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When Algorithms Influence Strategic Choices: Exploring the Interaction Between Machine-Generated Insights and Human Managerial Judgment

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Abstract

The rapid integration of artificial intelligence (AI) and algorithmic systems into organizational decision processes has transformed how strategic choices are made. Machine-generated insights provide data-driven predictions, pattern recognition, and scenario analyses that augment human managerial judgment. Yet, they also introduce tensions such as over-reliance, algorithmic bias, and reduced interpretive flexibility. This theory-development article synthesizes the literature on human-AI collaboration in strategic contexts to propose a conceptual model that explains the dynamic interplay between algorithmic outputs and human cognition. Drawing on the automation-augmentation paradox and related frameworks, we highlight complementarities—where algorithms enhance speed and objectivity—and tensions—where human intuition contextualizes uncertainty and ethical considerations. We develop propositions addressing algorithmic influence on strategic interpretation, managerial cognition under data-driven conditions, organizational factors moderating reliance on insights, and governance mechanisms for accountable AI-informed choices. This work advances understanding of hybrid decision systems in digital organizations, offering implications for balancing augmentation with human oversight to foster effective strategic outcomes.

Keywords Managerial judgment, Human-AI collaboration, Algorithmic decision support, Strategic choices, Machine-generated insights, Automation-augmentation

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Introduction

Organizations increasingly operate in data-rich, fast-moving, and uncertain environments where strategic choices must be made amid information abundance and interpretive complexity [1–4]. The proliferation of digital technologies, interconnected platforms, and real-time data streams has fundamentally transformed the informational landscape of strategy, shifting the challenge from data scarcity to data overload and signal interpretation. In this context, algorithmic systems powered by artificial intelligence (AI) and machine learning have emerged as critical tools for processing vast datasets, identifying latent

patterns, forecasting outcomes, and generating actionable recommendations [5].

These machine-generated insights are reshaping the foundations of strategic decision-making by enabling organizations to move beyond purely intuition-driven or experience-based approaches toward hybrid decision models in which human judgment and algorithmic outputs interact [1, 6, 7]. Rather than replacing managers, AI systems increasingly function as analytical partners that expand cognitive capacity, enhance environmental sensing, and support anticipatory strategic thinking. As a result, strategy formulation is becoming a socio-technical process

in which outcomes are co-produced through the interplay of human cognition and machine intelligence.

Despite these promises of enhanced accuracy, speed, and scalability, integrating algorithmic insights into strategic decision-making poses fundamental theoretical and practical challenges. At the core lies the question of how machine-generated outputs influence—and are influenced by—human managerial judgment [2, 8–10]. Strategic decisions are inherently complex, involving ambiguity, incomplete information, and competing objectives.

Managers must therefore interpret algorithmic recommendations within broader organizational, social, and ethical contexts that algorithms are often ill-equipped to fully capture [6, 11–14].

This interaction between human and machine intelligence is inherently ambivalent, producing both complementarities and tensions. On one hand, algorithmic systems can augment managerial cognition by providing data-driven insights that improve decision quality, reduce uncertainty, and uncover non-obvious opportunities [1, 15–19]. On the other hand, tensions arise when managers distrust or misinterpret algorithmic outputs, leading to phenomena such as algorithm aversion, where decision-makers discount machine-generated insights due to perceived lack of contextual understanding or transparency [10, 16]. Conversely, excessive reliance on algorithms may lead to automation bias, in which managers defer uncritically to algorithmic recommendations, potentially undermining critical thinking and accountability.

This duality is encapsulated in the automation–augmentation paradox [1], which highlights the tension between the efficiency gains of automation and the cognitive enhancements of augmentation. While algorithms can automate routine analytical tasks, their integration into strategic decision-making raises concerns about over-dependence, erosion of human expertise, and the potential marginalization of judgment. In high-level strategic contexts—such as long-term resource allocation, competitive positioning, and organizational adaptation—human judgment remains indispensable for sense-making, ethical reasoning, and value alignment [4], functions that extend beyond the capabilities of current AI systems [15].

Although a growing body of research has examined algorithmic decision support in operational domains such as supply chain management, marketing analytics, and human resource management, relatively limited attention

has been devoted to algorithmic influence in strategic decision-making [3, 8]. Existing studies suggest that managers do not passively accept algorithmic outputs; rather, they actively negotiate their influence by selectively interpreting, contextualizing, or overriding recommendations based on experience, intuition, and situational awareness [14]. This highlights the importance of understanding the interpretive dynamics that mediate the relationship between machine-generated insights and strategic choices.

