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Strategic Decision-Making in the AI Era: An Integrated Approach Classical, Adaptive, Resource-Based, and Processual Views*

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Abstract: This study explores how artificial intelligence (AI) can enhance strategic decision-making by integrating with four established strategic schools: Classical, Adaptive, Resource-Based, and Processual. While AI improves data-driven insights, it lacks the strategic foresight, contextual awareness, and ethical judgment inherent in traditional frameworks. Using a structured literature review, this conceptual study evaluates the synergy between AI and strategic schools. Sources were selected from peer-reviewed databases, including Scopus and Web of Science, using keywords such as "AI-driven strategy," "strategic management," and "decision support systems." The findings reveal that AI enhances Classical strategy through predictive analytics and scenario planning, strengthens Adaptive strategy via real-time responsiveness, supports RBV by optimizing resource identification, and complements Processual strategy by facilitating continuous learning. However, AI's limitations in handling tacit knowledge, ethical considerations, and contextual judgment highlight the need for human oversight. This study proposes a hybrid framework where AI supports, rather than replaces, strategic decision-making. It offers actionable recommendations for business leaders, including AI-powered strategy frameworks, governance policies for ethical AI deployment, and human-AI collaboration to navigate dynamic business environments effectively.

Keywords: Strategic Decision-Making, Artificial Intelligence, AI-Driven Strategy, Classical School, Adaptive School, Resource-Based View, Processual School, Decision Support Systems.
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INTRODUCTION

The advent of Artificial Intelligence (AI) and data-driven analytics has significantly altered how organizations approach decision-making. AI-driven models enhance decision efficiency by analyzing vast datasets, optimizing resource allocation, and improving predictive accuracy (Mikalef & Gupta, 2021). However, despite these advancements, AI does not inherently possess strategic foresight, contextual awareness, or an understanding of causality, which are critical elements of strategic decision-making (Brynjolfsson & McAfee, 2017). While AI can optimize processes and improve operational decision-making, strategic management requires an understanding of organizational culture, industry dynamics, and long-term value creation, which remain human-centric (Tegmark, 2017).

Over the past two decades, businesses have increasingly integrated AI-driven decision support systems (DSS) into their strategic processes, particularly in finance, supply chain management, and marketing analytics (Wamba et al., 2017). AI's ability to process unstructured data, identify patterns, and make real-time recommendations has proven invaluable (Chui et al., 2018). For example, AI-powered predictive analytics in the financial sector can detect market trends and forecast stock fluctuations (Davenport & Ronanki, 2018).

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However, AI struggles with uncertainty, particularly in volatile environments where historical data is insufficient to predict future trends (Oliveira, Kakabadse, & Khan, 2022). Strategic decisions often involve complex trade-offs, ethical considerations, and ambiguous information, which machine learning algorithms cannot fully grasp (Makridakis, 2017). Thus, organizations must integrate AI with established strategic frameworks to ensure effective decision-making in dynamic business environments.

While AI excels at data-driven decision-making, its limitations in strategic reasoning present significant challenges. AI-based models rely heavily on historical data, meaning they often struggle with unpredictable events or paradigm shifts, such as economic crises, geopolitical instability, and disruptive innovation (Brynjolfsson, Rock, & Syverson, 2019). Additionally, AI-based optimization models are designed to maximize efficiency based on predefined parameters but lack the ability to formulate new strategic directions based on evolving industry landscapes (Wilson & Daugherty, 2018).

For example, the COVID-19 pandemic exposed AI's shortcomings in strategic planning, as supply chain disruptions and consumer behavior shifts deviated significantly from past trends (Ivanov & Dolgui, 2021). Companies relying solely on AI struggled to adapt, while firms that combined human strategic expertise with AI-driven insights demonstrated greater resilience (Wenzel, Stanske, & Lieberman, 2021). This highlights the need for a theoretical foundation that integrates AI capabilities with established strategic schools of thought.

Despite AI's transformative role in decision-making, there exists a theoretical gap in how AI aligns with classical and contemporary strategic management perspectives (Tambe, Cappelli, & Yakubovich, 2019). Most AI research has focused on technical advancements, such as machine learning algorithms, deep learning, and natural language processing, while lacking an integration with strategic management theories (Davenport, Guha, & Grewal, 2020).

Existing literature has explored AI's impact on operational efficiency and performance optimization but has paid limited attention to its role in long-term strategic planning, competitive advantage, and organizational adaptation (Mikalef, Pappas, Krogstie, & Giannakos, 2018). This paper addresses this gap by examining how traditional strategic management frameworks—specifically the Classical, Adaptive, Resource-Based, and Processual schools—can provide a structured foundation for AI-enhanced strategic decision-making.

