic system is itself the decision maker processing input factors, producing suggestions, and making decisions without real-time human input. The human role at this end of the spectrum is system monitoring at a macro level, parameter setting, and periodic model upkeep (Vats et al., 2024).

Within predictable automation models, the algorithm computes baseline operational decisions or predictions as a matter of course but allows human managers a specific window of

intervention in which to assess and edit or reject recommendations before the execution (Duin & Pedersen, 2023).

In full augmentation interactions, the AI entity is an interactive cognitive partner or analysis interface that offers scenario analysis, trade-off analyses, and uncertainty measures, with the human manager maintaining final decision dominion and actively integrating algorithmic results with situational domain expertise (Duffy et al., 2026). The choice of collaboration mode is key for the operation involved, as for the execution of full automation for a very ambiguous task leads to systemic failure, and the enforcement of human augmentation mode on rapid, highly structured tasks creates cognitive bottlenecks and human-caused variance (Sturm, 2023).

2.2 Trust in Automation and the Dual-Process Cognitive Paradigm

The psychological model of human-AI interaction is largely based on Trust in Automation theory, which conceptualizes trust as an individual's propensity to rely on an automated system in a situation with risk and uncertainty. Trust is the key psychological mediator that connects system design features to operational reliance and decision quality (Fitriani & Basir, 2025).

From a cognition standpoint, human decision-makers working with algorithms are thought to perform dual-process cognition. System 1 heuristic processing is based on fast, emotional and experiential decisions. When an algorithm displays a first apparent mistake, System 1 processing is often triggered toward an immediate loss of confidence, and to an uncalibrated disuse and irrational abandonment of the technology (Chen et al., 2026).

On the other hand, System 2 deliberative processing is an assessment of the logic behind the calculation, the statistical grounding, and the contextual appropriateness of the algorithm outputs. Because System 2 thinking is so effortful, employees shy away from engaging in deliberate assessments in the absence of compensatory organizational incentives or advice from system use instructions that can be viewed (Litvinova et al., 2024). When calibrated, the user's trust* aligns with the true predictive ability and applicability region of the AI system, when uncalibrated it may result in overtrust and following automation bias that is a critical acceptance of the erroneous outputs of the machine, or undertrust which in turn leads to the disuse of the algorithm and lost computational efficiency (Zhang & Abdullah, 2026).

2.3 Algorithm Aversion versus Algorithm Appreciation

Previous literature on behavioral decision support documents two opposing human tendencies when confronted with algorithmic advice. Algorithm aversion refers to the systematic unwillingness of human decision-makers to follow the recommendations of an algorithm, especially if

they have seen the algorithm make a mistake. Human managers punish machine mistakes much more severely than human mistakes that are factually similar, even when the algorithm is demonstrably superior to human judgment on average, because they have an underlying expectation of machine perfection (Jussupow et al., 2024).

On the other hand, algorithm appreciation refers to the phenomenon where people prefer to rely on algorithmic advice over human advice when making complex quantitative or predictive decisions, particularly as the task becomes more difficult or when the system performance history is transparently presented (Jussupow et al., 2020). Recent integrative behavioral research has shown that algorithm aversion and appreciation are not mutually exclusive personality traits, but rather are context-dependent responses influenced by cognitive metaknowledge, task framing, performance incentives, and the availability of explanations (Jin & Li, 2025).

3. Impact of Algorithmic Support on Managerial Judgment and Delegation

3.1 The Metaknowledge Imperative and Delegation Asymmetry

Task delegation is an important predictor of human-AI performance: human managers have to decide if a particular decision instance should be run on their side or sent to the algorithm. Experimental evidence suggests a significant structural asymmetry in the efficiency of delegation depending on who holds the right to delegate (Cristofaro & Bañón-Gomis, 2026).