Furthermore, the degree to which organizations rely on algorithmic insights is shaped by a range of organizational and technological conditions, including data quality, system transparency, cultural readiness, and governance structures [20]. These factors influence not only trust in AI systems but also the extent to which their outputs are integrated into decision processes. At the same time, the increasing use of opaque or “black-box” algorithms raises significant concerns regarding accountability and responsibility [18], particularly when decision outcomes have far-reaching strategic or societal implications.

Taken together, these developments point to the need for a more comprehensive theoretical understanding of how human and machine intelligence interact in strategic contexts. Existing research tends to treat algorithms either as tools that enhance decision-making or as sources of bias and risk, but rarely as participants in a dynamic, co-evolving decision system. There remains a critical gap in explaining the mechanisms by which managers interpret, integrate, and enact machine-generated insights, as well as the conditions under which these interactions lead to effective or problematic outcomes.

In response, this article develops a theoretical framework of human–AI hybrid strategic decision-making that conceptualizes the interaction between machine-generated insights and managerial judgment as a process shaped by interpretive dynamics, cognitive complementarities and tensions, contextual moderators, and governance mechanisms. By synthesizing recent literature and advancing a set of novel propositions, the study contributes to emerging scholarship on AI-informed strategy by offering a structured lens for understanding how algorithmic influence operates at the strategic level.

Ultimately, the article seeks to reposition AI from a deterministic decision tool to an interactive and interpretive component of strategic cognition, thereby providing a

foundation for future empirical research and practical application in organizations navigating increasingly complex, data-driven environments.

Theoretical Foundations of Human–AI Strategic Interaction

This article develops a comprehensive theoretical explanation of how machine-generated insights interact with human managerial judgment to shape strategic choices in data-intensive environments. Moving beyond simplistic substitution narratives, the framework conceptualizes human–AI interaction as a dynamic, interpretive, and contextually embedded process. It foregrounds four interdependent dimensions: (1) interpretive dynamics, (2) cognitive complementarities and tensions, (3) contextual moderators of reliance, and (4) governance mechanisms for responsible integration. By synthesizing recent interdisciplinary literature, the article advances a set of novel propositions and a unifying conceptual model that collectively reposition AI not as a decision-maker, but as an augmentative epistemic partner in strategic reasoning.

Machine-generated insights in data-driven strategy

Machine-generated insights emerge from advanced artificial intelligence techniques—including predictive analytics, machine learning, and deep learning—which enable the extraction of complex patterns from large-scale, high-velocity datasets beyond the limits of human cognitive capacity [17, 19]. These systems excel at identifying latent correlations, forecasting trends, and generating probabilistic scenarios, thereby expanding the information base for strategic decision-making.

Within strategic management contexts, such insights play a critical role in domains such as market forecasting, competitive intelligence, resource allocation, and long-term scenario planning [15, 21–29]. By transforming raw data into actionable signals, AI systems enhance organizational sensing capabilities and enable more anticipatory forms of strategy formulation.

However, the strategic value of machine-generated insights is inherently non-autonomous. Their relevance and applicability depend on managerial interpretation,

contextualization, and alignment with organizational objectives and constraints [2, 5]. Without interpretive mediation, algorithmic outputs risk being misapplied, overgeneralized, or ignored altogether. Thus, machine-generated insights should be understood not as definitive prescriptions but as informational inputs whose strategic significance is co-constructed through human judgment.

Human managerial judgment amid algorithmic influence

Human managerial judgment remains indispensable in strategic decision-making due to its capacity to integrate intuition, experiential knowledge, ethical reasoning, and contextual awareness [6, 7]. Unlike algorithms, which operate within predefined data structures and optimization criteria, human decision-makers can navigate ambiguity, interpret weak signals, and incorporate socio-political and organizational considerations that are difficult to formalize computationally.

In hybrid decision environments, algorithms provide structured, data-driven inputs, while managers act as interpretive agents who evaluate, contextualize, and selectively integrate these inputs into strategic choices [1, 10]. This interpretive process is shaped by cognitive schemas, prior experiences, and organizational norms, which can both enhance and constrain decision quality. **Table 1** clarifies the functional division of labor between algorithmic systems and managerial judgment across major dimensions of strategic decision-making.