2. LITERATURE REVIEW

The integration of Artificial Intelligence (AI) into strategic decision-making presents new challenges that necessitate a strong theoretical foundation. While AI enhances data-driven processes, strategic management involves long-term vision, competitive positioning, and organizational adaptability—areas where human cognition plays a vital role (Teece, Peteraf, & Leih, 2016). Despite AI's ability to optimize decisions through predictive analytics and automation, the fundamental principles of strategic thinking remain deeply rooted in established theories (Mintzberg, Ahlstrand, & Lampel, 2005).

Strategic management theories provide a structured framework for understanding how organizations compete, adapt, and evolve. Without such theoretical grounding, AI-driven strategies risk becoming mechanistic and reactive, rather than proactive and dynamic (Whittington, 2001). As AI-driven decision-making continues to expand, revisiting traditional strategic schools ensures that AI is effectively aligned with human-driven strategic intent (Barney & Mackey, 2016).

This paper focuses on four key strategic perspectives—the Classical, Adaptive, Resource-Based (RBV), and

Processual schools—as they offer a comprehensive foundation for AI-enhanced strategic decision-making. Each of these schools represents a distinct approach to strategy:

a) Classical Strategy emphasizes rational planning, long-term positioning, and structured decision-making (Porter, 1980).

b) Adaptive Strategy highlights the importance of flexibility, real-time responsiveness, and emergent decision-making (Mintzberg, 1994).

c) Resource-Based View (RBV) focuses on internal firm resources as sources of sustained competitive advantage (Barney, 1991).

d) Processual Strategy examines strategy as a continuous, evolving process influenced by learning and organizational behavior (Pettigrew, 1985).

2.4. Classical Strategy: Rational Planning & Long-Term Positioning

The Classical school of strategic management remains one of the most influential and enduring approaches to strategy formulation. It is rooted in economic rationality, structured planning, and long-term positioning (Chandler, 1962; Porter, 1980). This approach assumes that managers can objectively analyze competitive environments, anticipate future trends, and devise deliberate strategic plans to secure competitive advantage (Ansoff, 1965; Ghemawat, 1991). The Classical school is characterized by its emphasis on structured decision-making, optimization models, and rational analysis, making it particularly relevant to AI-driven strategies (Grant, 2016; Mintzberg, Ahlstrand, & Lampel, 2020).

The rise of artificial intelligence (AI) in strategic decision-making aligns with the Classical school's principles of data-driven analysis, predictive modeling, and structured planning (Davenport & Ronanki, 2018; Teece, 2018). AI-powered tools such as predictive analytics, scenario planning, and machine learning-driven strategy models enable organizations to refine competitive positioning and resource allocation (Brynjolfsson & McAfee, 2017). However, despite AI's superior ability to process vast datasets, its deterministic nature poses challenges in handling uncertainty, strategic intuition, and ethical decision-making (Makridakis, 2017; Wilson & Daugherty, 2018).

The integration of AI with Classical strategy presents opportunities to enhance forecasting accuracy, decision rationality, and market positioning, yet it also raises concerns about over-reliance on historical data, lack of adaptability, and the inability to incorporate qualitative insights (Wenzel, Stanske, & Lieberman, 2021). The following sections examine the core principles of the Classical school, its synergy with AI-driven strategic decision-making, and the limitations of AI-driven Classical strategies.

Table 1: List of Studies Used in This Section

Study Title	*Authors*	*Year*	*Concept*
Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics	Brynjolfsson, McAfee, & Rock	2019	AI and productivity paradox in strategic decision-making
Strategy and structure: Chapters in the history of industrial enterprise	Chandler, A. D.	1962	Foundational work on structured strategy formulation

