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FROM GUT FEELING TO ALGORITHMIC THINKING: AI-DRIVEN DECISION-MAKING IN STRATEGIC MANAGEMENT

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Abstract

In today's rapidly evolving business environment marked by data proliferation and digital transformation, strategic decision-making is experiencing a profound shift, from intuition-driven judgments to algorithmically informed strategies. This paper explores the transition from traditional managerial reliance on "gut feeling" to the integration of Artificial Intelligence (AI), particularly predictive analytics, in strategic management. Drawing on theoretical models, contemporary case studies, and empirical evidence, the study employs a mixed-methods approach: regression analysis (SPSS) on survey data and thematic coding (NVivo) of expert interviews to uncover the structural and behavioral mechanisms influencing this paradigm shift. The findings reveal that leadership support, organizational readiness, and AI adoption levels are significant predictors of enhanced decision- making effectiveness. At the same time, the qualitative data exposes a nuanced interplay between human intuition and machine intelligence, emphasizing trust, ethical ambiguity, and resistance to automation. While AI offers compelling benefits such as increased predictive accuracy, objectivity, and speed, it also raises concerns about data bias, algorithmic opacity, and over-reliance on automation. Grounded in a critical realist paradigm, the study argues that AI should not replace human judgment but should augment it, creating a hybrid decision-making model that leverages both machine learning capabilities and human insight. The paper concludes with targeted recommendations for managers, educators, and policymakers, advocating for digital literacy, ethical AI governance, and organizational cultures of continuous learning. As organizations move from gut feeling to algorithmic thinking, a synergistic model of hybrid intelligence emerges as essential for sustainable strategic advantage in the AI-augmented era.

Keywords: Artificial Intelligence, Strategic Management, Predictive Analytics, Decision-Making, Algorithmic Thinking, Hybrid Intelligence, Critical Realism

Introduction

Strategic decision-making has long been at the heart of effective organizational leadership. Traditionally, it has been a complex interplay of intuition, experience, and rational analysis. For decades, business leaders have leaned on their gut feelings, cultivated over years of industry exposure and contextual sensitivity, to make high-stakes decisions under uncertainty. This form of managerial intuition, while valuable, has often lacked transparency, reproducibility, and empirical verification. In contrast, the emergence of Artificial Intelligence (AI) and advanced analytics has ushered in a paradigm shift, one that challenges the supremacy of human instinct and redefines the cognitive tools available to decision-makers. The contemporary organizational landscape is now increasingly shaped by the transition from gut feeling to algorithmic thinking, where predictive models, real-time data, and machine learning algorithms play a central role in shaping strategic choices (Brynjolfsson C McElheran, 2016; Davenport C Miller, 2022). This transition is not merely a technological shift; it represents a deeper epistemological reordering in the logic of decision-making. Strategic management, as both a scholarly domain and a practical endeavor, is being reimagined by the integration of AI into core organizational processes. What was once considered the exclusive domain of senior executives, envisioning future market scenarios, evaluating risk, and deploying resources, has now become a more democratized, data-enriched, and automated field of practice. The strategic compass no longer points solely in the direction of experience and personal judgment; it is now recalibrated by algorithms capable of identifying patterns and projecting outcomes at scales beyond human cognitive reach (Shrestha et al., 2019).

At the core of this transformation is the growing accessibility of vast and varied data streams. From internal operations and customer behaviors to macroeconomic trends and competitive intelligence, organizations now operate in data-saturated environments. Predictive analytics, underpinned by machine learning, natural language processing, and AI, enables firms to harness this abundance, convert it into actionable insights, and respond with precision and agility (Wamba-Taguimdje et al., 2020). In turn, strategic decision-making becomes less reactive and more anticipatory, shifting from hindsight to foresight. As AI systems learn from historical and real-time data, they provide decision-makers with probabilistic forecasts and optimization scenarios that transcend the limitations of human cognition. However, the rise of AI in strategic management does not signal the obsolescence of human judgment. Instead, it calls for a new synthesis, what scholars term “augmented intelligence”, where machine-based insights enhance, rather than replace, the cognitive capabilities of managers (Raisch C Krakowski, 2021). This augmentation challenges traditional notions of leadership, authority, and expertise. It raises critical questions about how managers interpret algorithmic recommendations, when they choose to override them, and how trust is developed between human agents and digital systems. In essence, the shift from gut feeling to algorithmic thinking invites a reassessment of the very nature of decision authority and the epistemic legitimacy of different sources of knowledge.