Although human - AI collaboration based on confidence thresholds when AI has the right to delegate work to the human exceeded the performance of the human and the AI-based system operating alone, team performance improved drastically in the case when AI systems were able to delegate the human team member based on machine confidence thresholds. They contend that AI-based systems are particularly good at self-assessment, because they know precisely what their limits are and refer unclear

edge cases to humans, leading to better combined outcomes, even in cases where they do so by routing to less capable human subjects (Harrison, 2026).

In contrast, when human operators have complete control over task delegation to AI, the combined system performance often deteriorates below that of the stand-alone algorithm. Behavioral results show that this non-delegation is not due to algorithm aversion humans are repeatedly observed to have very high algorithm appreciation and try their best to comply with given delegation rules but to some "deeper" metacognitive knowledge-constraints (Munnia, 2026).

Metaknowledge is a number of real-time conscious possession that enables an individual to make accurate estimation about how knowledgeable he/she is, how capable he/she is, and how much errors he/she is making. Since human self-assessment is distorted by overconfidence bias and other cognitive biases subconsciously, managers are not always aware that their judgment is worse than the algorithm's. As a result, managers keep decision tasks that they are bad at (and that they could be better at with help from an algorithm) and instead delegate work that they could have done better than the machine, destroying the synergy that is critical for hybrid intelligence (Kull, 2026).

3.2 Environmental Boundary Conditions: Horizon and Uncertainty

Distal conditions of the environment have a large effect on the success of human interaction with algorithms in decision support. Retail supply chain practical training shows that the effectiveness of management decision overrides is limited by decision time horizons and uncertainty of context (Petryna, 2015).

Machinery forecasts are most effectively supplemented by human intervention in long-horizon, low-uncertainty scenarios, which means the highest level of augmentation value is provided. In this area of planning for distant future, person involved in management makes decisions with the help of qualitative contextual factors such as the needs for promotional events, structural changes in vendors, or changes in macroeconomic environment which are not reflected in historical training data (Schulz & Huwe, 1999).

On the other hand, human interventions tend to degrade accuracy of the baseline predictions in short-horizon, high operational volatility cases. Against a backdrop of scarce time and abundant disorder, Godesses lead a hive mind of human managers, emotionally responding to ephemeral change in demand, superimposing micromanagement and intuitive overrides through which they inject artificial volatility into inventory schedules. Pure machine learning forecasts outperform hybrid human-in-the-loop interventions in these uncertain, short-horizon settings, (Slawinski et al., 2017).

Table 1: Environmental Contingency Matrix of Human-AI Collaboration Modalities

Task Time Horizon	Level of Environmental Uncertainty	Optimal Collaboration Archetype	Operational Dynamics & Behavioral Mechanisms	Impact on Decision Quality
Long-Term	Low Uncertainty	Human Augmentation	Human integrates long-range qualitative context with stable statistical baselines.	Maximum accuracy gain via complementary domain knowledge.
Long-Term	High Uncertainty	Interactive Co-Design	Joint scenario modeling; human establishes strategic boundaries	High resilience; balances statistical probability with strategic risk management.

			while AI generates probabilistic paths.	
Short-Term	Low Uncertainty	Fully Automated (No-Touch)	Machine executes standardized rules at scale without human intervention.	Maximum computational velocity and efficiency; eliminates human noise.
Short-Term	High Uncertainty	Algorithmic Optimization	Pure algorithm baseline enforced; human overrides restricted to prevent noise injection.	Superior performance; prevents emotional micro-adjustments and variance propagation.

3.3 Behavioral Overrides and Heuristic Biases in Tactical Planning

In tactical operational functions, such as inventory control and demand forecasting, managerial overrides of algorithmic suggestions are frequent. Behavioral analysis identifies two main types of managerial override: rational domain-informed overrides and systematic biased overrides (Miao et al., 2025).

Rational domain-informed overrides arise when managers have unmodeled qualitative context, such as unanticipated supplier delays or localized competitive actions, and they manipulate algorithmic baselines to better reflect operational reality (Robert Mortlock, 2021).