Table 1. Functional division of labor in human–ai strategic decision-making across core decisions

Strategic decision dimension	Primary algorithmic contribution	Primary managerial contribution	Hybrid value created
Environmental scanning	Large-scale data ingestion, trend detection, and anomaly recognition	Interpretation of weak signals, relevance assessment, and strategic framing	Broader and faster sensing with contextual prioritization
Forecasting and scenario analysis	Predictive modeling, probabilistic	Plausibility judgment, scenario	More disciplined anticipation

	estimation, and pattern extrapolation	plausibility testing, and assumption critique	under uncertain
Strategic problem framing	Structured representation of variables and options	Definition of objectives, boundary setting, political and ethical framing	Better alignment between data structure and strategic intent
Option evaluation	Ranking alternatives, consistency of comparison, multi-variable optimization	Trade-off reasoning, value judgment, interpretation of non-quantifiable effects	More rigorous comparison without losing strategic nuance
Resource allocation	Detection of efficiency opportunities, portfolio scoring, and capacity analysis	Judgment on strategic fit, long-term commitment, and legitimacy considerations	Improve allocation discipline with strategic discretion
Competitive positioning	Detection of market shifts and competitor pattern recognition	Strategic narrative construction, timing judgment, and differentiation logic	More adaptive positioning decision
High-stakes exceptional decisions	Rapid synthesis of large evidence sets and sensitivity analysis	Final accountability, override authority, and ethical adjudication	Decision support without surrendering responsibility
Post-decision learning	Outcome tracking, model updating, and error detection	Interpretation of failure causes, institutional learning, and governance adjustment	Recursive improvement of both models and routines

On one hand, managerial judgment can enrich algorithmic outputs by embedding them within broader strategic narratives and ethical considerations. On the other hand, cognitive biases—such as confirmation bias, overconfidence, or algorithm aversion—may distort the interpretation of machine-generated insights [4], leading to suboptimal decisions [14]. Consequently, understanding how managers engage with and interpret AI outputs becomes central to explaining strategic outcomes in data-driven organizations.

Complementarities and Tensions in Hybrid Decision Dynamics

The interaction between machine intelligence and human judgment gives rise to a duality of complementarity and tension that defines hybrid decision systems.

Complementarities emerge when the distinct strengths of each agent are effectively integrated. Algorithms contribute computational scalability, pattern recognition, and consistency [1], while humans provide creativity, contextual reasoning, and ethical judgment [21]. When aligned, these capabilities produce synergistic effects, enabling more robust and adaptive strategic decisions.

However, these complementarities are often counterbalanced by inherent tensions. These include algorithm aversion, where managers distrust or underutilize AI outputs [10]; automation bias, where decision-makers over-rely on algorithmic recommendations [16]; and accountability dilution, where responsibility becomes unclear in hybrid systems. Additionally, the risk of bias amplification—where flawed data or models reinforce existing inequalities or errors—further complicates the integration process.

Balancing these complementarities and tensions requires a nuanced understanding of the interaction mechanisms through which human and machine inputs are combined, negotiated, and enacted in practice [8, 20]. This balance is not static but evolves as organizations learn, adapt, and recalibrate their reliance on AI.

Organizational contexts shaping AI reliance

The degree to which organizations rely on machine-generated insights is not uniform but is shaped by a range of contextual factors. These include task characteristics (e.g., complexity, uncertainty, time pressure), technological attributes (e.g., transparency, accuracy, explainability), and organizational dimensions (e.g., culture, leadership orientation, and digital maturity) [12, 18].

For instance, highly complex and uncertain tasks may increase reliance on AI for analytical support while simultaneously heightening the need for human judgment to interpret ambiguous outputs. Similarly, transparent and explainable AI systems are more likely to be trusted and adopted, whereas opaque “black-box” models may trigger skepticism or resistance.

Organizational culture also plays a pivotal role. Cultures that emphasize data-driven decision-making and learning are more likely to embrace AI integration, whereas those rooted in intuition or hierarchical authority may resist algorithmic influence. Importantly, governance mechanisms—such as accountability frameworks, ethical guidelines, and oversight structures—serve as critical enablers of responsible AI adoption, ensuring alignment with organizational values and societal expectations [18, 23].

Theory Development: Dynamics of Algorithmic Influence on Strategic Judgment

Building on the automation–augmentation paradox, which highlights the tension between replacing and enhancing human capabilities [1], this article theorizes that machine-generated insights influence strategic decision-making through three interrelated mechanisms: interpretive filtering, cognitive augmentation, and contextual moderation.

