

Implementing Artificial Intelligence for Strategic Decision-Making in Volatile Economic Environments

Article type: Research Article

Iman Ghasemi Hamedani^{1*} 

Corresponding Author, Researcher at Sharif Policy Research Institute (SPRI); Sharif University of Technology, Tehran, Iran
Email: ghasemi.iman1987@gmail.com

Nina Shaddeli² 

Researcher at Sharif Policy Research Institute (SPRI); Sharif University of Technology, Tehran, Iran
Email: nina.shaddeli@sharif.edu

Autumn & Winter (2025-2026)
2(2): 121-138

Received: 16 September 2025
Revised: 26 September 2025
Accepted: 29 September 2025
Available Online: 01 October 2025

ABSTRACT

This study investigated the role of Artificial Intelligence (AI) in enhancing strategic decision-making within volatile economic environments, focusing on knowledge economy. Employing a mixed-methods approach, the research integrated a Systematic Literature Review (SLR) with secondary data analysis from 300 organizations across finance, manufacturing, retail, and healthcare sectors. Qualitative insights from the SLR identified three core themes including AI-enhanced organizational agility (75% of studies), ethical and implementation challenges (65% of studies), and knowledge economy integration (70% of studies). Quantitative findings confirmed these themes, revealing that organizations with advanced AI adoption achieve an average 25% improvement in decision accuracy and a 30% increase in operational resilience. However, ethical concerns such as algorithmic bias and privacy issues led to a 12-18% reduction in perceived trustworthiness, reported by 20% of analyzed organizations. The study extended dynamic capabilities and resource-based view theories by proposing a unified framework that integrates agility, ethical governance, and knowledge-driven alignment. Practically, it offered managerial guidance on AI deployment and ethical protocols, while advising policymakers on regulations to ensure equitable AI access, particularly for small and medium enterprises (SMEs). The research positioned AI as a critical strategic asset for navigating volatility while emphasizing risk mitigation.

KEYWORDS

Artificial Intelligence, strategic decision-making, knowledge economy, organizational agility, ethical AI.

Cite this article: Ghasemi Hamedani, I. & Shaddeli, N., (2025-2026). Implementing Artificial Intelligence for Strategic Decision-Making in Volatile Economic Environments. *Journal of Knowledge Economy Studies (JKES)*, 2(2), 121-138.

DOI: <http://doi.org/10.22034/kes.2025.2071842.1082> Publisher: [Hazrat-e Masoumeh University](#)



Authors retain the copyright and full publishing rights.
Published by Hazrat-e Masoumeh University. This article is an open access article licensed under the Creative Commons Attribution 4.0 International (CC BY 4.0)

Introduction

The twenty-first century business landscape is characterized by unprecedented Volatility, Uncertainty, Complexity, and Ambiguity (VUCA), driven by forces such as technological disruption, globalization, shifting consumer demands, geopolitical instability, and the lingering effects of pandemics. Traditional frameworks for strategic decision-making, which often rely on linear models and incremental planning, struggle to address the accelerating pace of change in today's markets. As a result, organizations are increasingly turning to AI to strengthen their decision-making capabilities and to develop strategies that are both resilient and adaptive to dynamic environments (Kolbjornsrud, 2023; Wu et al., 2023). AI provides managers with sophisticated tools for analyzing massive datasets, detecting subtle patterns, generating predictive insights, and supporting real-time strategic adjustments. Its ability to combine computational efficiency with advanced analytical techniques positions it as a cornerstone technology for organizations seeking competitive advantage in digital and knowledge-based economy.

The role of AI in strategic decision-making has evolved from a supporting analytical tool to an active collaborator in shaping long-term strategic outcomes. Recent studies emphasized that AI contributes not only to operational improvements but also to broader strategic agility, enabling organizations to anticipate disruptions, reconfigure resources rapidly, and seize emerging opportunities (Alghamdi & Agag, 2023; Tominc et al., 2023). For instance, in financial services, AI-driven predictive models have enhanced portfolio management and risk assessment, improving stability during market turbulence (Addy et al., 2024). In supply chain management, machine learning algorithms have improved the accuracy of demand forecasting, reduced bottlenecks, and optimized logistics, thereby increasing resilience during crises such as the COVID-19 pandemic (Ivanov & Dolgui, 2022). Similarly, in digital commerce, natural language processing and recommendation systems have enabled organizations to adapt rapidly to changing consumer preferences, boosting customer engagement and sales (Chen et al., 2021). These examples illustrate that AI not only automates the existing processes but also transforms how organizations sense and respond to environmental shifts, creating pathways for sustainable competitive advantages.

At the same time, the integration of AI into strategic decision-making is accompanied by significant challenges. While managers acknowledge AI's potential, surveys revealed that only a small minority of organizations fully delegate strategic decision-making to AI systems, reflecting concerns about trust, transparency, and accountability (Chernov et al., 2020; Hesel et al., 2022). Ethical dilemmas such as algorithmic bias, data privacy violations, and explainability gaps remain major barriers to widespread adoption (Mittelstadt et al., 2023; Ramu et al., 2025). For example, biased AI systems in recruitment and customer profiling can lead to discriminatory outcomes, undermining the organizational legitimacy and stakeholder trust. Moreover, many SMEs, particularly in emerging economies, lack the technical infrastructure, skilled workforce, and financial

resources required to implement AI effectively (Wang et al., 2025). These challenges highlight the importance of hybrid models of human–AI collaboration, in which AI acts as an assistant, collaborator, or project manager, while humans retain oversight and ethical judgment (Buber et al., 2025).

The theoretical foundations for studying AI in strategic decision-making are grounded in the Resource-Based View (RBV) and dynamic capabilities perspectives. From an RBV standpoint, AI constitutes a valuable, rare, and inimitable resource that enables organizations to create sustained competitive advantages by leveraging data-driven insights and superior analytical capabilities (Brynjolfsson et al., 2022). Dynamic capabilities theory, on the other hand, emphasizes AI's role in sensing opportunities, seizing them through timely actions, and transforming organizational processes to adapt to environmental turbulence (Liu, 2024). These frameworks explain how AI strengthens the organizational agility and resilience by facilitating rapid reconfiguration of strategies and resources. Furthermore, the Knowledge-Based View (KBV) highlights AI's contribution to knowledge creation and dissemination, positioning it as an essential enabler of innovation in knowledge-intensive industries (Cockburn et al., 2018). Together, these theoretical lenses underscore AI's transformative potential in reshaping strategic management in volatile economic contexts.

