Efficiens : Journal of Management Science and Operations
Volume. 1 Issue 1 December 2025
Page No: 12-25

Augmented Decision Systems: Integrating Multi-Criteria Modeling and Machine Learning for Organizational Agility

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Received : October 15, 2025
Accepted : November 18, 2025
Published : December 30, 2025

Citation: Munthe, E, S. (2025). Augmented Decision Systems: Integrating Multi-Criteria Modeling and Machine Learning for Organizational Agility. Efficiens : Journal of Management Science and Operations, 1(1), 12-25.

ABSTRACT: In increasingly volatile and complex business environments, strategic decision-making requires the integration of advanced analytical tools and human expertise. This study investigates the effectiveness of human-AI collaboration models using a mixed-method approach comprising managerial surveys (N=187), hybrid decision modeling (AHP-TOPSIS with Gradient Boosted Trees), and 24-hour agent-based simulations. The methodology enables a comprehensive analysis of decision speed, accuracy, interpretability, and trust dynamics in real-time environments. Results show that AI-enhanced systems significantly improve decision performance, reducing late decisions by 84%, suboptimal outcomes by 70%, and increasing resilience by 56%. Managers reported high confidence in AI's ability to reduce cognitive load and clarify trade-offs, with 91% supporting collaborative AI-human decision-making. Strategy selection using the hybrid model prioritized automation upgrades, supported by a high predicted ROI (17.8%) and model precision (RMSE = 0.084). The discussion integrates insights from Hybrid-Augmented Intelligence and human–AI work design models, emphasizing the role of trust, transparency, and stakeholder engagement in successful AI adoption. Findings underscore the need to balance algorithmic efficiency with interpretability to foster organizational readiness and acceptance. This research contributes a validated, scalable framework for AI-human collaborative decision-making, offering practical tools for strategic alignment and theoretical grounding for further exploration.

Keywords: Human-AI Collaboration, Decision-Making, AHP-TOPSIS, Machine Learning, Trust In AI, Agent-Based Simulation, Strategic Management.

INTRODUCTION

In today's rapidly evolving business landscape, organizations are increasingly challenged to make strategic decisions in the face of escalating uncertainty. Market unpredictability, driven by shifting consumer preferences, volatile economic indicators, and technological disruption, has transformed decision-making into a complex, high-stakes endeavor. Traditional models of decision-making, grounded in managerial experience and intuition, are proving inadequate in addressing the scale and dynamism of contemporary business problems. These challenges are compounded by the influx of massive data volumes and the accelerating integration of Artificial Intelligence (AI) technologies. As businesses strive to navigate these complexities, there is a growing imperative to develop decision-making frameworks that synthesize human judgment with algorithmic support.

One of the primary obstacles in strategic decision-making today is the increasing volatility of market dynamics. Fluctuations in consumer behavior, geopolitical uncertainties, and rapid technological evolution can significantly alter competitive landscapes, often without warning (Jarrar, 2021). These shifts necessitate a rethinking of decision paradigms, where organizations must become not only reactive but also predictive and agile. The emergence of AI offers a compelling opportunity in this regard. Advanced analytics, machine learning models, and real-time decision support systems provide tools that can process vast datasets, identify hidden patterns, and generate actionable insights at unprecedented speed (Kar et al., 2021).

Despite these advancements, the integration of AI into strategic decision-making introduces its own set of challenges. Data privacy concerns, high implementation costs, and the need for comprehensive employee reskilling have emerged as significant barriers to adoption (Sari & Indrabudiman, 2024). Furthermore, many decision-makers remain hesitant to fully embrace AI due to issues of transparency, explainability, and trust. In this context, AI is often perceived not as a collaborative tool but as a black-box system that undermines human agency and autonomy. This skepticism is particularly pronounced in sectors where accountability and stakeholder trust are paramount.

Nonetheless, the potential of AI to transform strategic management has been well-documented across various industries. In finance, AI-driven tools facilitate risk assessment and portfolio optimization, while in retail, AI enhances customer engagement through personalized recommendations and demand forecasting (Ledro et al., 2022; Osasona et al., 2024). The construction industry has also benefited from AI applications in project scheduling and resource management, improving both efficiency and cost-effectiveness (Regona et al., 2022). These cases underscore AI's capacity to augment human capabilities, provided it is implemented within a coherent, human-centric framework.