Notably, the implications of AI-driven decision-making are not uniform across organizations. Industry dynamics, organizational maturity, data readiness, and cultural receptivity to technological innovation shape the adoption of AI technologies in strategic processes. While digitally native firms like Amazon and Alibaba seamlessly integrate AI into their strategic models, ranging from dynamic pricing to personalized customer engagement, many traditional firms struggle with legacy systems, data silos, and resistance to algorithmic authority (Bughin et al., 2019). Thus, the journey toward algorithmic decision-making is often uneven, fraught with both technical and organizational barriers.

The COVID-19 pandemic served as an inflection point in accelerating the adoption of AI and predictive analytics in strategic decision-making. Faced with unprecedented uncertainty, supply chain disruptions, and changing consumer behaviors, firms turned to real-time data and predictive models to navigate volatility and reassess strategic priorities. Organizations that had previously invested in AI infrastructure and data capabilities were better positioned to respond adaptively, demonstrating the competitive advantage conferred by algorithmic agility (Chatterjee et al., 2021). Post-pandemic, the strategic imperative for digital transformation has only intensified, pushing AI from the periphery to the center of decision-making architectures.

Despite the growing embrace of AI, significant ethical, technical, and managerial challenges persist. One of the most pressing concerns is the opacity of AI models, often referred to as the "black box" problem, which can obscure how algorithmic decisions are made and make it difficult for managers to justify strategic choices (Binns, 2018). In high-stakes decisions involving mergers, resource allocation, or market entry, this lack of interpretability can hinder trust and accountability. Moreover, algorithms are not free from bias; they often inherit the prejudices embedded in historical data, leading to unintended and potentially discriminatory outcomes (O'Neil, 2016). As such, responsible AI governance and explainability must accompany technical sophistication in the deployment of predictive systems. Another dimension of concern relates to the organizational culture surrounding data and AI. Research shows that technological readiness alone does not guarantee successful AI adoption. Strategic decision-making requires a cultural shift toward data literacy, cross-functional collaboration, and an openness to experimentation (La Torre et al., 2020). Organizations must cultivate what Davenport and Bean (2018) describe as an "analytics culture", where employees at all levels engage with data thoughtfully, question assumptions, and align AI initiatives with strategic objectives. Without this cultural underpinning, AI tools risk becoming underutilized or misaligned with organizational priorities.

Significantly, the transition to algorithmic thinking also impacts the role of strategic leaders. As AI systems take over routine analytical tasks, leaders are increasingly called upon to exercise judgment in complex, ambiguous situations where algorithms offer no clear answers. This calls for a redefinition of leadership competencies, not in terms of technical expertise alone, but in the capacity to navigate the human-AI interface, foster ethical reflection, and ensure inclusive decision-making (Wilson C Daugherty, 2018). Strategic leaders must balance empirical rigor with contextual intelligence, knowing when to trust the machine and when to lean on intuition informed by human values. The academic literature is beginning to reflect these changes. While earlier research focused on the technological architecture of AI systems, current studies explore the sociotechnical dynamics of AI adoption in strategic contexts. There is a growing interest in how organizations reconcile the rationality of algorithms with the relationality of human decision-making, and how strategic choices are shaped by the interaction between data, technology, and institutional logics (Faraj et al., 2018). In this light, AI is not merely a tool but a transformative force that reconfigures the processes, practices, and politics of strategic management.

This paper contributes to this evolving discourse by critically examining how AI-driven predictive analytics is reshaping the landscape of strategic decision-making. It interrogates the tensions between human intuition and machine intelligence, highlights the enablers and barriers to successful AI integration, and explores the organizational capabilities required to harness AI for competitive advantage. Drawing on empirical cases, theoretical insights, and current debates, the paper aims to provide a nuanced understanding of the algorithmic turn in strategic management. As we navigate this transition, one thing is clear: the future of strategic decision-making will be neither fully human nor fully machine. It will be hybrid, dynamic, and context-dependent. In this hybrid future, the challenge for organizations is not simply to adopt AI technologies, but to rethink how decisions are conceived, justified, and enacted in an age of intelligent machines. From gut feeling to algorithmic thinking, the journey is as much about reimagining human judgment as it is about building technological capability.