Systematic biased overrides are when managers change algorithmic outputs as a result of cognitive biases, such as anchoring on historical baselines, recompense bias where managers feel compelled to change a tool's output to validate their managerial role or recency bias from a recent stockout. Uncontrolled biased overrides eat into operational margins, result in more bullwhip effects across supply networks, and erode long-term organizational confidence in predictive analytics (Cook et al., 1997).

4. Drivers of Employee Trust and Operational Decision Effectiveness

4.1 Structural Drivers of Planner Trust: Transparency and Interpretability

Operations architectures must include explainability mechanisms to mitigate harmful overrides and promote adequate reliance. Empirical Behavioural Operations Research

shows that trust is influenced by concrete technical features of the decision support interface (Hong et al., 2020).

An AI decision is transparent (ADT) to the extent that it discloses, at least in some degree, its data input, its processing procedure within the algorithm and its certainty levels to the operational user. Procedural transparency enables operators to confirm that the right parameters were considered, fulfilling the cognitive System 2 verification requirements (Visave, 2025).

Transparency of AI Interpretability (AI-I) is the extent to which the rationale of an algorithm is presented in human-intelligible expressions that relate system's predictions to domain-specific cause-and-effect relations directly (El Guermai et al., 2026).

Human-AI Decision Alignment (HADA) quantifies the alignment at a structural level between algorithmic recommendations and human domain logic, bridging the cognitive divides between machine-generated and employee mental models (Kovari, 2024).

4.2 Empirical Mechanisms in Algorithmic Decision Support

Empirical studies utilizing structural equation modeling (SEM) in retail supply chain planning quantify these behavioral mechanisms. The structural model demonstrates that transparency and interpretability account for significant variance in employee trust, which directly drives operational planning effectiveness. Table 2 presents empirical path coefficients, statistical

significance levels, and variance explained (R^2) derived from field investigations of human-AI collaboration in distribution planning (Wang, 2026).

4.3 The Moderating Role of Task Complexity

The results of the statistical analysis show that there is a significant interaction effect: Task Complexity positively moderates the effect of Planner Trust on Planning Effectiveness ($\beta=0.14, p=0.001$) (Wood et al., 1987).

In routine, low-complexity activities (e.g., operating a leveled AI system), trusting the system is of limited value since human operators can easily verify the correct results. As complexity (defined by high dimensional interdependencies, real-time demand shifts, and multivariate logistics constraints) increases, human planners become cognitively overloaded and are increasingly unable to compete with assisted planners (Sia & Appu, 2015).

“In complex systems, when trust is high, managers can delegate to algorithmic optimization without losing cognitive bandwidth to micromanagement verification.” Conversely, low trust at high task complexity leads to paralysis of the decision making process, prolonged cycles of verification, and resulting catastrophic consequences in operations (Yoo, 2023).

5. Organizational Performance, Accountability, and Governance

5.1 Strategic Delegation and the Blame Avoidance Paradox

Together organizational incentive structures, politics and accountability mechanisms with the algorithmic decision support system is more than just enhancing the quality of decisions. Managers are continuously subject to psychological and social hazards around errors at work (Cooper et al., 2023).

A key related behavioral dynamic in organizational decisionmaking is blame avoidance through algorithmic delegation. Indeed, there is increased psychological pressure for executives to cede decision making authority to an algorithm in

high-stakes uncomfortable or socially punishing operational decisions like mass workforce lay-offs, plant shutdowns, or aggressive performance dismissals (Tu, 2026).

Managers frame hard operational decisions as cold statistical outputs of an objective AI tool, to aide in deflecting personal moral accountability, to shield themselves from social backlash, and obscure institutional responsibility. This operates to turn the automated system into a moral crumple zone, in which the algorithmic tool absorbs political blame, and human leadership relinquishes ethical oversight (Flinders, 2008).