First, interpretive filtering refers to the process by which managers selectively attend to, evaluate, and contextualize algorithmic outputs based on their cognitive frames, experience, and organizational priorities. This mechanism determines which insights are accepted, modified, or rejected.

Second, cognitive augmentation captures the synergistic interaction between human and machine capabilities, in which algorithmic analysis enhances human reasoning, and human judgment enriches algorithmic outputs. This

reciprocal relationship enables more comprehensive and nuanced strategic thinking.

Third, contextual moderation reflects the influence of organizational, technological, and environmental factors that shape how interpretive filtering and cognitive augmentation unfold in practice. These moderators determine the conditions under which complementarities are realized or tensions are amplified.

Importantly, the interaction between these mechanisms is iterative and recursive. Strategic decisions informed by hybrid processes generate outcomes that feed back into both managerial learning and algorithmic refinement, creating continuous adaptation loops. Over time, this dynamic process reshapes both human judgment and machine performance, leading to evolving patterns of reliance, trust, and effectiveness.

Together, these mechanisms form a cohesive theoretical model that explains how human–AI interaction operates as a coevolutionary system, in which cognition, technology, and organizational context jointly shape strategic outcomes.

Proposition 1

Machine-generated insights positively influence strategic choice quality when managers engage in active interpretation, as algorithmic objectivity complements human contextualization [1, 2, 14].

Proposition 2

Algorithm aversion reduces reliance on machine-generated insights in uncertain strategic contexts, leading managers to favor intuitive judgment over data-driven recommendations [10, 16].

Proposition 3

Complementarities between algorithms and humans are stronger in complex, ambiguous strategic tasks where machine pattern recognition augments human sense-making [1, 5, 19].

Proposition 4

Tensions arise when algorithmic opacity erodes perceived accountability, prompting managers to discount insights and revert to traditional judgment [6, 18].

Proposition 5

Organizational data governance and transparency mechanisms moderate reliance, thereby enhancing the positive influence of algorithms on strategic choices [20, 23].

Proposition 6

Feedback from strategic outcomes to algorithmic systems creates learning loops that iteratively improve insight quality, contingent on human oversight [7, 21].

Proposition 7

In high-stakes strategic decisions, hybrid governance—combining algorithmic support with human veto rights—mitigates over-reliance while preserving the benefits of augmentation [4, 8].

Figure 1 illustrates the hybrid strategic decision system through which machine-generated insights are interpretively filtered, contextually moderated, and recursively refined through feedback from strategic outcomes.

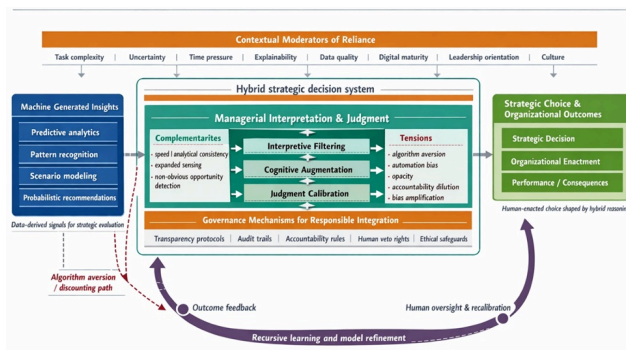


Figure 1. Conceptualizes strategic decision-making as a hybrid human–AI system in which machine-generated insights are filtered through managerial interpretation and judgment. Complementarities and tensions coexist within the interaction zone, while contextual moderators and governance mechanisms shape the degree and quality of reliance. Strategic outcomes feed back into both algorithmic refinement and managerial learning through recursive oversight-enabled loops.

Theoretical Implications

This article contributes to theory in digital business and management studies by advancing a nuanced

understanding of hybrid decision architectures in strategic contexts. Central to our contribution is the refinement of the automation-augmentation paradox [1], which posits that algorithmic systems simultaneously automate routine cognitive tasks and augment human capabilities through novel pattern detection. We extend this paradox to strategic choice processes, demonstrating that augmentation is not automatic but contingent on active human interpretation of machine-generated insights [1, 2, 14]. By foregrounding interpretive filtering as a core mechanism, our propositions illuminate how managerial cognition mediates algorithmic influence, addressing gaps in prior work that often treat human-AI interaction as dichotomous rather than dynamic [4, 6].

A key theoretical advance lies in explicating complementarities and tensions as interdependent forces. Proposition 3 highlights task-contingent synergies, where complexity amplifies mutual enhancement between algorithmic objectivity and human sense-making [5, 19]. Conversely, Proposition 4 underscores how opacity exacerbates tensions, eroding accountability and prompting reversion to intuition [6, 18]. This duality enriches paradox theorizing by showing that tensions are not merely barriers but potential catalysts for refined governance [20, 23].