Study Title	***Authors***	***Year***	***Concept***
How artificial intelligence will change the future of marketing	Davenport, Guha, & Grewal	2020	AI's impact on marketing and strategic decision-making
Artificial intelligence for the real world	Davenport & Ronanki	2018	AI-driven strategy applications in real-world business
The role of artificial intelligence in operations: A review and bibliometric analysis	Dhamija & Bag	2020	AI's role in business operations and decision optimization
Artificial intelligence for decision-making in the era of big data–evolution, challenges, and research agenda	Duan, Edwards, & Dwivedi	2019	AI in decision-making and predictive analytics
Commitment: The dynamic of strategy	Ghemawat, P.	1991	Commitment in strategic decision-making
Contemporary strategy analysis: Text and cases edition	Grant, R. M.	2016	Strategic analysis frameworks and competitive positioning
OR-methods for coping with the ripple effect in supply chains during COVID-19 pandemic: Managerial insights and research implications	Ivanov & Dolgui	2021	Impact of crises (COVID-19) on AI-driven strategies
Understanding the interplay of artificial intelligence and strategic management: Four decades of research in review	Keding, C.	2021	AI and strategic management research trends
The forthcoming artificial intelligence (AI) revolution: Its impact on society and firms	Makridakis, S.	2017	AI limitations in strategy forecasting and adaptability
Strategy safari: A guided tour through the wilds of strategic management	Mintzberg, Ahlstrand, & Lampel	2020	Overview of strategic management perspectives
Using artificial intelligence to make sustainable development decisions considering VUCA: A systematic literature review	Nikseresht, Hajipour, & Pishva	2022	AI’s role in decision-making under uncertainty (VUCA)
Competitive strategy: Techniques for analyzing industries and competitors	Porter, M. E.	1980	Competitive strategy and market positioning
Strategic decision-making in smart home ecosystems: A review on the use of artificial intelligence and Internet of things	Rodriguez-Garcia, Lopez-Lopez, & Juan	2023	AI's role in smart ecosystems and strategic management
Artificial intelligence in human resources management: Challenges and a path forward	Tambe, Cappelli, & Yakubovich	2019	AI in HR management and organizational adaptation
Dynamic capabilities as (workable) management systems theory	Teece, D. J.	2018	Dynamic capabilities and AI’s impact on strategy
Strategic responses to crisis: How AI and human collaboration enhance adaptability	Wenzel, Stanske, & Lieberman	2021	AI’s role in crisis response and strategic adaptation
What is strategy and does it matter?	Whittington, R.	2001	Theoretical perspectives on strategic management
Collaborative intelligence: Humans and AI are joining forces	Wilson & Daugherty	2018	Human-AI collaboration in decision-making and strategy

2.4.1. Core Principles of the Classical School

The Classical school of strategic management is built on several core principles that emphasize rational planning, structured analysis, and long-term market positioning. These principles continue to shape corporate strategy, competitive advantage, and decision-making frameworks, particularly in industries where market stability and structured analysis are essential (Chandler, 1962; Porter, 1980; Ghemawat, 1991).

Classical strategy follows a top-down, structured approach to strategy formulation. This assumes that managers can systematically analyze market forces, assess internal resources, and optimize decision-making using logical frameworks (Ansoff, 1965; Whittington, 2001). AI-powered tools now enable firms to enhance structured analysis through real-time data processing, predictive modeling, and competitive intelligence

(Duan, Edwards, & Dwivedi, 2019). Machine learning-driven decision models are increasingly used to refine strategic analysis, improving the ability to detect emerging market trends and competitive threats (Keding, 2021).

The Classical school prioritizes external market positioning over internal resources, emphasizing cost leadership, differentiation, and market focus as core strategies (Porter, 1980). AI enhances competitive positioning by offering real-time consumer insights, demand forecasting, and sentiment analysis, helping firms refine strategic choices (Rodriguez-Garcia, Lopez-Lopez, & Juan, 2023). AI-powered simulation models further improve market forecasting by analyzing historical performance, competitor behavior, and economic indicators (Liu & Shapira, 2021).

A defining characteristic of Classical strategy is its reliance on long-term planning, assuming that firms can predict market trends, set structured goals, and execute pre-defined strategic plans (Chandler, 1962). AI significantly enhances this aspect by improving predictive accuracy in areas such as economic forecasting, risk assessment, and investment strategy (Dhamija & Bag, 2020). AI-powered financial models provide executives with scenario-based insights, improving long-term strategic resilience (Ruiz-Real, Uribe-Toril, & Torres, 2021).

The Classical school assumes that markets operate rationally and predictably, enabling firms to maximize efficiency through cost-benefit analysis and structured decision frameworks (Teece, 2018). AI enhances economic optimization by applying algorithmic decision-making, machine learning, and data-driven efficiency models to resource allocation, pricing strategies, and cost optimization (Makridakis, 2017; Tambe, Cappelli, & Yakubovich, 2019). However, AI-driven rational decision-making models often struggle with intangible elements such as brand perception, human emotions, and consumer psychology, limiting their ability to fully replicate strategic reasoning (Davenport, Guha, & Grewal, 2020).