In contrast, when it comes to attributing positive performance results like promotions, performance bonuses, or strategic expansions, managers tend to keep all the power, and use that power to protect their ability to generate social capital and credit. The ethical asymmetry between ‘doing’ and ‘allowing’ harm with algorithms needs to be addressed in the organizational governance models to ensure the responsible deployment of algorithms (Araral, 2026).

5.2 Productivity Dynamics: Avoiding Mistakes at Scale

Although AI tools offer the potential for fast improvements in labor productivity, unrestricted use often results in a productivity paradox. Rampant AI deployment and empty socio-technical governance become drivers of decision errors en masse and in real-time within and across enterprise networks (Lei et al., 2016).

When managers place uncalibrated trust in AI models that run in production on data outside of the distributions on which they were trained, minor statistical mistakes cascade through automated Enterprise Resource Planning (ERP) pipelines into organization-wide misallocations of inventory, disruptions in supply chains, and damage to reputations (Repenning & Sterman, 2002).

Additionally, abrupt deprecation of system or model removal may result in AI debris such as persistent organizational dependencies, deskilled humans, corrupted data lineages, and broken

institutional memory which permanently hinders operational resilience. "Highest productivity gain is achieved by matching pace of deployment with building of institutional capacity" (Knudsen et al., 2014).

5.3 Organizational Capability Building and AI Literacy Frameworks

For organizations to reap lasting operational benefits, they need to move beyond transactional AI implementation to organization-wide capability development. This capability transformation is based on three modular pillars: job-crafting, metaknowledge training, and institutional governance (Benlian & Pinski, 2025).

Both job-crafting and fit construction have a common core activity in which front-line employees learn to systemically reorganize their work around AI affordances, cognitively aligning tasks with human domain expertise while offloading statistical calculations to the system (Benlian et al., 2026).

Systemic metaknowledge training requires designing educational interventions that are able

to provide individual employees with clear insights into their own error profiles and their relative capacities compared to automated tools, and that directly address issues of delegation deficiencies (Mohasseb et al., 2026).

Institutional AI governance protocols necessitate the development of multidisciplinary supervisory mechanisms to review algorithmic decision boundaries, to ensure unambiguous human moral authorship, to detect model drift, and to retain full-time operational rollback means (Chukhlomin, 2026).

6. Synthesis and Future Research Directions

6.1 Synthesis of Conceptual Archetypes

The synthesis of behavioral operations literature demonstrates that organizational performance is an emergent property of human cognition, task characteristics, and algorithmic capability. Table 3 compares the core operational archetypes, detailing their behavioral mechanics, optimal environmental conditions, failure modes, and performance consequences (Bronstein & Reihlen, 2014).

Figure 2: Taxonomy and Integrated Framework for Human-AI Operational Augmentation and Synthesis