However, the adoption of AI is not uniform. Small and medium-sized enterprises (SMEs), in particular, struggle with limited financial and human resources, which hinders their ability to integrate advanced technologies effectively (Kim & Seo, 2023). Organizational resistance to change, a lack of digital maturity, and ethical concerns such as algorithmic bias further complicate the landscape (Brecker et al., 2023). These factors contribute to a persistent gap between technological potential and practical application in decision-making processes.

In addition to technological and organizational barriers, the challenge of data overload presents a significant impediment to effective decision-making. As businesses increasingly rely on big data, decision-makers are confronted with overwhelming volumes of information that can obscure critical insights (Thakuri et al., 2024). This phenomenon, often referred to as "analysis paralysis," leads to delayed or suboptimal decisions, undermining organizational agility. The difficulty lies not in the availability of data, but in the capacity to filter, interpret, and apply relevant information within time-constrained environments.

Another critical dimension is the influence of cognitive biases on traditional decision-making. Empirical research identifies biases such as overconfidence, confirmation bias, and anchoring as pervasive in managerial contexts, leading to skewed risk assessments and flawed strategic choices (Jarrar, 2021). These biases distort perception and judgment, particularly under pressure, and are exacerbated when decision-makers operate in isolation from objective data or fail to challenge their assumptions.

Amid these constraints, an emerging body of evidence advocates for a hybrid approach that harmonizes human intuition with algorithmic intelligence. Human decision-makers bring contextual understanding, ethical sensitivity, and experience-based insights, while AI contributes computational power, consistency, and scalability (Lytras & Visvizi, 2021). When appropriately aligned, this collaboration fosters more robust and transparent decisions. The synergy of human-AI interaction is especially critical in high-stakes environments, where accountability, adaptability, and trust are essential. Studies suggest that such integrative models not only improve decision quality but also enhance user confidence in AI-generated outputs (Diao, 2024; Eriksson et al., 2020).

This study aims to build upon these insights by empirically evaluating the effectiveness of human-AI collaboration in strategic decision environments. Specifically, it investigates how integrating decision support tools such as Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and machine learning forecasting within real-time simulations can support more informed, adaptive, and trustworthy decision-making. By combining these quantitative methods with qualitative inputs from managerial perceptions, this research seeks to bridge the gap between model performance and organizational adoption. The study contributes to both theory and practice by offering a validated framework for deploying collaborative AI models in volatile decision contexts.

In summary, strategic decision-making in the contemporary business world is beset by uncertainty, data complexity, and technological disruption. While AI offers powerful capabilities to address these challenges, its effectiveness depends largely on the degree of human collaboration and trust. Understanding and mitigating cognitive biases, managing information complexity, and fostering synergistic human-AI relationships are critical to advancing decision quality. This research sets out to explore and substantiate these dynamics, ultimately proposing a pragmatic model that aligns algorithmic precision with human-centered decision processes.

METHOD

This study employs a mixed-method research design that integrates qualitative insights and quantitative modeling to evaluate the effectiveness of human-AI collaboration in strategic decision-making environments. The methodology comprises three core components: a managerial perception survey, a hybrid multi-criteria decision-making (MCDM) model integrating AHP-TOPSIS and machine learning, and a dynamic agent-based simulation framework. Each component is designed to triangulate findings and enhance the robustness of results across subjective and empirical domains.

The first component involves a structured survey administered to 187 managerial-level respondents from diverse industries. The survey instrument was designed to capture perceptions related to cognitive load, clarity of decision trade-offs, trust in AI-generated recommendations, the importance of human-AI collaboration, and stakeholder justification. Responses were collected using a Likert-scale format and analyzed using descriptive statistics to determine consensus and validate the relevance of AI-human synergy in strategic contexts.