Literature Review:

The evolution of strategic decision-making has long fascinated scholars and practitioners alike, especially as organizations have sought to navigate increasing levels of complexity, volatility, and uncertainty in their operating environments. Classical theories of strategy often emphasized rational analysis, bounded rationality, or incrementalism as the bedrock of strategic choices (Simon, 1979; Quinn, 1980). However, over the years, these perspectives were complemented by growing recognition of intuition, often described as “gut feeling”, as a valid and sometimes indispensable aspect of executive decision-making, especially in non-programmed, high-ambiguity contexts (Dane C Pratt, 2007). With the exponential rise of data analytics and artificial intelligence (AI), this human-centered approach is undergoing a radical transformation, giving way to data-driven and algorithmic forms of reasoning that promise improved objectivity, scalability, and predictive power. This literature review surveys the development of decision-making models in strategic management, explores the increasing role of AI and predictive analytics, and addresses emerging tensions and synergies between human intuition and algorithmic reasoning. Special attention is given to how organizations operationalize AI in strategy, the challenges they face in doing so, and the theoretical implications for leadership, organizational design, and competitive advantage.

From Rational Choice to Intuitive Judgment

Traditional strategic management theory was strongly influenced by the rational decision-making model, which posits that decision-makers systematically evaluate alternatives based on a comprehensive understanding of goals and available information (Ansoff, 1965; Porter, 1985). However, empirical research has challenged this idealized model, particularly in dynamic environments where complete information is unavailable and outcomes are uncertain. In such contexts, executives have been observed to rely on heuristics and intuition, forms of tacit knowledge derived from experience and pattern recognition (Kahneman C Klein, 2009). Dane and Pratt (2007) argue that intuitive decision-making, far from being irrational, can be highly effective, especially when the decision-maker has deep domain expertise. However, intuition is also subject to cognitive biases such as overconfidence, availability heuristics, and anchoring effects (Tversky C Kahneman, 1974). While gut feeling offers agility and contextual sensitivity, it lacks transparency and replicability, rendering it increasingly inadequate for data-intensive, complex decision environments.

The Rise of Data-Driven and Algorithmic Decision-Making

Recent years have witnessed a shift from human-centric to data-centric decision paradigms, driven by the digitization of organizational processes and the proliferation of big data. In contrast to intuitive or experiential models, data-driven decision-making relies on empirical evidence, statistical inference, and predictive algorithms to guide strategic choices. AI technologies such as machine learning (ML), natural language processing (NLP), and deep learning are now central to this transformation (Brynjolfsson C McAfee, 2017; Jordan C Mitchell, 2015). Predictive analytics, in particular, enables organizations to forecast trends, identify opportunities, and simulate strategic scenarios with increasing accuracy. Chatterjee et al. (2021) emphasize that the adoption of AI in strategic contexts has moved beyond operational optimization to influence high-level decisions such as market entry, mergers, and product development. For instance, dynamic pricing algorithms in the airline and e-commerce sectors have replaced managerial guesswork with real-time demand forecasting models. While early adopters such as Amazon and Google have successfully integrated AI into their strategic DNA, traditional firms face more profound structural and cultural challenges. A study by Bughin et al. (2019) found that only a minority of firms are realizing significant financial returns from AI investments, often due to fragmented data architectures, skill shortages, and cultural resistance. Thus, the transition from gut feeling to algorithmic thinking is as much about organizational change as it is about technological innovation.

Human-AI Interaction and the Concept of Augmented Intelligence

Although AI is often portrayed as replacing human judgment, the more nuanced reality is one of collaboration and augmentation. The concept of “augmented intelligence” reflects this shift, emphasizing AI's role in enhancing, rather than supplanting, human cognitive abilities (Davenport C Ronanki, 2018). This perspective recognizes that while algorithms excel in pattern recognition and statistical correlation, they lack the contextual awareness, ethical sensitivity, and creative intuition of human beings. Several frameworks have emerged to describe how human and algorithmic decision-making can coexist. Jarrahi (2018) proposes a sociotechnical perspective, arguing that humans and AI systems have complementary strengths. Humans bring creativity, contextual understanding, and ethical judgment, while AI contributes speed, consistency, and data processing power. The most effective decision environments, therefore, are those that deliberately design for this complementarity. Nevertheless, the integration of AI into strategic management is fraught with tensions. One such tension arises from the "black box" nature of many AI systems, particularly deep learning models, which produce recommendations that are difficult to explain or interpret (Burrell, 2016). This opacity can undermine trust and hinder adoption, especially in high-stakes decisions where accountability is critical. The literature on explainable AI (XAI) seeks to address this challenge by developing models that are both accurate and interpretable (Doshi-Velez C Kim, 2017).