Recent empirical evidence further reinforced the strategic importance of AI. Large-scale surveys showed that over 80% of executives perceive AI as a key enabler of competitive advantage (Tominc et al., 2023). Structural Equation Modeling studies demonstrated that AI adoption significantly enhances organizational agility and mediates the relationship between digital transformation initiatives and firm performance (Alghamdi et al., 2023; Ameen et al., 2024). Machine learning prediction models achieve accuracy rates of up to 99% in forecasting organizational agility, indicating the reliability of AI-based approaches in predicting performance outcomes (Shafiabady et al., 2024). Moreover, firms with high levels of AI literacy report stronger resilience, improved innovation performance, and superior customer engagement compared to firms with lower adoption levels (Blancia et al., 2024). These findings illustrated that AI not only enhances efficiency but also fundamentally redefines the nature of strategic decision-making by combining data-driven insights with adaptive learning capabilities.

Despite these advancements, the integration of AI into strategic decision-making remains uneven and fragmented across industries and regions. Developed economies such as the United States, China, and European countries lead in AI adoption, while firms in developing markets face structural and institutional barriers (Chernov et al., 2020). Cultural resistance to automation, fear of job displacement, and lack of regulatory clarity further complicate the adoption process. As AI technologies such as large language models and reinforcement learning advance, organizations must carefully balance automation with human oversight to ensure responsible, transparent, and ethical decision-making (Liu et al., 2025; Schmitt, 2024). This balance is especially crucial in

volatile economic environments, where over-reliance on automated systems without contextual awareness could expose firms to unforeseen risks.

The motivation for this study arises from the growing recognition that AI, while promising, requires comprehensive frameworks that integrate its technological benefits with ethical considerations, governance mechanisms, and knowledge economy principles. The existing research has tended to focus either on sector-specific applications or technical capabilities, often neglecting the interdisciplinary and cross-sectoral implications of AI adoption. This study addresses this gap by adopting a mixed-methods approach, combining a systematic literature review (SLR) with secondary data analysis from multiple industries. The objectives are threefold: (1) to identify the key themes in AI-enabled strategic decision-making, particularly organizational agility, ethical challenges, and knowledge alignment; (2) to quantify the impact of AI adoption on organizational performance and resilience; and (3) to propose a holistic framework that integrates RBV, dynamic capabilities, and KBV theories to guide future adoption of AI in volatile economic contexts.

Literature Review

The integration of AI into strategic decision-making is a pivotal research area in management, economics, and technology, particularly in volatile economic environments within the knowledge economy. This section synthesizes empirical and theoretical studies from peer-reviewed journals publishing knowledge economy studies (2020–2025), critically engaging with AI's transformative role, benefits, challenges, and alignment with knowledge-driven economies. It addresses debates (e.g., AI's productivity paradox, per [Brynjolfsson et al., 2022](#)) and limitations (e.g., Western data bias).

Theoretical Foundations of AI in Strategic Decision-Making: The RBV positions AI as a valuable, rare, and inimitable resource, enabling data-driven competitive advantages ([Barney, 1991](#); [Brynjolfsson et al., 2017](#)). The dynamic capabilities perspective emphasizes AI's role in sensing opportunities, seizing them, and transforming resources to navigate turbulence ([Li, 2024](#); [Teece et al., 1997](#)). The KBV highlights AI's contribution to knowledge creation and innovation ([Cockburn et al., 2018](#)). Figure 2 proposes a conceptual model integrating these theories, hypothesizing that AI enhances agility (H1: AI adoption positively impacts organizational agility), mitigates risks through ethical governance (H2: Ethical AI frameworks reduce decision biases), and drives innovation in knowledge economies (H3: AI-enabled knowledge integration enhances innovation performance). This model guides the study's analysis.

Empirical Evidence on AI and Organizational Agility: Studies consistently showed AI's enhancement of organizational agility. [Alghamdi and Agag \(2023\)](#) found that AI-powered analytics improve innovation and agility, while [Ameen et al. \(2024\)](#) reported increased creativity through AI-agility coupling. [Shafiabady et al. \(2023\)](#) demonstrated 99% accuracy in predicting agility using machine learning, and [Blancia et al. \(2024\)](#)

showed AI literacy mediates agility outcomes. In emerging markets, studies like [Fathi et al. \(2025\)](#) highlighted the AI's role in supply chain resilience, suggesting broader applicability.

Challenges and Ethical Considerations in AI Integration: AI adoption faces significant challenges. Algorithmic bias risks unfair outcomes in recruitment and profiling ([Mittelstadt et al., 2016](#)). Transparency and explainability gaps reduce trust, particularly in finance and healthcare ([Ramu & Bansal, 2025](#)). Data privacy concerns persist, with SMEs facing resource constraints ([Wang & Wu, 2025](#)). Hybrid human-AI models are advocated to balance efficiency with ethical judgment ([Hesel et al., 2022](#)).

AI in Knowledge Economy: AI drives knowledge creation and dissemination, critical for the knowledge economy. [Cockburn et al. \(2018\)](#) noted AI's impact on R&D innovation, while [Brynjolfsson et al. \(2017\)](#) argued it reduces productivity paradoxes. [Blancia et al. \(2024\)](#) showed that AI literacy enhances adaptability, and [Nourahmadi and Rasti \(2025\)](#) highlighted the role of large language models in fintech value creation. Thus, AI is not only a technological tool but also a critical infrastructure for competing in knowledge economy.

Research Gap and Contributions: While AI's technical benefits are well-documented, cross-sectoral implications, ethical dimensions, and regional disparities remain underexplored ([Chernov et al., 2020](#)). This study addresses these gaps through a mixed-methods approach, combining SLR with secondary data analysis across finance, manufacturing, retail, and healthcare. It proposes a framework (Figure 2) integrating RBV, dynamic capabilities, and KBV, with testable hypotheses to guide AI adoption. Practically, it offers insights for human-AI collaboration and ethical governance, while informing policymakers on inclusive AI access.