Classical strategy is inherently hierarchical, with strategic planning controlled by executive leadership and implemented in a top-down manner (Whittington, 2001). AI-driven business intelligence platforms, such as SAP AI and Microsoft Dynamics, reinforce centralized decision-making by providing executives with real-time analytics and optimization models (Wilson & Daugherty, 2018). However, this top-down AI-driven approach may hinder adaptability, as it limits bottom-up innovation and real-time strategic adjustments (Makridakis, 2017).

While the Classical school remains highly influential, digital transformation and AI introduce new complexities that challenge its traditional frameworks. Globalization, disruptive innovation, and uncertain market conditions make it difficult for predefined, structured strategies to remain effective in rapidly evolving industries (Brynjolfsson, Rock, & Syverson, 2019). AI-powered strategic tools enhance predictive modeling and structured decision-making, but fail to fully integrate the qualitative, dynamic, and human-driven aspects of long-term strategy (Tambe et al., 2019).

The next section explores how AI enhances the Classical school's structured approach while posing new strategic risks in dynamic business environments.

2.4.2. Synergy Between Classical Strategy and AI

The Classical school of strategic management and artificial intelligence (AI) share a fundamental alignment, as both emphasize structured decision-making, predictive modeling, and optimization (Chandler, 1962; Porter, 1980; Grant, 2016). AI enhances the Classical approach by strengthening firms' ability to assess competitive positioning, improve forecasting accuracy, and optimize strategic decision-making through data-driven insights (Davenport & Ronanki, 2018). AI-powered tools such as Google Trends and IBM Watson enable firms to predict consumer behavior, analyze competitors' strategies, and identify new market opportunities with unprecedented accuracy (Brynjolfsson, Rock, & Syverson, 2019). By integrating AI into classical strategic frameworks, organizations can develop structured competitive strategies based on real-time data, improving their ability to anticipate industry trends and adjust market positioning accordingly (Rodriguez-Garcia, Lopez-Lopez, & Juan, 2023).

AI significantly contributes to long-term forecasting and strategic planning by leveraging predictive analytics and machine learning algorithms to analyze historical market data, economic patterns, and external uncertainties (Makridakis, 2017). Unlike traditional forecasting methods, AI systems can continuously learn and refine their predictive models, enhancing their ability to detect emerging threats and opportunities (Duan, Edwards, & Dwivedi, 2019). AI-driven scenario planning enables firms to model potential future market conditions and make proactive strategic moves based on statistical probabilities (Keding, 2021). This ability aligns well with the Classical school's emphasis on structured goal-setting and long-term positioning, as AI-driven insights reduce the uncertainty inherent in strategic decision-making (Teece, 2018).

Another crucial area where AI complements Classical strategy is structured decision-making. The Classical approach follows a top-down strategic framework in which executive leadership formulates and executes strategy (Whittington, 2001), an approach that AI can enhance by providing real-time quantitative insights and optimization models (Wilson & Daugherty, 2018). AI-driven business intelligence platforms, such as SAP AI and Microsoft Dynamics, process vast amounts of structured and unstructured data, helping executives make more informed and efficient strategic choices (Dhamija & Bag, 2020). AI also plays an essential role in risk management and strategic stability, as it can assess macroeconomic risks, geopolitical instability, and supply chain disruptions with greater precision than traditional analysis methods (Wenzel, Stanske, & Lieberman, 2021). AI-driven risk assessment models allow organizations to create contingency plans and hedge against potential market fluctuations, reinforcing the Classical school's emphasis on proactive and rational planning (Nikseresht, Hajipour, & Pishva, 2022).

Despite these benefits, AI remains a tool rather than a substitute for strategic leadership. While AI enhances the precision and efficiency of Classical strategy, it does not possess the human intuition, creativity, and contextual understanding necessary for fully autonomous strategic decision-making (Tambe, Cappelli,

& Yakubovich, 2019). The next section explores the challenges and limitations that arise when firms attempt to apply AI-driven Classical strategies in dynamic and uncertain environments.