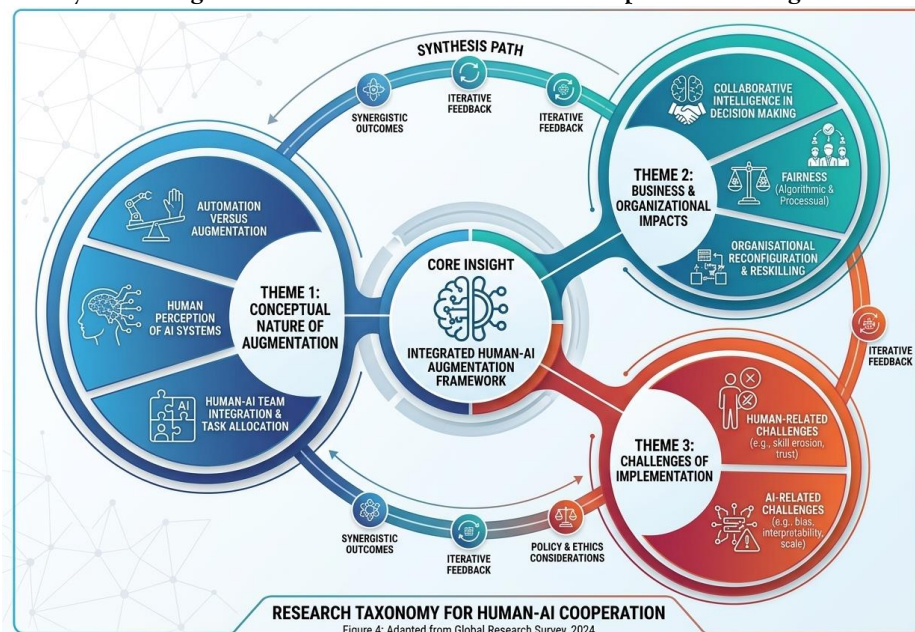


Table 2: Comparative Analysis of Human-AI Collaboration Archetypes and Performance Outcomes

Collaboration Archetype	Primary Decision Authority	Cognitive Mechanism	Optimal Task Environment	Primary Failure Vector	Impact on Organizational Performance
Automation (No-Touch)	Machine Algorithm	Rule-based statistical inference.	High frequency, short horizon, low ambiguity.	Model drift during structural breaks; operational blindspots.	Maximum speed/scalability; high vulnerability to black swan disruptions.
Adjustable Automation	Human Default / AI Override	System 1 heuristic override vs System 2 review.	Moderate volatility, medium planning horizons.	Biased human overrides driven by noise; anchoring bias.	Moderate productivity; prone to noise-induced variance if uncalibrated.
Human Augmentation	Human-in-the-Loop Co-Design	Interactive context integration.	High complexity, long time horizon, low uncertainty.	Metaknowledge deficits in delegation; cognitive overload.	Superior decision quality; high resilience and strategic fit.
Strategic Delegation	Strategic Human Boundary Assignment	Blame avoidance & moral displacement.	High-stakes, unpleasant, or ethically contentious tasks.	Responsibility avoidance; creation of moral crumple zones.	Short-term political insulation; long-term legitimacy erosion.

6.2 Strategic Implications for Operations Leaders

Review is relevant and highlights action-oriented strategic principles for operations executives, industry practitioners, and enterprise architects: 1) information content in products and services has been increasing, 2) use of information technology within and across organisations enables new supply chain coordination behaviours and 3) supply chain coordination behaviours supported by information technology can be leveraged by SC partners to facilitate improved SC integration between partners.

To begin with, designers of enterprise systems need to proactively address metaknowledge deficiencies, and not take for granted that managers know when to trust AI tools. They should be designed to have explicit delegation-support interfaces that make clear the uncertainty bounds of the models and that visually alert managers about when human contextual judgment is required (Salmoni et al., 2010).

Secondly, the system should require context-aware levels of overrides. In high noise environments, restricting tactical short-term overrides minimizes the contamination of managerial bias in dispersion, while actively advocating managerial augmentation in long-term strategic planning, captures long-term qualitative human expertise (Serfontein, 2010).

Third, technology investment needs to focus on enablement of explainability by default. When one designs decision aids to enhance people's procedural transparency and to provide them domain-aligned rationale, one builds calibrated employee trust which in essence leads directly to higher level of effectiveness in planning in complex operational environment (Wong, 2004). Finally, leadership needs to establish formal governance boundaries that limit responsibility evasion. Guidelines must be designed so that "the questions of the mind and heart particularly in deciding operational and people management

matters with high stakes have clear human moral authorship and are not obscured by reliance on algorithmic systems as shields to risk political challenge or holding back institutional responsibility” (Schweitzer, 2014).