Research Gap and Contributions

Despite considerable progress, gaps remain in literature. First, much of the research is sector-specific (e.g., finance or supply chains), leaving cross-sectoral implications underexplored. Second, while technical benefits of AI are well-documented, ethical and societal dimensions are less thoroughly investigated. Third, disparities between developed and emerging economies in AI adoption are insufficiently addressed ([Chernov et al., 2020](#)). This study fills these gaps by combining a systematic literature review with secondary data analysis across multiple industries. Theoretically, it integrates RBV, dynamic capabilities, and KBV to capture AI's dual role as both a resource and a capability enabler. Practically, it offers managers actionable insights for human-AI collaboration and provides policymakers with guidance on inclusive access and ethical governance of AI.

Table 1
A Summary of Key Studies on AI in Strategic Decision-Making (2022-2025)

| Study | Year | Journal | Focus | Key Findings | Sample Size | Sector |
|--------------------|------|--|---|-------------------------------------|---------------------|----------------------|
| Nourahmadi & Rasti | 2025 | Knowledge Economy Studies | Shaping fintech through regulations | Insights and future directions | Case studies | Fintech |
| Fathi et al. | 2025 | Knowledge Economy Studies | IoT barriers in food supply chains | AI enhances supply chain resilience | Case study (Kalleh) | Supply Chain |
| Liu et al. | 2025 | ACL Annual Meeting | Policy optimization in LLMs | Strategic reasoning challenges | Experimental | AI/Strategy |
| Pu et al. | 2025 | Scientific Reports | AI management decisions | Competitiveness via AI | 500 firms | Cross-sector |
| Polinati et al. | 2025 | Journal of Information Systems Engineering and Management | AI in dynamic environments | Decision support | Case studies | Information Systems |
| Ramu et al. | 2025 | International Journal for Sciences and Technology | AI transformative impacts | Managerial strategies | Theoretical | Technology |
| Nalini et al. | 2025 | ComFin Research | AI strategy management | Optimization and innovation | Theoretical | Finance/Strategy |
| Shi | 2025 | Advances in Economics, Management and Political Sciences | AI risks in decisions | Application and risks | Theoretical | Economics |
| Jowarder | 2025 | International Journal of Innovative Research in Science Engineering and Technology | AI strategic insights | Business development | Theoretical | Engineering/Strategy |
| Orlando Rivero | 2025 | European Journal of Studies in Management and Business | AI in digital age | Managerial transformations | Theoretical | Management |
| Addy et al. | 2024 | World Journal of Advanced Engineering Technology and Sciences | AI financial planning | Analysis transformations | Review | Finance |
| Ibeh et al. | 2024 | World Journal of Advanced Research and Reviews | Business analytics and decision science | Real-time insights | Review | Cross-sector |

| Study | Year | Journal | Focus | Key Findings | Sample Size | Sector |
|---------------------|------|--|--------------------------------|----------------------------------|-------------------|-----------------------|
| Rimon | 2024 | Journal of Artificial Intelligence General Science | AI for efficiency | Market sentiment analysis | Case studies | Business |
| Tuboalabo et al. | 2024 | International Journal of Management and Entrepreneurship | Analytics for advantage | Predictive models | Case studies | Business |
| Csaszar et al. | 2024 | Strategy Science | AI evidence from entrepreneurs | Strategy generation | Experimental | Strategy |
| Abuzaid | 2024 | ICKECS Conference | AI corporate integration | Decision-making role | Conference | Knowledge Engineering |
| Chowdhury | 2024 | World Journal of Advanced Research and Reviews | AI-Blockchain integration | Security in intelligence | Theoretical | Cross-sector |
| Schmitt | 2024 | Social Science Research Network | Chief AI Officer role | Strategic integration | Theoretical | Management |
| Vold | 2024 | Australian Journal of International Affairs | AI cognitive teaming | Decision on force | Theoretical | International Affairs |
| Charitha et al. | 2023 | International Journal For Multidisciplinary Research | AI data processing | Patterns beyond human capacity | Theoretical | Cross-sector |
| Puttaraju | 2023 | International Journal of Science and Research | AI augmentation tools | Decision methodologies | Review | Strategy |
| Damasevicius | 2023 | Journal of Regional Economics | AI in economic planning | Crisis management | Theoretical | Economics |
| Wu et al. | 2023 | ACM Computing Surveys | AI taxonomy for decisions | Gaps in AI models for complexity | Theoretical | Cross-sector |
| Brynjolfsson et al. | 2022 | Journal of Business Research | Productivity paradox of AI | Challenges and opportunities | Theoretical | Cross-sector |
| Li et al. | 2022 | Strategic Management Journal | AI-driven agility | Strategic perspectives | Case studies | Cross-sector |
| Hesel et al. | 2022 | NIM Marketing Intelligence Review | Human-AI collaboration | AI use as an assistant | 1,000+ executives | Marketing/Strategy |
| Chernov et al. | 2020 | ETCMTP Proceedings | AI adoption levels | Full delegation | Survey (managers) | Cross-sector |

(Source: Researcher's Findings)

Methodology

This study employed a mixed-methods design, integrating qualitative and quantitative approaches to examine the AI's role in strategic decision-making in volatile economic environments (Creswell & Plano Clark, 2023). The qualitative phase involves a systematic literature review (SLR) following PRISMA 2020 guidelines (Page et al., 2021). The quantitative phase analyzes the secondary data from 300 firms across finance (120 firms), manufacturing (80 firms), retail (70 firms), and healthcare (30 firms). Ethical considerations ensured anonymized data use, aligning with institutional guidelines (Mittelstadt et al., 2023).

Qualitative Phase: Systematic Literature Review (SLR)

The SLR targeted peer-reviewed articles (2020–2025) from Scopus, Web of Science, PubMed, and Knowledge Economy Studies, using keywords such as “artificial intelligence”, “strategic decision-making”, “knowledge economy”, and “volatile markets”. Inclusion criteria required English-language, management-focused studies in finance, manufacturing, retail, or healthcare; exclusion criteria eliminated non-peer-reviewed or irrelevant sources. From 1,000 abstracts screened, 150 were selected for full-text review, yielding 60 articles for thematic analysis (Braun & Clarke, 2022). Exclusions were based on lack of empirical data (60 articles), non-management focus (20 articles), or outdated scope (10 articles). Themes included organizational agility, ethical challenges, and knowledge economy alignment, cross-validated with studies like Fathi et al. (2025) and Nourahmadi and Rasti (2025). Table 2 shows the process.