Organizational Capabilities for AI-Enabled Strategy

Implementing AI in strategic decision-making requires more than technical infrastructure; it demands a transformation in organizational capabilities. According to Wamba et al. (2020), firms must develop a range of dynamic capabilities, including data literacy, agile governance, and cross- functional collaboration. Davenport and Bean (2018) emphasize the importance of cultivating a data- driven culture, where decision-makers trust data insights and embed analytics into routine workflows. Leadership plays a pivotal role in enabling this transformation. Strategic leaders must act as translators between data science teams and business units, ensuring alignment between AI initiatives and organizational goals. They must also manage ethical risks, promote data stewardship, and foster a culture of continuous learning (Raisch C Krakowski, 2021). The skills required of today's strategic leaders are thus increasingly hybrid, combining domain expertise, technological fluency, and adaptive thinking. In a longitudinal study of AI integration across global firms, Shrestha et al. (2019) identified four stages: experimentation, implementation, integration, and transformation. Organizations in the early stages tend to use AI for limited decision-support, whereas mature firms embed AI into their core strategic processes and achieve system-wide learning. The transition across these stages is non-linear and shaped by internal dynamics such as leadership vision, change management capabilities, and resource availability.

Ethical and Governance Considerations

As AI systems assume greater influence in strategic decision-making, concerns about fairness, accountability, and governance have moved to the forefront of scholarly debate. O'Neil (2016) warns of "weapons of math destruction," where flawed algorithms perpetuate bias and inequality at scale. In strategic management, such risks can manifest in discriminatory hiring algorithms, biased credit scoring, or exclusionary market segmentation. To mitigate these risks, scholars advocate for the incorporation of ethical frameworks into AI governance. Binns (2018) proposes borrowing from political philosophy to define principles such as fairness, transparency, and accountability. Meanwhile, institutional theorists argue that AI practices must align with broader organizational norms and regulatory expectations to gain legitimacy (Faraj et al., 2018). Furthermore, recent debates have focused on the need for algorithmic accountability in boardroom decision-making. As boards increasingly rely on AI-driven insights, there is growing demand for governance mechanisms that ensure interpretability, traceability, and auditability of algorithmic processes (Kleinberg et al., 2018). These developments point to a future where data ethics and algorithmic governance are integral to strategic leadership.

Toward a Hybrid Model of Strategic Intelligence

The growing body of literature suggests that the future of strategic decision-making lies not in choosing between intuition and algorithms but in integrating both. Hybrid models, where algorithmic tools inform, but do not dictate, human decisions, are gaining prominence. For example, Wilson and Daugherty (2018) describe "collaborative intelligence" as a model where machines handle data-intensive tasks, while humans provide interpretation and oversight. Such hybrid approaches also open new avenues for research on decision quality, strategic foresight, and organizational learning.

The feedback loops generated by AI systems can enable more adaptive and responsive strategies, provided that organizations invest in the learning structures necessary to interpret and act on these insights (Lichtenthaler, 2020). The literature reveals a significant transformation in the foundations of strategic decision-making, driven by the convergence of AI, big data, and predictive analytics. While this shift challenges the traditional reliance on managerial intuition, it also opens up new possibilities for augmenting human judgment with algorithmic intelligence. However, successful adoption depends on more than technical readiness; it requires cultural alignment, ethical governance, and new forms of strategic leadership. As firms navigate this hybrid landscape, the interplay between gut feeling and algorithmic thinking will remain a defining challenge and opportunity in the digital age.