Conclusion

We show that organizational performance in AI-augmented operations is an emergent property of human cognition, task characteristics, and algorithmic capability not merely a direct function of technological sophistication. We draw four conclusions. First, the most actionable finding is the delegation asymmetry: given that AI systems are more accurate at self-assessing than people, systems should be designed to hand off uncertain edge cases to people rather than expecting managers to know when to trust the algorithm. Explicit delegation interfaces indicating model uncertainty bounds can help to mitigate some metaknowledge deficits. Second, the mode of collaboration needs to be appropriate to the environment. Human augmentation adds the most value in long-horizon, low-uncertainty planning, while algorithmic optimization should be enforced in short-horizon, high-volatility settings where emotional micro-adjustments introduce detrimental variance. Context-aware override rules operationalize this contingency logic. Third, the governance goal is calibrated trust, not maximal trust. Transparency, interpretability, and human-AI decision alignment contribute to the kind of trust that directly enhances planning performance, particularly in complex tasks where unassisted cognitive capacity falls short. Fourth, ungoverned adoption carries serious risks: biased overrides eat into margins and cause bullwhip effects to worsen, uncritical reliance spreads errors enterprise-wide, and blame-avoidance delegation creates moral crumple zones that undermine institutional legitimacy. As a result, organizations should approach AI adoption as a capability-building exercise involving job crafting, metaknowledge training, and cross-functional governance with model-drift monitoring, rollback capability, and

explicit human moral authorship. Future work should explore longitudinal aspects of trust calibration, training interventions for delegation, and governance mechanisms across different cultures and sectors.

REFERENCES

- Araral, E. (2026). *Agency Theory in Public Administration: A Comparative Study of the US, China, and EU*. Cambridge University Press.
- Benlian, A., & Pinski, M. (2025). The AI literacy development canvas: Assessing and building AI literacy in organizations. *Business Horizons*.
- Benlian, A., Jaki, P., Alizadeh, A., & Özdemir, F. (2026). Scaling AI literacy in organizations: A framework and roadmap for managers. *Business Horizons*.
- Bronstein, J., & Reihlen, M. (2014). Entrepreneurial university archetypes: A meta-synthesis of case study literature. *Industry and Higher Education*, 28(4), 245-262.
- Chen, X., Liu, Y., Ma, Y., Zhang, X., Chen, Y., Wang, Z., ... & Shen, M. (2026). How Cognitive Load Affects Dynamic Trust Calibration in Human-AI Collaboration: Evidence for Selective Pathway Effects. *Human Factors*, 00187208261477486.
- Chukhlomin, V. (2026). From AI literacy to professional AI fluency: The PAF-Business framework, maturity progression, and assessment. *Maturity Progression, and Assessment* (January 04, 2026).
- Cook, M. J., Elder, L., & Ward, G. (1997, April). Decision making, planning, and teams. In *IEE Colloquium on Computer Mediated Complex Supervisory and Decision Making in Teams* (pp. 5-1). London UK: IEE.
- Cooper, C., Elston, T., & Bilous, A. (2023). Shifting the deckchairs: How blame avoiders cope with the loss of a scapegoat.
- Cristofaro, M., & Bañón-Gomis, A. J. (2026).