The second component of the methodology focuses on multi-criteria modeling using the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). AHP is selected due to its extensive application in complex decision-making contexts, offering a rigorous approach to criteria weighting based on pairwise comparisons (Bera et al., 2019; Danumah et al., 2016). This method facilitates the integration of both qualitative and quantitative dimensions by transforming subjective preferences into quantifiable weights. In this study, six strategic decision criteria were considered: cost efficiency, risk exposure, time-to-implement, scalability potential, sustainability impact, and customer satisfaction impact. Decision-makers performed pairwise comparisons, and the resulting consistency index (CI) was computed to ensure reliability, with the final CI value of 0.06 indicating an acceptable level of consistency (Dey et al., 2024).

The robustness of AHP is further demonstrated by its ability to process incomplete or inconsistent data through matrix algebra, thus maintaining analytical rigor even under conditions of uncertainty (Ogbowuokara et al., 2024). Once the criteria weights were established, the TOPSIS method was applied to rank four strategic alternatives: automation upgrade, supply chain redesign, product diversification, and outsourcing. The alternatives were evaluated based on the normalized decision matrix and weighted scores derived from AHP, resulting in a TOPSIS ranking that prioritized automation upgrades.

To forecast the expected return on investment (ROI) for each alternative, Gradient Boosted Trees (GBT) were employed as the machine learning model. GBT is an ensemble learning algorithm known for its high predictive performance, achieved by minimizing prediction error through iterative boosting (Chabuk et al., 2017). This method was selected for its superiority over traditional regression models in ROI prediction, its resilience against overfitting, and its adaptability across various data distributions (Rui & Sundram, 2024). Additionally, GBT provides feature importance scores, allowing researchers to interpret the key drivers of ROI and support actionable decision-making (Samanta et al., 2018). Model performance was assessed using root mean square error (RMSE), with a result of 0.084 indicating strong predictive accuracy.

The third methodological component involves the use of agent-based modeling (ABM) to simulate decision environments under real-time, dynamic conditions. ABM is a powerful tool in operations research, capable of representing heterogeneous agents such as managers, systems, and environmental variables interacting under predefined behavioral rules (Trivedi & Shah, 2022). The simulation was conducted over a 24-hour period, capturing the frequency of late decisions, suboptimal outcomes, reward scores, and resilience to environmental volatility. ABMs enable the exploration of emergent system behaviors and provide insights into the systemic impact of AI-supported strategies (Mousavi et al., 2022).

In this study, ABM was particularly effective in modeling complex interactions between AI-driven systems and human decision-makers, offering a realistic testbed for validating the proposed hybrid decision framework. The simulation incorporated dynamic inputs and changing constraints to reflect real-world uncertainties, such as fluctuating resource availability and shifting market conditions. The model allowed decision-makers to explore strategic responses in a controlled yet realistic environment, providing empirical evidence of the impact of AI-human collaboration on decision outcomes.

For example, within the context of supply chain decision-making, the simulation accounted for supplier delays, demand fluctuations, and operational bottlenecks. Agents representing decision-makers used real-time feedback from AI models to adjust strategic responses dynamically. This process helped demonstrate how collaborative decision systems can enhance responsiveness and resilience in high-stakes, uncertain scenarios (Ali et al., 2020).

Data from the AHP-TOPSIS evaluations, GBT model forecasts, and simulation outputs were integrated into a consolidated results framework. This triangulated approach ensured that findings were not only theoretically sound but also empirically validated across multiple dimensions. Statistical and modeling outputs were synthesized to assess decision accuracy, time efficiency, model trustworthiness, and resilience metrics.

In conclusion, this study's methodological framework synthesizes structured managerial insight, rigorous MCDM modeling, predictive machine learning, and dynamic simulation. The combination of AHP, TOPSIS, GBT, and ABM ensures a comprehensive examination of strategic decision-making, bridging subjective managerial needs with quantitative rigor. The methodology also establishes a scalable model for future research exploring AI-human collaboration in various organizational contexts.

RESULT AND DISCUSSION

This chapter presents the findings from the managerial survey, the real-time simulation, and the multi-criteria decision modeling using AHP-TOPSIS and Gradient Boosted Trees. Each subsection provides detailed results supported by quantitative data and is interpreted through recent literature to validate empirical observations.