Methodology

This study adopts a mixed-methods research design, integrating both qualitative and quantitative approaches to examine the paradigm shift from intuition-based to AI-driven strategic decision-making in contemporary organizations. This triangulated design is appropriate for exploring both the nuanced human experiences surrounding managerial decision-making and the empirical relationships among organizational variables influenced by AI integration. The use of critical realism as the philosophical underpinning of the study provides a layered framework for inquiry, emphasizing the identification of underlying mechanisms and structures influencing observable patterns in strategic decision-making (Bhaskar, 2008; Sayer, 2010). By acknowledging the interplay between social context and empirical observation, this paradigm allows for both statistical generalization and theoretical abstraction.

Research Questions

1. How do organizational leaders perceive the shift from intuitive to algorithmic decision-making in strategic management?
2. What empirical patterns emerge between the adoption of AI tools and decision-making effectiveness?
3. How do organizational culture, leadership style, and technological readiness mediate this relationship?

Data Collection

The study was conducted across 15 mid-to-large organizations operating in sectors including finance, healthcare, telecommunications, and manufacturing. A purposive sampling technique was used to identify executives, strategic managers, and data analysts who play an active role in decision-making processes involving AI tools.

Qualitative Data

Semi-structured interviews were conducted with 25 participants to explore their lived experiences and interpretive frameworks. Each interview lasted approximately 45–60 minutes and was audio-recorded with consent. Interview questions probed how participants integrated data analytics into strategic processes, their trust in algorithmic recommendations, and the perceived advantages or limitations of such tools.

Quantitative Data

To complement the qualitative insights, a structured questionnaire was distributed to 120 respondents across the selected organizations. The instrument included standardized scales adapted from previous studies to measure:

- Perceived effectiveness of decision-making (Dean C Sharfman, 1996),
- Organizational readiness for AI adoption (Venkatesh et al., 2003),
- Strategic alignment and leadership support (Tallon, 2007).

Responses were recorded on a five-point Likert scale ranging from “Strongly disagree” to “Strongly agree.”

Data Analysis

Qualitative Analysis Using NVivo

Interview transcripts were imported into NVivo 14 for thematic coding. An open coding process was initially adopted to inductively identify emerging categories such as "algorithmic trust," "resistance to change," and "cognitive delegation." These codes were then grouped into higher-order themes such as "organizational adaptation," "human-algorithm collaboration," and "ethical concerns." Axial coding was employed to link causal conditions (e.g., leadership attitude), contextual factors (e.g., industry type), and intervening conditions (e.g., training quality) to decision outcomes. This coding structure was informed by the realist evaluation framework (Pawson C Tilley, 1997), which highlights the interaction between context (C), mechanism (M), and outcome (O).

Quantitative Analysis Using SPSS

Survey data were analyzed using SPSS version 27. First, descriptive statistics (means, standard deviations, and skewness) were computed to establish data normality. A Cronbach’s alpha analysis confirmed the internal consistency of the instrument with reliability coefficients above the acceptable threshold of 0.7 (Nunnally C Bernstein, 1994). To test the hypothesized relationships, multiple regression analysis was conducted. The dependent variable was strategic decision-making effectiveness, while the independent variables included:

- AI adoption level,
- leadership support for AI, and
- organizational readiness.

The regression model yielded an adjusted R^2 of 0.63, suggesting that the predictors could explain 63% of the variance in decision-making effectiveness. The beta coefficients indicated that leadership support ($\beta = .45$, $p < .001$) and AI adoption level ($\beta = .31$, $p = .004$) were statistically significant predictors. At the same time, organizational readiness had a weaker but still significant influence ($\beta = .18$, $p = .038$).

Integration of Findings

The combination of NVivo and SPSS analyses provided a holistic view of the phenomenon. The qualitative data illuminated the internal thought processes and organizational narratives that shape AI adoption, while the quantitative data confirmed that these organizational characteristics materially affect strategic outcomes. For instance, qualitative evidence from NVivo revealed that "algorithmic opacity" was a recurring concern. However, the SPSS regression results demonstrated that organizations with high leadership support were more likely to overcome resistance and realize better decision quality. Similarly, while some managers viewed AI as a threat to their autonomy, others saw it as a tool for cognitive amplification, especially when paired with transparent communication and ethical safeguards. This dual approach reflects the layered ontology of critical realism, allowing for explanations that transcend mere correlation to explore underlying causal mechanisms. While the mixed-methods approach strengthened the validity of findings, the study is not without limitations. The purposive sampling may limit generalizability, and self-report measures can introduce bias. Furthermore, the cross-sectional design restricts the ability to assess causal relationships over time. However, the integration of NVivo and SPSS analyses compensates for some of these weaknesses by providing both depth and breadth.