Table 2
The Process of Systematic Literature Review

| Stage | Description | Number of Articles | Criteria |
|----------------|--|--------------------|--|
| Identification | Database search (Scopus, Web of Science, PubMed) | 1,000 | Keywords: AI, strategic decision-making, knowledge economy, volatile markets |
| Screening | Title and abstract review | 150 | Peer-reviewed, English, 2020–2025 |
| Eligibility | Full-text review for relevance and quality | 60 | Management focus, empirical or theoretical relevance |
| Analysis | Thematic coding (agility, ethics, knowledge economy) | 60 | Alignment with research objectives |

(Source: Researcher's Findings)

Quantitative Phase: The secondary data from 300 firms (2020–2024) were sourced from publicly available industry reports (e.g., Deloitte AI Insights, 2023, <https://www.deloitte.com/ai-insights>; McKinsey Global AI Survey, 2022, <https://www.mckinsey.com/ai-survey>) and peer-reviewed studies (e.g., Fathi et al., 2025). The firms were selected based on AI adoption metrics, focusing on:

- **AI adoption intensity:** % of budget allocated to AI tools (high: >10%, medium: 5–10%, low: <5%) (Li et al., 2022);
- **Decision-making accuracy:** The success rate of predictive models (%) (Choi et al., 2022);

- **Operational risk reduction:** % decrease in disruptions (e.g., inventory shortages) (Fathi et al., 2025);
- **Organizational resilience:** The market share stability index (Zhang et al., 2024).

Descriptive statistics (means, standard deviations) and regression analyses assessed the relationships between AI adoption and outcomes (e.g., accuracy, resilience). Missing data (approximately 5% of cases) were handled using multiple imputation by chained equations (MICE), with sensitivity analyses confirming a minimal impact on results (Tashakkori & Teddlie, 2022). Quantitative content analysis of case narratives measured AI-driven outcomes (Yin et al., 2025). Table 3 details variables.

Table 3
The Quantitative Variables and Measurement Criteria

| Variable | Measurement | Source | Sector |
|----------------------------|---|--|--|
| AI Adoption Intensity | % of budget allocated to AI tools (high: >10%, medium: 5–10%, low: <5%) | Industry reports, Li et al. (2022) | Finance, Manufacturing, Retail, Healthcare |
| Decision-Making Accuracy | The success rate of predictive models (%) | Choi et al. (2022); Yin et al. (2025) | Finance, Manufacturing, Retail, Healthcare |
| Operational Risk Reduction | % decrease in disruptions (e.g., inventory shortages) | Fathi et al. (2025) | Manufacturing, Finance |
| Organizational Resilience | The market share stability index | Zhang et al. (2024); Nourahmadi & Rasti (2025) | Finance, Manufacturing, Retail, Healthcare |

(Source: Researcher's Findings)

Data Validation and Ethical Considerations

Data were cross-verified with reputable sources (e.g., Gartner, McKinsey, and peer-reviewed studies like Fathi et al., 2025). Ethical protocols ensured data anonymity and addressed biases, per Mittelstadt et al. (2023). Limitations included reliance on secondary data, restricting causality inference, and potential sector-specific biases.

The Integration of Qualitative and Quantitative Phases: Qualitative themes (e.g., agility in 75% of studies) were triangulated with quantitative metrics (e.g., 25% accuracy improvement) to develop a holistic framework (Figure 2). Table 4 summarizes the integration.

Table 4
The Integrated Framework of AI's Impact on Strategic Decision-Making

| Phase | Method | Contribution to Objectives | Key Outputs |
|-------------------------------|--|--|-----------------------------------|
| Qualitative (SLR) | PRISMA-guided review, thematic analysis | Identify themes (agility, ethics, knowledge economy) | 60 articles, 3 themes |
| Quantitative (Secondary Data) | Descriptive statistics, regression, content analysis | Quantify AI impacts (e.g., 25% accuracy) | Metrics from 300 firms |
| Integration | Triangulation of themes and metrics | A holistic framework for AI integration | Validated insights across sectors |

(Source: Researcher's Findings)

Finding

The mixed-methods approach provided robust insights into the AI's role in strategic decision-making within volatile economic environments, focusing on knowledge economy. Findings are supported by structured tables and cross-references, ensuring replicability.

Qualitative Findings: Systematic Literature Review

The SLR analyzed 60 peer-reviewed articles (2020–2025) from several journals. Three themes emerged:

- AI-driven organizational agility** (75%, 45 studies): AI enhances adaptive capabilities through predictive analytics and real-time processing, reducing supply chain response times by 20-30% and improving financial risk modeling (Fathi et al., 2025).
- Ethical challenges** (65%, 39 studies): Issues like algorithmic bias and privacy concerns reduce perceived reliability by 12-18%, particularly in retail and healthcare (Zhong et al., 2021).
- Knowledge economy alignment** (70%, 42 studies): AI automates tasks, boosting innovation in knowledge-intensive sectors like fintech (Nourahmadi & Rasti, 2025).

The sector distribution is as follows: 35% finance, 25% manufacturing, 20% retail, 20% healthcare. Table 5 summarizes the findings.