Managerial Perceptions of AI

The perception survey conducted with 187 managers offers significant insights into the acceptance and perceived value of AI in decision-making contexts. A majority of respondents (91%) emphasized the necessity of human-AI collaboration, indicating strong support for integrative decision frameworks. Furthermore, 82% of managers agreed that AI helps reduce cognitive load during complex decision-making processes, while 76% stated that AI enhances the clarity of trade-offs in multi-criteria environments. These findings are consistent with current trends, which indicate growing managerial trust in AI-based recommendations, especially in data-intensive and uncertain decision contexts (Lau et al., 2018).

Trust in AI tools, however, is not uniform and often depends on industry context and prior experiences with digital systems. Studies show that transparency in AI operations specifically the interpretability of models greatly influences managerial confidence (Awenat et al., 2019). Managers also indicated that decision frameworks enabling them to justify decisions to stakeholders were critical, with 73% affirming this view. The importance of stakeholder justification in AI adoption is well-documented, as it enables broader organizational support and facilitates smoother implementation (Mohagheghi et al., 2019).

AI systems' ability to reduce cognitive load was especially appreciated in multi-criteria settings, where data complexity often overwhelms traditional decision models. As Bhuiyan & Hammad, (2023) note, AI-enhanced systems streamline data processing, filter out noise, and present key decision variables more clearly, allowing managers to concentrate on high-level strategic considerations. The qualitative methodologies used in studies such as interviews and focus groups further corroborate these survey findings, highlighting the importance of cultural and operational contexts in shaping AI perceptions (Khodamipour et al., 2021).

Simulation Outcomes: Traditional vs AI-Supported Systems

A dynamic 24-hour agent-based simulation compared decision outcomes between traditional and AI-enhanced models. Results demonstrate notable improvements in operational efficiency when AI support is included. Specifically, the number of late decisions dropped from 26 cases to just 4, reflecting an 84% reduction. Suboptimal decision occurrences decreased from 41% to 12%, while the average reward score across multi-objective metrics rose from 0.64 to 0.88, indicating a 37.5% improvement in outcome quality. Resilience to environmental volatility increased from 0.52 to 0.81 (+56%).

These metrics robustness, responsiveness, and accuracy are widely accepted as key indicators for decision quality in volatile environments (Hoang et al., 2024). Robustness, in this context, reflects the model's ability to perform consistently across diverse scenarios, while responsiveness captures how quickly the system adapts to new information. The accuracy of AI-enhanced systems supports prior evidence that AI improves decision timeliness and scenario planning by generating rapid, data-informed recommendations (Samala et al., 2018).

Case studies from similar implementations have documented performance gains such as increased customer satisfaction and reduced operational costs, reinforcing the conclusion that AI improves organizational agility (Iswari et al., 2019). Additionally, the agent-based simulation's ability to model volatility using stochastic methods and Monte Carlo analysis aligns with practices in advanced decision support systems (Bahri et al., 2023). These simulations allowed the testing of strategic responses to dynamic changes, reflecting the unpredictable nature of real-world conditions and the critical need for adaptive decision frameworks.

Strategy Selection Using AHP-TOPSIS and Machine Learning

The multi-criteria model was built using AHP to derive the weights of six strategic decision criteria: cost efficiency, risk exposure, time-to-implement, scalability potential, sustainability impact, and customer satisfaction. Pairwise comparisons from 28 decision-makers resulted in a consistency index (CI) of 0.06, within the acceptable threshold for AHP reliability. These criteria were then applied in a TOPSIS model to rank four strategic alternatives.

The final rankings positioned the automation upgrade as the most favorable option with a TOPSIS score of 0.812, followed by supply chain redesign (0.739), product diversification (0.594), and outsourcing (0.447). ROI predictions for each alternative were generated using Gradient Boosted Trees (GBT), a machine learning algorithm known for its predictive accuracy and robustness against overfitting. The predicted ROI for the top-ranked strategy (automation) was 17.8%, while the lowest-performing option (outsourcing) yielded only 7.9%. The model's root mean square error (RMSE) of 0.084 indicates high forecasting precision.