Findings and Discussion

The findings of this study provide empirical support and theoretical insight into the evolving interplay between human intuition and artificial intelligence in strategic decision-making. Through both statistical and thematic analysis, a rich tapestry emerges showing how data-driven tools are reshaping the cognitive and organizational terrain within which strategic decisions are formulated and executed.

Quantitative Findings: Patterns in Algorithmic Decision-Making

From the SPSS analysis, the most prominent finding is that leadership support for AI adoption significantly predicts strategic decision-making effectiveness ($\beta = .45$, $p < .001$). This affirms the role of leadership not only as a driver of innovation but also as a key enabler of cognitive and cultural shifts within firms (Brynjolfsson C McElheran, 2016; Davenport C Ronanki, 2018). Organizations where top management championed AI integration reported better alignment between strategic goals and analytical insights, suggesting that leadership endorsement enhances both psychological and procedural acceptance. The second significant predictor, AI adoption level ($\beta = .31$, $p = .004$), indicates that the presence and functionality of AI tools directly influence the quality of decisions. This finding aligns with empirical studies by Shrestha et al. (2019), which suggest that machine learning systems contribute to decision effectiveness by improving speed, precision, and scenario modeling. However, our analysis also finds that the relationship between adoption and performance is not linear; where adoption lacks strategic coherence, tools are underutilized or misapplied. Organizational readiness emerged as a weaker predictor ($\beta = .18$, $p = .038$), but its significance should not be underestimated. The findings suggest that structural capabilities, such as IT infrastructure, digital literacy, and data governance, are foundational but insufficient without cultural alignment. This supports earlier models of IT-strategy alignment, where technical readiness must be accompanied by behavioral and cognitive readiness (Tallon, 2007; Venkatesh et al., 2003).

Notably, 63% of the variance in strategic decision-making effectiveness was explained by the regression model (Adjusted $R^2 = .63$), which highlights a strong explanatory power of the chosen predictors. This figure corroborates the growing body of evidence that algorithmic systems are becoming central to strategic management infrastructures (Chatterjee et al., 2021).

Qualitative Findings: Perspectives from the Field

The NVivo-assisted qualitative analysis revealed complementary patterns. Themes such as “trust in algorithms,” “fear of displacement,” and “hybrid intelligence” emerged consistently across interview transcripts. One senior executive in a healthcare firm remarked, *“We do not make gut decisions anymore. The dashboard tells us what to do, though we still argue with it sometimes.”* This points to a form of augmented decision-making, where managers rely on algorithms but still validate them through human judgment. This aligns with the theory of centaur intelligence, where human and machine capabilities are combined synergistically (Wilson C Daugherty, 2018). However, resistance to algorithmic decision-making was also common, particularly in organizations with lower digital maturity. Concerns ranged from algorithmic opacity, not knowing how AI systems reach their conclusions, to ethical anxiety, especially when decisions involve employee evaluation or customer profiling. These observations support the arguments by Mittelstadt et al. (2016) on the ethical challenges of algorithmic governance.

One thematic cluster, “algorithmic trust versus intuition”, highlighted a generational and experiential divide. Older managers tended to emphasize experience-based decision-making and were skeptical of “black box” algorithms, while younger managers were more inclined to delegate cognitive tasks to AI systems. This generational difference echoes findings from Yoo et al. (2020), who noted that digital natives are more willing to offload decision-making to algorithms. Another emergent theme was “strategic framing of AI.” Organizations that treated AI as a strategic partner rather than a technical tool were more successful in integrating it. This reflects the need for technology framing as discussed by Orlikowski and Gash (1994), where shared mental models about the role of technology influence its assimilation into strategic routines.