Moreover, by emphasizing organizational moderators (Proposition 5), we bridge micro-level cognitive processes with macro-level structures. Data governance and transparency emerge as critical levers for aligning algorithmic influence with strategic goals [20, 23]. This multilevel integration advances theories of AI-informed strategy by linking individual judgment to institutional conditions, offering a foundation for examining how digital transformation reshapes managerial roles [15, 29].

For practitioners, the proposed framework highlights that effective strategic decision-making in data-rich environments is no longer a question of whether to use AI, but how to intentionally design and govern human–AI hybrid systems. The central managerial challenge lies in structuring interactions between algorithmic outputs and human judgment such that complementarities are realized without amplifying cognitive biases or technological overdependence.

A critical implication is the need for formalized interpretive infrastructures. Rather than treating AI outputs as self-evident recommendations, organizations should institutionalize structured interpretation routines.

Mechanisms such as post-analytics debrief sessions, cross-functional insight validation workshops, and “insight challenge” protocols—where managers are explicitly tasked with questioning algorithmic outputs—can enhance critical engagement and reduce passive acceptance or outright rejection of AI-generated insights [1, 10, 14]. These practices operationalize Proposition 2 by actively managing the tension between algorithm aversion and over-reliance.

Equally important is the role of algorithmic transparency as a managerial lever. In uncertain or high-ambiguity environments, managers often default to intuition when algorithmic reasoning is opaque. By embedding explainability features—such as interpretable model outputs, scenario-based justifications, and confidence intervals—organizations can foster algorithm appreciation, thereby increasing calibrated trust rather than blind reliance [10, 16]. Transparency should not be viewed merely as a technical add-on but as a strategic design principle that shapes how decision-makers cognitively engage with AI outputs.

From a governance perspective, firms must invest in multi-layered oversight architectures that regulate the degree and conditions of algorithmic influence. This includes implementing explainable AI tools, comprehensive audit trails, and hybrid approval workflows that explicitly document and reconcile both human and algorithmic inputs [18, 23]. Such infrastructures directly support Proposition 5 by moderating reliance patterns and ensuring that decision authority remains accountable and traceable.

In high-stakes strategic contexts—such as mergers and acquisitions, capital allocation, or regulatory-sensitive decisions—organizations should incorporate formal override and veto mechanisms. These mechanisms preserve human judgment as the ultimate decision authority while still benefiting from algorithmic augmentation. Importantly, override rights should be governed by clearly defined criteria to avoid arbitrary dismissal of AI insights, thereby aligning with Proposition 7 and maintaining decision integrity [4, 8].

The framework also underscores the importance of closed-loop learning systems. Managers should establish systematic feedback mechanisms that capture decision outcomes and feed them back into algorithmic models, enabling continuous recalibration and performance improvement [7, 21]. This requires integrating performance analytics with decision logs, thereby creating a dynamic

interplay between human learning and machine adaptation. Such feedback loops transform AI systems from static tools into evolving strategic partners.

In parallel, organizations must prioritize capability development through targeted training programs. Rather than focusing exclusively on technical proficiency, training initiatives should emphasize interpretive AI literacy—including the ability to contextualize outputs, recognize limitations, and integrate machine-generated insights with domain expertise [5, 19]. This shift from technical mastery to interpretive competence is essential for enabling managers to operate effectively in hybrid decision environments.

Table 2 presents a governance design matrix showing how the appropriate degree of algorithmic influence varies across strategic decision contexts.

Table 2. Governance design matrix for calibrating algorithmic influence in strategic choice contexts

Strategic context	Typical decision characteristics	Recommended level of algorithmic influence	Recommended human role
Routine but strategically relevant decisions	Moderate ambiguity, recurring patterns, and sufficient historical data	High decision support influence	Validation and exception handling
Complex but analyzable strategic decisions	Multi-variable trade-offs, high information load, and partial uncertainty	Strong advisory influence	Interpretation and synthesis across channels
Highly ambiguous strategic decisions	Novel environments, weak signals, and unstable causal relations	Moderate advisory influence	Dominant interpretive authority
High-stakes irreversible decisions	Mergers, major capital allocation, restructuring,	Limited but important support influence	Final decision authority and formal override rights

	and regulatory exposure		
Ethically sensitive or legitimacy-laden decisions	Social impact, stakeholder scrutiny, and reputational exposure	Restricted advisory influence	Ethical adjudication and stakeholder balance
Rapid response situations	Time pressure, incomplete information, and the need for fast triage	Temporarily elevated support influence	Time-bound approvals and post-hoc adjustments
Learning-intensive adaptive settings	Repeated decisions with measurable outcomes	Iteratively increasing support influence	Oversight, feedback loops, interpretation, and model recalibration