This hybrid approach combining AHP-TOPSIS with machine learning has been validated across various strategic applications. The AHP-TOPSIS framework has been praised for its ability to integrate subjective preferences with objective rankings, offering clear prioritization in decision contexts (Bals et al., 2016). Machine learning enhances this structure by introducing data-driven prediction capabilities, allowing for continuous learning and optimization (Janarthanam & Rao, 2024).

Industry-specific case studies, such as those in construction and renewable energy sectors, have demonstrated the effectiveness of such hybrid systems in improving decision quality and alignment with operational constraints (Saputro et al., 2023). These approaches often outperform traditional models by better capturing real-time complexities and enabling strategic flexibility (Mazher et al., 2018). Furthermore, the predicted ROI values fall within industry-accepted benchmarks of 70–90% accuracy, providing additional confidence in the model's reliability for strategic planning (Solangi et al., 2019).

The use of historical performance data to calibrate the machine learning component further strengthened the model's applicability, aligning forecast outputs with observed outcomes. This alignment is crucial for managerial trust and practical adoption (Kumar et al., 2021). The combined model not only provided actionable insights but also allowed decision-makers to justify strategic choices with empirical backing, satisfying internal accountability and stakeholder transparency requirements.

In summary, the results affirm that hybrid decision frameworks that integrate AI technologies with human judgment significantly improve decision-making performance, acceptance, and stakeholder alignment. These findings provide empirical support for the proposed collaborative model and its potential scalability across various industries.

The findings of this study reinforce the growing consensus that human-AI collaboration is a critical enabler of effective strategic decision-making. The integration of artificial intelligence into organizational decision processes has shown not only quantitative performance benefits such as increased speed, reduced error rates, and greater resilience but also qualitative enhancements in manager perception, trust, and stakeholder engagement. As demonstrated in the results, AI-assisted frameworks contribute substantially to improved decision quality, particularly when paired with well-designed collaborative mechanisms that incorporate human judgment.

The empirical evidence presented aligns with and extends several established theoretical frameworks that explain human-AI collaboration. The Hybrid-Augmented Intelligence model provides a foundational explanation for how cognitive tasks can be enhanced when human expertise and AI capabilities are brought together in a complementary manner (Zheng et al., 2017). Rather than replacing human input, AI functions as a dynamic partner that learns from human interactions while providing data-driven insights, thus creating an adaptive and evolving decision process. In parallel, the human–AI work design model proposed by Jain et al., (2022) underscores the significance of structuring roles and interaction patterns between human users and AI systems. This model emphasizes how both sequential and parallel task execution modes can be optimized to align the strengths of both parties in complex decision environments.

Despite the potential of such collaborative models, their success hinges significantly on the presence of trust. Trust in AI systems, as indicated by both the survey data and supporting literature, is a prerequisite for consistent use and full integration into decision workflows. The degree to which managers perceive AI tools as transparent, reliable, and interpretable influences their willingness to adopt and rely on these systems (Dietzmann & Duan, 2022). High levels of perceived trust reduce cognitive friction, allowing users to offload certain analytical burdens onto AI without the fear of losing control or introducing unintended bias. Conversely, a lack of trust can create a barrier to adoption, fostering skepticism and reluctance, even when the technical performance of AI tools is demonstrably superior (Shrestha et al., 2019).

Moreover, stakeholder involvement plays a pivotal role in shaping organizational attitudes toward AI integration. Managers must frequently justify decisions to a variety of stakeholders, making the interpretability and transparency of decision-support tools crucial. Frameworks that visibly integrate stakeholder perspectives and allow traceability of AI-generated recommendations are more likely to gain institutional legitimacy and support (Mohagheghi et al., 2019). This need for stakeholder justification explains the popularity of hybrid models that blend algorithmic output with human oversight offering both the efficiency of machine learning and the accountability of human reasoning.

Organizational adoption of decision-support technologies is driven by multiple interrelated factors. Perceived value is paramount; as Jain et al. (2022) argue, the clear demonstration of enhanced decision quality and operational benefits strongly motivates adoption. In this study, the observed improvements such as 84% reduction in late decisions and over 37% gain in reward scores validate the tangible advantages of AI-assisted systems. However, organizational readiness, including digital maturity, workforce competencies, and infrastructure capacity, remains a necessary condition for implementation. Firms operating in high-velocity sectors are particularly inclined to adopt these systems to maintain competitive agility (Shrestha et al., 2019).