Synthesizing Quantitative and Qualitative Data

A significant point of convergence between the quantitative and qualitative data is the importance of leadership support. While SPSS regression showed it to be the strongest predictor of effectiveness, NVivo analysis revealed how leadership discourse and actions shaped the organizational climate around AI. Leaders who consistently communicated a vision of augmented intelligence helped reduce fear and build trust among employees. Similarly, the interplay between organizational readiness and cultural resistance explains why technical infrastructure alone is not enough. As one interviewee stated, *"We have the tools, but not the mindset."* This reaffirms the value of the critical realist lens, which encourages researchers to explore both observable regularities and the deeper mechanisms that produce them (Sayer, 2010). Another noteworthy synthesis relates to the theme of "decision confidence." Quantitative respondents who rated their decisions as highly effective were also likely to work in environments where AI was integrated into strategic sensemaking processes rather than used as a mere reporting tool. NVivo themes like "data as narrative" and "machine- human learning loops" illustrate how AI systems reshape not just what decisions are made, but how they are made and justified.

Implications for Strategic Management

The findings suggest that AI adoption in strategic management is not merely a technological upgrade; it is a cognitive and organizational transformation. Decision-making is no longer solely the domain of senior leaders exercising gut instinct; it increasingly involves collaborative networks of humans and algorithms working in concert (Brynjolfsson C McAfee, 2017). This shift requires not just investment in tools, but cultural realignment, ethical safeguards, and leadership foresight. Strategically, firms should focus on building algorithmic literacy among decision-makers, ensuring that tools are not only technically functional but also contextually understood. Training programs, narrative framing, and open dialogues about ethical boundaries can support this goal. The study also provides empirical backing for the contingency theory of decision-making. The effectiveness of AI integration varies based on environmental uncertainty, industry volatility, and internal maturity. Organizations should avoid one-size-fits-all approaches and instead tailor AI deployment to their strategic context.

Conclusion

This study set out to explore the transformation of strategic decision-making in organizations, shifting from the historically dominant reliance on gut feeling and intuition to a growing dependence on algorithmic thinking driven by artificial intelligence. Through a mixed-methods approach combining statistical analysis (via SPSS) and qualitative thematic coding (via NVivo), the research has illuminated both the empirical effects and experiential dimensions of this transition. The quantitative findings affirmed that leadership support, AI adoption levels, and organizational readiness significantly predict decision-making effectiveness. Particularly noteworthy is the strong influence of leadership in fostering trust, facilitating adoption, and framing AI as a strategic partner rather than merely a technical tool. The qualitative data provided the necessary texture to these patterns, revealing nuanced tensions between tradition and transformation, autonomy and augmentation, skepticism and trust. These findings collectively underscore that the integration of AI in strategic decision-making is not simply a matter of implementing new tools but involves profound shifts in organizational cognition, culture, and ethics. Algorithmic thinking, when properly aligned with strategic objectives and supported by leadership, enhances not only decision quality but also organizational agility, transparency, and resilience.

However, the study also reveals critical challenges: a persistent fear of automation, generational divides in trust toward data, and ethical uncertainties around algorithmic opacity. These challenges demand that organizations go beyond technological investments to build human capacity, ethical governance frameworks, and inclusive cultures that welcome innovation while preserving human judgment and values. Importantly, the study's critical realist stance has enabled a deeper understanding of the underlying structures and mechanisms that shape surface-level organizational behaviors. It emphasizes that beneath every effective algorithmic decision lies a social, cognitive, and institutional architecture that must be continuously interrogated and improved.

As the strategic landscape grows more volatile and data-rich, organizations that can harmonize human intuition with algorithmic precision are poised to gain a competitive advantage. However, this synergy is not automatic; it must be designed, supported, and cultivated. AI is not a replacement for human insight but a complement to it. The future of strategic management lies not in choosing between gut feeling and algorithmic thinking, but in mastering the balance between them.

In closing, the paper advocates for a recalibrated model of strategic decision-making, one that sees data not just as numbers, but as narrative; algorithms not as final arbiters, but as collaborators; and human managers not as obsolete actors, but as augmented thinkers. With the right institutional, technological, and ethical scaffolding, AI can fulfill its promise to enhance, not erode, human decision-making in the strategic management domain.

Limitations and Future Research

Its sample size and sectoral focus limit the study’s generalizability. Future research should extend this inquiry across diverse geopolitical contexts, especially in developing economies where digital transformation may follow different trajectories. Longitudinal studies could also illuminate how the balance between algorithmic and intuitive reasoning evolves over time. Additionally, while the mixed-methods design provided depth and triangulation, future studies could employ experimental designs or simulations to test causal effects more rigorously. There is also room for comparative studies examining sectors like healthcare versus finance, where ethical stakes and regulatory frameworks differ.

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