- Dancing with the algorithm: a framework to navigate knowledge and autonomy in AI-assisted managerial decisions. *Journal of Knowledge Management*, 30(11), 1-31.
- Duffy, V. G., Karwowski, W., & Salvendy, G. (Eds.). (2026). *Advances in Human-AI Collaboration*. John Wiley & Sons.
- Duin, A. H., & Pedersen, I. (2023). *Augmentation technologies and artificial intelligence in technical communication: Designing ethical futures*. Taylor & Francis.
- Edisen, A. (2026). *The Impact of Artificial Intelligence on Decision-Making in Manufacturing Supply Chain Management* (Doctoral dissertation, Birmingham City University).
- El Guermai, R., Jamal, A., & Aissaoui, K. (2026). Exploring Explainable AI Transparency in Managerial Decision-Making: A Multi-Sectoral Analysis of Organizational Trust in Morocco. In *Transparency in AI-Assisted Management Decisions* (pp. 45-78). IGI Global Scientific Publishing.
- Fitriani, N., & Basir, I. (2025). Understanding user acceptance of AI-powered financial advisory: A dual-process model integrating trust, satisfaction, and perceived risk. *Global Review of Tourism and Social Sciences*, 1(3), 225-239.
- Flinders, M. (2008). *Delegated governance and the British state: Walking without order*. Oxford University Press (UK).
- Fügener, A., Walzner, D. D., & Gupta, A. (2026). Roles of artificial intelligence in collaboration with humans: Automation, augmentation, and the future of work. *Management Science*, 72(1), 538-557.
- Harrison, J. (2026). Epistemic Justice and the Moral Limits of Algorithmic Authority: How AI Systems Challenge the Knowledge Foundations of Organizational Decision-Making. *Inclusive Growth and Management Quarterly*, 1(1).
- Hong, S. R., Hullman, J., & Bertini, E. (2020). Human factors in model interpretability: Industry practices, challenges, and needs. *Proceedings of the ACM on Human-Computer Interaction*, 4(CSCW1), 1-26.
- Jin, X., & Li, J. (2025). The influence of 'algorithm aversion' and 'algorithm appreciation' among consumers in unstructured tasks. *International Journal of Consumer Studies*, 49(6), e70133.
- Jussupow, E., Benbasat, I., & Heinzl, A. (2020). Why are we averse towards algorithms? A comprehensive literature review on algorithm aversion.
- Jussupow, E., Benbasat, I., & Heinzl, A. (2024). An integrative perspective on algorithm aversion and appreciation in decision-making. *MIS quarterly*, 48(4), 1575-1590.
- Knudsen, T., Levinthal, D. A., & Winter, S. G. (2014). Hidden but in plain sight: The role of scale adjustment in industry dynamics. *Strategic Management Journal*, 35(11), 1569-1584.
- Koushik, P. (2024). *Supply Chain Synergy Integrating AI and ML for Optimal Order Management*. Xoffencer international book publication house.
- Kovari, A. (2024). AI for decision support: Balancing accuracy, transparency, and trust across sectors. *Information*, 15(11), 725.
- Kull, R. (2026). *Automation for Third Sector Accountability? Designing and Evaluating a Governance-First Generative AI Workflow for NGO Grant Work*.
- Lee, J. (2025). *AI Behavior OS v1. 0: A Consciousness-Aligned Behavioral Operating System for Deterministic, Non-Escalatory, and Measurable AI Behavior*.
- Lei, Z., Naveh, E., & Novikov, Z. (2016). Errors in organizations: An integrative review via level of analysis, temporal dynamism, and priority lenses. *Journal of management*, 42(5), 1315-1343.