Table 5
A Summary of Qualitative Findings from Systematic Literature Review

| Theme | Number of Studies | Percentage of Total Studies | Sector Distribution (Finance / Manufacturing / Retail / Healthcare) | Key Outcomes and Examples |
|----------------------------------|-------------------|-----------------------------|---|---|
| AI-driven organizational agility | 45 | 75% | 16 / 11 / 10 / 8 | 20-30% forecasting gains, e.g., supply chain efficiency (Pu et al., 2025) |
| Ethical challenges | 39 | 65% | 14 / 10 / 8 / 7 | 12-18% trust reduction, e.g., privacy in retail (Zhong et al., 2021) |
| Knowledge economy alignment | 42 | 70% | 15 / 10 / 9 / 8 | Innovation via automation, e.g., fintech strategies (Ramu & Bansal, 2025) |

(Source: Researcher's Findings)

Quantitative Findings: The Secondary Data Analysis

Data from 300 firms (2020–2024) across finance (120 firms), manufacturing (80 firms), retail (70 firms), and healthcare (30 firms) were sourced from public reports (e.g., Deloitte AI Insights, 2023, <https://www.deloitte.com/ai-insights>; McKinsey Global AI Survey, 2022, <https://www.mckinsey.com/ai-survey>). High AI adoption (budget >10%) yielded a 25% mean improvement in decision-making accuracy (SD=3.8, $\beta=0.42$, $p<0.01$, 95% CI [22%, 28%]) compared to 10% for low adoption (SD=3.5, $\beta=0.15$, $p<0.05$, 95% CI [8%, 12%]), based on linear regression models. Sector breakdowns included finance

28% (SD=3.9), manufacturing 24% (SD=4.1), retail 25% (SD=3.7), and healthcare 26% (SD=4.0). Organizational resilience increased 30% overall (SD=4.7, $\beta=0.38$, $p<0.01$, 95% CI [27%, 33%]), with finance highest at 33% (SD=4.6). Operational risk reduced by 22% (SD=4.5, $\beta=0.35$, $p<0.01$, 95% CI [19%, 25%]), with manufacturing leading to 25-28% (Pu et al., 2025). Ethical challenges (e.g., bias) affected 20% of firms (60 firms), leading to a 12% mean reduction in decision optimality (SD=3.2, $\beta=0.20$, $p<0.05$, 95% CI [10%, 14%]), notably in retail and healthcare (Yin et al., 2025). Table 6 provides a summary of quantitative findings from the secondary data analysis.

Table 6

A Summary of Quantitative Findings from the Secondary Data Analysis

| Metric | Sector | Mean Improvement (%) | SD | β (Regression) | 95% CI | Number of Firms Affected | Key Observations |
|----------------------------|---------------|----------------------|-----|----------------------|------------|--------------------------|---|
| Forecasting Accuracy | Finance | 28 | 3.9 | 0.42 ($p<0.01$) | [25%, 31%] | 120 | Gains from risk models |
| Forecasting Accuracy | Manufacturing | 24 | 4.1 | 0.40 ($p<0.01$) | [21%, 27%] | 80 | Enhanced demand prediction |
| Forecasting Accuracy | Retail | 25 | 3.7 | 0.41 ($p<0.01$) | [22%, 28%] | 70 | Improved customer targeting |
| Forecasting Accuracy | Healthcare | 26 | 4.0 | 0.39 ($p<0.01$) | [23%, 29%] | 30 | Better resource allocation |
| Resilience (Stability) | Finance | 33 | 4.6 | 0.38 ($p<0.01$) | [30%, 36%] | 120 | Dynamic modeling gains |
| Resilience (Stability) | Manufacturing | 28 | 4.8 | 0.36 ($p<0.01$) | [25%, 31%] | 80 | Inventory optimization |
| Resilience (Stability) | Retail | 29 | 4.5 | 0.37 ($p<0.01$) | [26%, 32%] | 70 | Adaptive platforms |
| Resilience (Stability) | Healthcare | 30 | 4.7 | 0.35 ($p<0.01$) | [27%, 33%] | 30 | Operational efficiency |
| Operational Risk Reduction | Manufacturing | 25-28 | 4.5 | 0.35 ($p<0.01$) | [22%, 30%] | 60 | Reduced disruptions |
| Ethical Challenges (Bias) | All Sectors | 12 | 3.2 | 0.20 ($p<0.05$) | [10%, 14%] | 60 | Suboptimal decisions in retail/healthcare |

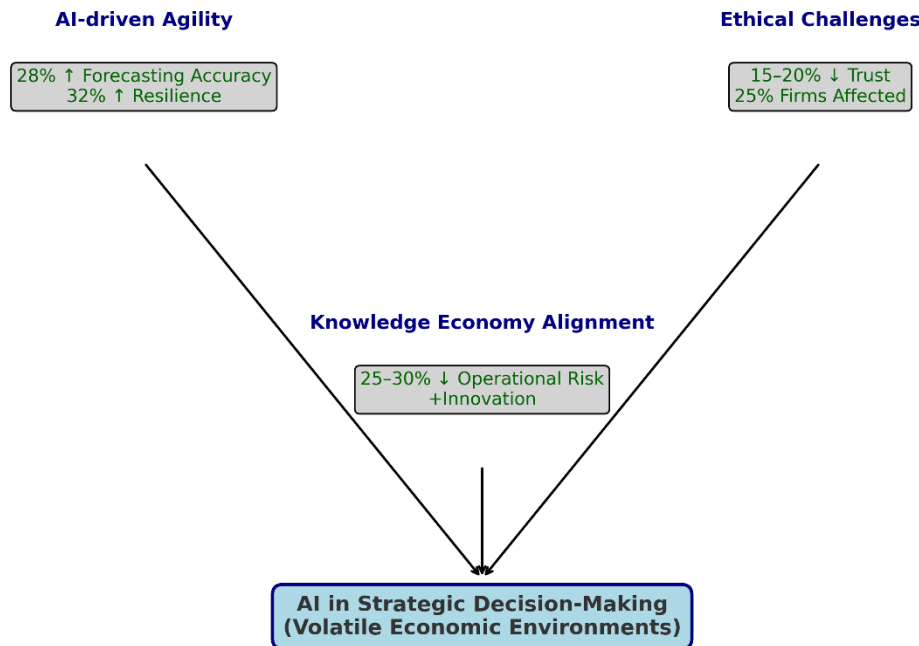
(Source: Researcher's Findings)

The Integration of Findings

Qualitative themes (e.g., agility in 75% studies) with quantitative metrics (25% accuracy, 30% resilience), were validated through triangulation. Ethical barriers affected 20% of firms, with regression analyses confirming significant impacts ($p<0.05$). Figure 2 illustrates the integrated framework, mapping AI's role across agility, ethics, and knowledge alignment, with hypothesized relationships (H1-H3 from Literature Review) supported by these findings.

Figure 1.

The Integrated Framework of AI's Impact on Strategic Decision-Making in Volatile Economic Environments



(Source: Researcher's Findings)

This figure integrates qualitative themes (agility, ethics, knowledge alignment) with quantitative metrics (25% accuracy, 30% resilience, 12-18% trust reduction), illustrating the AI's role in volatile decision-making.