Finally, at the organizational level, firms should cultivate a culture of hybrid intelligence, where algorithmic precision and human judgment are viewed as complementary rather than competing sources of insight. This involves reinforcing norms that value critical engagement, ethical reflection, and creative synthesis of data-driven and experiential knowledge. Organizations that successfully embed such cultural orientations are more likely to develop resilient strategic processes capable of navigating volatility, complexity, and information abundance [1, 20].

Future Research Directions

The proposed framework opens several promising avenues for future empirical and theoretical development, particularly in advancing our understanding of how human–AI hybrid systems function in complex strategic contexts.

First, there is a need for longitudinal and process-oriented empirical studies that examine how interpretive practices evolve within organizations. While existing research often captures static snapshots of decision-making, future work should investigate dynamic trajectories—such as how repeated interaction with AI systems reshapes managerial cognition, trust calibration, and reliance patterns. Empirical settings such as board-level deliberations, strategic investment decisions, and mergers and acquisitions provide rich contexts for testing the framework’s

propositions [14, 20]. Such studies could also explore temporal shifts in the balance between intuition and algorithmic reasoning.

Second, boundary condition analysis remains a critical area for extension. The effectiveness of human–AI complementarities is likely contingent on contextual factors such as industry characteristics, regulatory intensity, and organizational maturity. For example, highly regulated sectors (e.g., healthcare, finance) may prioritize accountability and transparency, while high-tech industries may emphasize speed and innovation. Cross-cultural research could further illuminate how societal norms and cognitive styles influence algorithm aversion, trust formation, and governance preferences [10, 16, 23]. Identifying these contingencies would enhance the generalizability and applicability of the framework.

Third, the concept of feedback loops and iterative learning invites deeper investigation into the co-evolution of human and algorithmic capabilities. Future research should examine how continuous feedback mechanisms influence model performance, managerial learning, and decision quality over time. A key question concerns how organizations can prevent undesirable dynamics such as bias reinforcement, model drift, or overfitting in environments where human inputs shape algorithmic updates [7, 21]. Integrating machine learning performance metrics with organizational outcomes would provide a more holistic understanding of hybrid system effectiveness.

Fourth, the framework raises important questions about ethics, accountability, and the distribution of responsibility in hybrid decision systems. As decisions increasingly emerge from interactions between humans and algorithms, traditional notions of accountability become blurred. Future research should develop normative and analytical frameworks that clarify how responsibility is allocated across human and machine actors, particularly in cases of adverse outcomes. The concept of responsible augmentation offers a promising starting point for integrating ethical considerations into the design and governance of hybrid systems [18].

Finally, the rapid emergence of generative AI technologies introduces new dimensions of strategic decision-making that extend beyond predictive analytics. Generative systems enable scenario creation, strategic simulation, and co-creative ideation, fundamentally altering how managers interact with AI. Future research should explore how these

capabilities reshape interpretive processes, decision framing, and strategic imagination. In particular, examining real-time co-creation dynamics—where managers iteratively refine AI-generated outputs—can extend the current framework to capture more interactive and generative forms of human–AI collaboration [19].

Conclusion

The integration of machine-generated insights into strategic choice processes represents a profound shift in managerial practice. While algorithms offer unprecedented analytical power, their effective influence depends on a sophisticated interplay with human judgment. Our propositions and conceptual model highlight that successful hybridization requires navigating complementarities through interpretation, mitigating tensions via governance, and sustaining learning through feedback.

By theorizing these dynamics, this article provides a roadmap for organizations seeking to leverage AI without diminishing the irreplaceable role of managerial cognition. As digital transformation accelerates, embracing hybrid decision systems—grounded in mutual augmentation rather

than substitution—will prove essential for strategic adaptation and sustained competitive advantage in an algorithmically augmented world.

Acknowledgements

None

Conflict of interest

None

Financial support

None

Ethics statement

None

Received: 25 Oct 2022 Revised: 05 Dec 2022 Accepted: 01 Feb 2023
Published online: 18 March 2023

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