- Litvinova, Y., Mikalef, P., & Luo, X. (2024). Framework for human-XAI symbiosis: extended self from the dual-process theory perspective. *Journal of Business Analytics*, 7(4), 224-255.
- Miao, X., Xu, N., Wang, X., Cao, L. Z., & Chi, L. (2025). A neurotemporal model of heuristic suppression failure in Bias responses during basketball passing decisions. *Journal of Sport and Exercise Psychology*, 47(6), 401-413.
- Mohasseb, A., Beukman, R., & Kanavos, A. (2026). The AI Literacy Leadership Framework (AILLF): A Framework for AI-Enabled Leadership in Higher Education. *AI*, 7(9), 328.
- Munnia, A. (2026). Artificial intelligence perception of strategic decision-makers: an exploratory study [La percezione dell'Intelligenza Artificiale da parte dei decisori strategici: uno studio esplorativo].
- Nunes, M. F., & Park, C. L. (2020, October). Machine learning, the Internet of Things, and the seeds of un-behavioral operations: Conceptual bases for the industry of the future. In *Industry 4.0-Shaping The Future of The Digital World: Proceedings of the 2nd International Conference on Sustainable Smart Manufacturing (S2M 2019)*, 9-11 April 2019, Manchester, UK (p. 84). CRC Press.
- Patel, R., Tripathi, H., Stone, J., Golilarz, N. A., Mittal, S., Rahimi, S., & Chaudhary, V. (2025). Towards secure mlops: Surveying attacks, mitigation strategies, and research challenges. *arXiv preprint arXiv:2506.02032*.
- Petryna, A. (2015). What is a horizon? Navigating thresholds in climate change uncertainty. *Modes of uncertainty: anthropological cases*, 147-64.
- Rane, N. L., Paramesha, M., Choudhary, S. P., & Rane, J. (2024). Artificial intelligence, machine learning, and deep learning for advanced business strategies: a review. *Partners Universal International Innovation Journal*, 2(3), 147-171.
- Repenning, N. P., & Sterman, J. D. (2002). Capability traps and self-confirming attribution errors in the dynamics of process improvement. *Administrative science quarterly*, 47(2), 265-295.
- Robert Mortlock, N. D. (2021). Behavioral biases within defense acquisition. *Acquisition Research Program*.
- Salmoni, B. A., Hart, J., McPherson, R., & Winn, A. K. (2010). Growing strategic leaders for future conflict. *The US Army War College Quarterly: Parameters*, 40(1), 10.
- Schulz, K., & Huwe, B. (1999). Uncertainty and sensitivity analysis of water transport modelling in a layered soil profile using fuzzy set theory. *Journal of Hydroinformatics*, 1(2), 127-138.
- Schweitzer, J. (2014). Leadership and innovation capability development in strategic alliances. *Leadership & Organization Development Journal*, 35(5), 442-469.
- Serfontein, J. J. (2010). The impact of strategic leadership on the operational strategy and performance of business organisations in South Africa (Doctoral dissertation, Stellenbosch: University of Stellenbosch).
- Sia, S. K., & Appu, A. V. (2015). Work autonomy and workplace creativity: Moderating role of task complexity. *Global business review*, 16(5), 772-784.
- Singh, P. K. (2023). Digital transformation in supply chain management: Artificial Intelligence (AI) and Machine Learning (ML) as Catalysts for Value Creation. *International Journal of Supply Chain Management*, 12(6), 57-63.

- Slawinski, N., Pinkse, J., Busch, T., & Banerjee, S. B. (2017). The role of short-termism and uncertainty avoidance in organizational inaction on climate change: A multi-level framework. *Business & Society*, 56(2), 253-282.
- Sturm, T. (2023). Exploring human and artificial intelligence collaboration and its impact on organizational performance: a multi-level analysis (Doctoral dissertation, Universitäts- und Landesbibliothek).
- Tu, W. (2026). The accountability paradox in the Chinese bureaucracy. Springer Nature Singapore.
- Vats, V., Nizam, M. B., Liu, M., Wang, Z., Ho, R., Prasad, M. S., ... & Davis, J. (2024). A survey on human-AI collaboration with large foundation models. *ACM Transactions on Intelligent Systems and Technology*.
- Visave, J. (2025). Transparency in AI for emergency management: building trust and accountability. *AI and Ethics*, 5(4), 3967-3980.
- Wang, Y. (2026). Algorithmic decision-making in organizations: a systematic review toward an integrated tension alignment framework. *Organization Management Journal*, 23(1), 115-131.
- Wong, L. (2004). Developing adaptive leaders: The crucible experience of Operation Iraqi Freedom. Strategic Studies Institute, US Army War College.
- Wood, R. E., Mento, A. J., & Locke, E. A. (1987). Task complexity as a moderator of goal effects: A meta-analysis. *Journal of applied psychology*, 72(3), 416.
- Yoo, J. (2023). The effects of augmented reality on consumer responses in mobile shopping: The moderating role of task complexity. *Heliyon*, 9(3).
- Zhang, Q., & Abdullah, F. (2026). AI Chatbot Anthropomorphism and Consumer Decision-Making: A Dual-Pathway Calibration Model. *Behavioral Sciences*, 16(8), 1269.
- Zhang, Q., Yan, P., Xu, Y., Fu, C., Fang, Y., & Liu, Y. (2025). The Agent Behavior: Model, Governance and Challenges in the AI Digital Age. *arXiv preprint arXiv:2508.14415*.