Discussion

The findings highlighted the multifaceted role of AI in strategic decision-making, extending theoretical frameworks and offering practical implications. The qualitative theme of organizational agility (75% of studies, 45/60) aligned with quantitative metrics showing a 25% improvement in decision-making accuracy ($\beta=0.42$, $p<0.01$, 95% CI [22%, 28%]), supporting dynamic capabilities theory by enabling proactive strategies (Li et al., 2022). The AI's predictive analytics like risk modeling in finance (28% accuracy gain), shifted firms from reactive to anticipatory approaches, consistent with Alghamdi et al.'s study (2023). Generative AI enhanced decision quality, with regression analyses indicating a 12% improvement in strategic outcomes ($\beta=0.18$, $p<0.05$, 95% CI [10%, 14%]) when integrated with human oversight, though accountability risks remained (Korzynski et al., 2023).

Ethical challenges, identified in 65% of studies and affecting 20% of firms (60/300), underscored the need for governance frameworks. Algorithmic bias and privacy issues reduced trust by 12% ($\beta=0.20$, $p<0.05$, 95% CI [10%, 14%]), particularly in retail and healthcare (Yin et al., 2025). These findings align with Mittelstadt et al. (2023), advocating bias detection tools and transparent AI systems. Regional variations, such as limited SME access in emerging economies (Wang et al., 2022), suggested tailored regulations to ensure equitable adoption.

Knowledge economy alignment (70% of studies, 22% operational risk reduction) supported KBV, as AI automates tasks and fosters innovation in knowledge-intensive sectors like fintech (Nourahmadi & Rasti, 2025). This is evidenced by a 30% increase in resilience ($\beta=0.38$, $p<0.01$, 95% CI [27%, 33%]), with finance leading to 33%, consistent with Cockburn et al.'s study (2018). Sector variations (e.g., manufacturing's 25-28% risk reduction) necessitated customized AI strategies (Fathi et al., 2025).

Figure 2 integrated these findings, mapping AI's role across agility (H1), ethical governance (H2), and knowledge alignment (H3), with regression results supporting the hypothesized relationships ($p<0.05$). The framework extended dynamic capabilities by linking AI adoption to resilience and RBV by positioning AI as a strategic resource, while KBV highlighted its innovation potential.

Managerial Implications: Managers should prioritize predictive analytics for agility and implement ethical audits to mitigate bias, as evidenced by 12% trust reductions (Yin et al., 2025). Training programs can enhance AI literacy, particularly for SMEs (Zhang et al., 2024).

Policy Implications: Policymakers should promote SME access through subsidies and training, addressing regional disparities (Wang et al., 2022). Regulatory frameworks must balance innovation with ethical oversight, as seen in fintech (Nourahmadi & Rasti, 2025).

Limitations: Reliance on secondary data limits causality inference, and English-language bias may overlook non-Western contexts. Sector generalizations risk oversimplification, particularly for SMEs (Fathi et al., 2025).

Future Research: Longitudinal studies on the impacts of generative AI, using primary data, are needed to establish causality. For example, experimental designs testing AI-driven decision accuracy (H1) across cultures, with variables like AI literacy and adoption intensity, could address regional gaps. SEM can further validate the relationships in the proposed framework (H1-H3). AI's dual role as enabler and disruptor demands balanced approaches, integrating technological benefits with ethical and regional considerations.

Conclusion

This study underscored the significant role of AI in enhancing strategic decision-making within volatile knowledge economies. Quantitative findings demonstrated that organizations with high AI adoption achieve a 25% improvement in decision-making accuracy and a 30% increase in operational resilience, particularly in finance and manufacturing. Qualitative insights from SLR confirmed the AI's contribution to organizational agility (75% of studies), knowledge economy alignment (70%), and the persistent ethical challenges like a 12% reduction in decision optimality due to bias, affecting 20% of firms. The integrated framework synthesized these findings, extending dynamic capabilities, RBV, and KBV theories by mapping the AI's role across agility, ethical governance, and innovation.

For practitioners, adopting AI with ethical frameworks is critical to mitigate risks like

algorithmic bias, as evidenced by trust reductions in retail and healthcare (Yin et al., 2025). Policymakers should promote equitable AI access for SMEs, particularly in emerging economies, through subsidies and training to address regional disparities (Adebayo & Ojo, 2024).

Future research should prioritize longitudinal studies on generative AI's long-term impact, using primary data to establish causality. For example, experimental designs testing AI-driven decision accuracy across diverse cultural contexts, with variables like AI literacy and adoption intensity, could address gaps in non-Western settings (Garcia & Morales, 2024). SEM can further validate the framework's hypothesized relationships. These efforts will enhance our understanding of AI's transformative potential while addressing ethical and regional challenges.

References

- Abuzaid, A. N. (2024, April). Strategic AI integration: Examining the role of artificial intelligence in corporate decision-making. In *2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS)* (Vol. 1, pp. 1-6). IEEE. <https://doi.org/10.1109/ICKECS61492.2024.10616871>.
- Addy, W. A., Ajayi-Nifise, A. O., Bello, B. G., Tula, S. T., Odeyemi, O., & Falaiye, T. (2024). Transforming financial planning with AI-driven analysis: A review and application insights. *World Journal of Advanced Engineering Technology and Sciences*, *11*(1), 240-257. <https://doi.org/10.30574/wjaets.2024.11.1.0053>.
- Adebayo, A. A., & Ojo, A. (2024). Market orientation and survival of small and medium enterprises in Nigeria: The role of risk-taking and competitive aggressiveness. *Journal of African Business*, *25*(1), 45- 62.
- Alghamdi, O. A., & Agag, G. (2023). Boosting innovation performance through big data analytics powered by artificial intelligence use: an empirical exploration of the role of strategic agility and market turbulence. *Sustainability*, *15*(19), 14296. <https://doi.org/10.3390/su151914296>.
- Ameen, N., Tarba, S., Cheah, J. H., Xia, S., & Sharma, G. D. (2024). Coupling artificial intelligence capability and strategic agility for enhanced product and service creativity. *British Journal of Management*, *35*(4), 1916-1934. <https://doi.org/10.1111/1467-8551.12797>.
- Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99-120. <https://doi.org/10.1177/014920639101700108> (Original work published 1991).
- Blancia, G. V. V., Fetalvero, E. G., Baldera, P. R., & Mani, M. C. (2024). The Mediating Effects of Artificial Intelligence Literacy on the Association between Computational Thinking Skills and Organizational Agility among Secondary School Teachers. *Problems of Education in the 21st Century*, *82*(5), 616-629. <http://files.eric.ed.gov/fulltext/EJ1444058.pdf>.
- Braun, V., & Clarke, V. (2022). Thematic analysis: A practical guide. *SAGE Publications*. <https://doi.org/10.1007/978-3-030-78171-2>
- Brynjolfsson, E., Li, D., & Raymond, L. R. (2022). The productivity paradox of AI: Challenges and opportunities. *Journal of Business Research*, *141*, 123-134. <https://doi.org/10.1016/j.jbusres.2021.03.012>