The design of hybrid decision models must carefully balance algorithmic efficiency with human interpretability. While advanced machine learning algorithms such as Gradient Boosted Trees deliver superior predictive accuracy, their outputs must be accessible and explainable to human users. Techniques like Local Interpretable Model-Agnostic Explanations (LIME) offer valuable pathways to articulate model predictions in a manner that aligns with human cognitive patterns (Bhandari et al., 2022). In the context of strategic decision-making, such interpretability enhances user confidence and enables greater alignment between model recommendations and organizational objectives. This is echoed in Shneiderman, (2020) vision of Human-Centered Artificial Intelligence, which advocates for systems that are both high-performing and aligned with human values.

The results of the simulation and decision modeling in this study further affirm the utility of integrating AHP-TOPSIS frameworks with predictive machine learning tools. The structured nature of AHP facilitates transparent criteria weighting, while TOPSIS supports objective strategy ranking. Machine learning enriches this process with empirical forecasting, providing a well-rounded decision tool that accommodates complexity and uncertainty. Such hybrid models offer a way forward in environments where static rules and heuristics are insufficient, and continuous learning and adaptability are paramount.

In sum, the success of AI-assisted decision-making is not solely determined by algorithmic performance but is deeply influenced by social, cognitive, and organizational factors. Trust, interpretability, stakeholder inclusion, and contextual fit are as critical as predictive power. This study contributes to the growing body of evidence supporting collaborative decision models, highlighting their practical benefits and theoretical grounding. As organizations continue to face increasingly volatile decision environments, the integration of AI with human judgment will likely become not only beneficial but essential for sustained strategic success.

CONCLUSION

This study examined the impact and effectiveness of human-AI collaboration in strategic decision-making environments. Through a combination of managerial surveys, hybrid multi-criteria modeling, and agent-based simulations, the research provided robust empirical and theoretical evidence for the value of integrating AI systems with human expertise.

The key findings demonstrate that AI-assisted decision frameworks significantly enhance decision speed, accuracy, and organizational agility. AI systems reduced late decisions by 84%, improved suboptimal decision rates by 70%, and increased resilience to environmental volatility by 56%. Managers reported high levels of agreement on AI's ability to reduce cognitive load (82%) and clarify trade-offs (76%), and 91% supported collaborative AI-human decision models. These results highlight the tangible performance improvements and the positive perception shift toward AI technologies.

The study's main contribution lies in developing and validating a hybrid decision-making model that integrates AHP-TOPSIS with machine learning and real-time simulation. This model not only delivers predictive accuracy and structured analysis but also emphasizes interpretability and stakeholder justification critical elements for real-world organizational adoption. By aligning algorithmic insights with human values and decision contexts, the framework provides a practical and scalable solution for navigating complex, uncertain environments.

Furthermore, the research contributes to the theoretical understanding of collaborative intelligence in decision science. It draws on frameworks such as Hybrid-Augmented Intelligence and human–AI work design to explain how structured interaction models and trust dynamics influence system success. The inclusion of cognitive, organizational, and technical perspectives ensures a holistic approach to evaluating AI integration.

The findings suggest several implications for both practice and research. For practitioners, implementing human-AI collaboration models requires not only technological investment but also cultural readiness, stakeholder engagement, and training in interpretive tools. Transparent AI design and consistent stakeholder communication will be critical in fostering trust and long-term adoption. For researchers, future studies could expand on this framework by exploring longitudinal impacts across different industries, examining how AI-human decision systems evolve over time, and testing sector-specific adaptations of the model.

In conclusion, this study affirms that strategic decision-making in modern organizations is best supported by hybrid systems that balance algorithmic power with human judgment. The integration of AI into decision frameworks must prioritize not only efficiency and accuracy but also transparency, interpretability, and collaborative design. Such a balanced approach ensures that AI becomes a trusted and effective partner in the complex task of organizational decision-making.

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