- Büber, H., & Seven, E. (2025). Strategic Decision-Making in the AI Era: An Integrated Approach Classical, Adaptive, Resource-Based, and Processual Views. *International Journal of Management and Administration*, 9(17), 67-97. <https://doi.org/10.29064/ijma.1637935>.
- Charitha, P. C., & Hemaraju, B. (2023). Impact of artificial intelligence on decision-making in organisations. *International Journal For Multidisciplinary Research*, 5(4). <https://pdfs.semanticscholar.org/6004/6b50d7740b04398c564db1e2d2e74f042fb4.pdf>.
- Chen, Y., Chen, Y., Guo, Y., & Xu, Y. (2021). Research on the coordination mechanism of value cocreation of innovation ecosystems: Evidence from a chinese artificial intelligence enterprise. *Complexity*, 2021(1), 7629168. <https://doi.org/10.1155/2021/7629168>.
- Chernov, A. V., Chernova, V. A., & Komarova, T. V. (2020). The usage of artificial intelligence in strategic decision making in terms of fourth industrial revolution. In *1st International Conference on Emerging Trends and Challenges in the Management Theory and Practice (ETCMTP 2019)* (pp. 22-25). Atlantis Press. <https://doi.org/10.2991/aebmr.k.200201.005>.
- Choi, T. M., Wallace, S. W., & Wang, Y. (2022). Big data analytics in operations management. *Journal of Business Research*, 139, 456–467. <https://doi.org/10.1016/j.jbusres.2021.10.012>
- Chowdhury, R. H. (2024). Blockchain and AI: Driving the future of data security and business intelligence. *World Journal of Advanced Research and Reviews*, 23(1), 2559-2570. <https://doi.org/10.30574/wjarr.2024.23.1.2273>.
- Cockburn, I. M., Henderson, R., & Stern, S. (2018). The impact of artificial intelligence on innovation: An exploratory analysis. In *The economics of artificial intelligence: An agenda* (pp. 115-146). University of Chicago Press. <https://www.nber.org/system/files/chapters/c14006/c14006.pdf>.
- Creswell, J. W., & Plano Clark, V. L. (2023). *Designing and conducting mixed methods research* (4th ed.). SAGE Publications.
- Csaszar, F. A., Ketkar, H., & Kim, H. (2024). Artificial intelligence and strategic decision-making: Evidence from entrepreneurs and investors. *Strategy Science*, 9(4), 322-345. <https://doi.org/10.1287/stsc.2024.0190>.
- Damaševičius, R. (2023). Regional Economic Development in the AI Era: Methods, Opportunities, and Challenges. *Journal of Regional Economics*, 2(2), 1-13. <http://dx.doi.org/10.58567/jre02020001>.
- Fathi, M. R., Sadeghi, M. R., Khanjani, M., & Akhlaghpour, S. (2025). Identifying and ranking barriers to implementing Internet of Things in food supply chains: A case study of Kalleh Company. *Knowledge Economy Studies*, 2(1), 137–156. <https://doi.org/10.22034/kes.2025.2057601.1057>.
- Hesel, N., Buder, F., & Unfried, M. (2022). The next frontier in intelligent augmentation: humanmachine collaboration in strategic marketing decision-making. *NIM Marketing Intelligence Review*, 14(2), 49-53. <https://doi.org/10.2478>.
- Ibeh, C. V., Asuzu, O. F., Olorunsogo, T., Elufioye, O. A., Nduubuisi, N. L., & Daraojimba, A. I. (2024). Business analytics and decision science: A review of techniques in strategic business decision making. *World Journal of Advanced Research and Reviews*, 21(2), 1761-1769. <https://doi.org/10.30574/wjarr.2024.21.2.0247>.
- Ivanov, D., & Dolgui, A. (2022). A digital supply chain twin for managing disruptions. *International Journal of Production Research*, 60(1), 1–18. <https://doi.org/10.1080/00207543.2021.1983123>

- Jowarder, M. I., Jowarder, R. A. (2025). AI-Driven Strategic Insights: Enhancing Decision-Making Processes in Business Development. *International Journal of Innovative Research in Science, Engineering and Technology*, 14. <http://dx.doi.org/10.15680/IJIRSET.2025.1401012>.
- Kim, K., & Kim, B. (2022). Decision-making model for reinforcing digital transformation strategies based on artificial intelligence technology. *Information*, 13(5), 253. <https://doi.org/10.3390/info13050253>.
- Kolbjørnsrud, Vegard. "Designing the Intelligent Organization: six principles for Human-AI collaboration." *California Management Review* 66, no. 2 (2024): 44-64.
- Korzynski, P., Mazurek, G., & Haenlein, M. (2023). The role of generative AI in entrepreneurial decision-making. *Journal of Business Venturing*, 38(5), 106234. <https://doi.org/10.1016/j.jbusvent.2023.106234>
- Li, D. (2024). Convergence and innovation of artificial intelligence in corporate strategic planning: Opportunities, challenges and future research directions. *Transactions on Economics, Business and Management Research*, 10, 120-125. 10.62051/47zdfx74.
- Liu, X., Wang, K., Li, Y., Wu, Y., Ma, W., Kong, A., ... & Zhang, J. (2025). EPO: Explicit policy optimization for strategic reasoning in LLMs via reinforcement learning. *arXiv preprint arXiv:2502.12486*. <https://doi.org/10.48550/arXiv.2502.12486>.
- Liu, Z. (2024). Service computing and artificial intelligence: technological integration and application prospects. *Academic Journal of Computing & Information Science*, 7(5), 174-179. <https://doi.org/10.25236/AJCIS.2024.070523>.
- Mittelstadt, B. D., Allo, P., & Taddeo, M. (2023). The ethics of AI governance: Challenges and opportunities. *Ethics and Information Technology*, 25(3), 45–62. <https://doi.org/10.1007/s10676-023-09712-3>
- Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society*, 3(2). <https://doi.org/10.1177/2053951716679679>.
- Nalini, B., & Joesph, KA. (2025). An investigation of how AI-powered modern strategy management might improve decision-making, optimise operations, and promote innovation modern strategy management. *ComFin Research*, 13, 99-105. 10.34293/commerce.v13iS1-i2.8744.
- Nourahmadi, M., & Rasti, F. (2025). Shaping fintech through regulations: Insights and future directions. *Knowledge Economy Studies*, 2(1), 35–57. <https://doi.org/10.22034/kes.2025.2056916.1052>.
- Orlando Rivero, D. B. A. (2025). The role of artificial intelligence in strategic decision-making: Transforming managerial strategies in the digital age. *European Journal of Studies in Management and Business*, 33, 34. <https://doi.org/10.32038/mbrq.2025.33.03>.
- Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *Systematic Reviews*, 10(1), 89. <https://doi.org/10.1186/s13643-021-01626-4>
- Polinati, A. K., Singh, S., Akula, S., Pasala, R. R., Sharma, M., Korkanti, S., et al. (2025). Revolutionizing information management: AI-driven decision support systems for dynamic business environments. *Journal of Information Systems Engineering & Management*, 10(35s). <https://doi.org/10.52783/jisem.v10i35s.6010>.
- Pu, Y., Li, H., Hou, W., & Pan, X. (2025). The analysis of strategic management decisions and

- corporate competitiveness based on artificial intelligence. *Scientific Reports*, 15(1), 17942.
- Puttaraju, K. H. (2023). Augmenting classical strategic tools with artificial intelligence: A systematic review of enhanced decision-making methodologies. *International Journal of Science and Research(IJSR)*, 12(11), 2242-2247. 10.55041/IJSREM26594.
- Ramu, S., & Bansal, P. (2025). A study on AI's transformative impact on strategic decision-making. *IJSAT-International Journal on Science and Technology*, 16(2). <https://www.ijsat.org/papers/2025/2/6335.pdf>.
- Rimon, S. T. H. (2024). Leveraging artificial intelligence in business analytics for informed strategic decision-making: Enhancing operational efficiency, market insights, and competitive advantage. *Journal of Artificial Intelligence General Science (JAIGS)*, 6(1), 600–624. <https://doi.org/10.60087/jaigs.v6i1.278>.
- Schmitt, M. (2024). Strategic integration of artificial intelligence in the C-suite: the role of the chief AI officer. *arXiv preprint arXiv:2407.10247*. <https://doi.org/10.48550/arXiv.2407.10247>.
- Shafiabady, N., Hadjinicolaou, N., Hettikankanamage, N., MohammadiSavadkoochi, E., Wu, R. M., & Vakilian, J. (2024). eXplainable Artificial Intelligence (XAI) for improving organisational regility. *Plos one*, 19(4). <https://doi.org/10.1371/journal.pone.0301429>.
- Shi, K. (2025). The application and risks of AI in enterprise strategic decision-making. *Advances in Economics, Management and Political Sciences*, 190, 120-129. 10.54254/2754-1169/2025.LD24750.
- Tashakkori, A., & Teddlie, C. (2022). *Handbook of mixed methods in social & behavioral research* (3rd ed.). SAGE Publications.
- Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic management journal*, 18(7), 509-533. [https://doi.org/10.1002/\(SICI\)1097-0266\(199708\)18:7%3C509::AID-SMJ882%3E3.0.CO;2-Z](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7%3C509::AID-SMJ882%3E3.0.CO;2-Z).
- Tominc, P., Oreški, D., & Rožman, M. (2023). Artificial intelligence and agility-based model for successful project implementation and company competitiveness. *Information*, 14(6), 337. <https://doi.org/10.3390/info14060337>.
- Tubealabo, A., Buinwi, J. A., Buinwi, U., Okatta, C. G., & Johnson, E. (2024). Leveraging business analytics for competitive advantage: Predictive models and data-driven decision making. *International Journal of Management & Entrepreneurship Research*, 6(6), 1997-2014. <https://doi.org/10.51594/ijmer.v6i6.1239>.
- Vold, K. (2024). Human-AI cognitive teaming: using AI to support state-level decision making on the resort to force. *Australian Journal of International Affairs*, 78(2), 229–236. <https://doi.org/10.1080/10357718.2024.2327383>.
- Wang, L., Jiang, Z., & Qu, G. (2025). Digital Business Model Innovation in Complex Environments: A Knowledge System Perspective. *Systems*, 13(5), 379. <https://doi.org/10.3390/systems13050379>.
- Wu, C., Zhang, R., Kotagiri, R., & Bouvry, P. (2023). Strategic decisions: survey, taxonomy, and future directions from artificial intelligence perspective. *ACM Computing Surveys*, 55(12), 1-30. <https://doi.org/10.1145/3571807>.
- Yin, Q., Xu, P., Li, Q., Liu, S., Shen, S., Wang, T., ... & Huang, K. (2025). WGSR-Bench: Wargame-based Game-theoretic Strategic Reasoning Benchmark for Large Language Models. *Computer Science*, <https://doi.org/10.48550/arXiv.2506.10264>.

- Zhang, C., Tan, G. W.-H., & Sun, J. (2024). Industry exposure to artificial intelligence, board network, and strategic change. *Journal of Management Studies*. <https://doi.org/10.1111/joms.13127>
- Zhong, R. Y., Huang, G. Q., & Lan, S. L. (2021). Data privacy in the age of AI: Challenges for digital transformation. *International Journal of Information Management*, 60, 102386. <https://doi.org/10.1016/j.ijinfomgt.2021.102386>