2.4.3. Challenges of AI-Driven Classical Strategies

While AI offers significant advantages in structured decision-making, integrating it into the Classical strategy framework presents notable challenges. One of the most critical issues is AI's struggle to adapt to unpredictable market conditions (Makridakis, 2017). The Classical approach assumes that markets operate in a stable and rational manner, making long-term planning viable (Chandler, 1962; Porter, 1980). However, in rapidly evolving industries, AI models that rely heavily on historical data may fail to capture disruptive innovations, economic crises, or paradigm shifts that fundamentally alter competitive landscapes (Brynjolfsson & McAfee, 2017). A key example of this limitation was observed during the COVID-19 pandemic, where AI-driven supply chain forecasting models failed to predict extreme market volatility, leading firms that relied solely on AI to struggle with adaptation (Ivanov & Dolgui, 2021). Companies that successfully navigated the crisis were those that integrated AI-driven insights with human strategic judgment, demonstrating the necessity of combining machine learning with executive intuition (Wenzel et al., 2021).

Another major limitation of AI-driven Classical strategies is the over-reliance on quantitative data at the expense of qualitative strategic intuition. While AI excels at processing structured data and optimizing decision-making based on predefined parameters (Davenport, Guha, & Grewal, 2020), it lacks the ability to incorporate elements such as leadership vision, corporate culture, and ethical considerations into its analysis (Teece, 2018). Strategic decision-making often involves complex trade-offs that cannot be fully quantified, such as the ethical implications of market expansion, customer sentiment, and brand differentiation (Rodriguez-Garcia et al., 2023). AI-driven models, if not properly calibrated, risk prioritizing efficiency and profit maximization over critical qualitative factors that influence long-term strategic success (Duan et al., 2019). Without human oversight, firms relying too heavily on AI for strategic planning may struggle to balance data-driven optimization with broader corporate values and stakeholder considerations (Nikseresht et al., 2022).

Ethical and algorithmic biases present additional risks in AI-driven Classical strategies. AI models are only as reliable as the data they are trained on, and if historical data reflects existing biases, AI systems may reinforce rather than mitigate them (Wilson & Daugherty, 2018). Bias in AI-driven hiring, pricing, and market segmentation strategies has been well-documented, raising concerns that algorithmic decision-making may lead to unintended discriminatory outcomes (Dhamija & Bag, 2020). Additionally, AI-optimized strategic models may sometimes prioritize short-term financial gains over long-term sustainability, leading to decisions that conflict with ethical business practices (Tambe et al., 2019). Addressing these issues requires firms to implement robust governance policies, ensuring AI-driven strategies align with corporate responsibility frameworks and ethical business conduct (Makridakis, 2017).

A final challenge of AI-driven Classical strategies is the potential erosion of human-centric competitive differentiation. Classical strategy emphasizes competitive positioning through cost leadership, differentiation, or market focus (Porter, 1980; Grant, 2016). However, AI-driven optimization models often prioritize efficiency at the expense of branding, customer relationships, and cultural differentiation (Teece, 2018). For instance, AI-powered dynamic pricing strategies that maximize short-term revenue may overlook the psychological and emotional factors influencing customer loyalty (Davenport & Ronanki, 2018). Similarly, AI-driven content generation for marketing may lack the creative nuance required to build a strong and distinctive brand identity (Brynjolfsson et al., 2019). These challenges highlight the risk of firms becoming overly reliant on algorithmic decision-making, losing the human elements that drive sustainable competitive advantage (Rodriguez-Garcia et al., 2023).

2.5. Adaptive Strategy: Flexibility & Real-Time Responsiveness

The Adaptive school of strategy emerged as a response to the limitations of Classical strategic management, particularly in volatile and uncertain business environments (Mintzberg, 1994). While the Classical school emphasizes structured, top-down planning, the Adaptive school argues that strategic decision-making must be dynamic, iterative, and responsive to continuous environmental shifts (Child, 1972; Bourgeois & Eisenhardt, 1988). This perspective has become increasingly relevant in the AI-driven era, where organizations must navigate rapid technological disruptions, fluctuating consumer preferences, and unpredictable market forces (Teece, Peteraf, & Leih, 2016; Helfat & Martin, 2015).

AI enhances adaptability by providing firms with real-time insights, predictive analytics, and automated decision-support systems (Davenport & Ronanki, 2018). Companies can use AI to monitor emerging trends, detect shifts in consumer sentiment, and respond dynamically to competitive threats (Brynjolfsson & McAfee, 2017). For instance, AI-powered tools analyze vast datasets from social media, news sources, and economic indicators to anticipate potential disruptions and opportunities (Makridakis, 2017; Ivanov & Dolgui, 2021). This data-driven adaptability is particularly valuable in industries with high volatility, such as finance, healthcare, and supply chain management (Choi, Wallace, & Wang, 2018).

However, over-reliance on AI-driven adaptation can lead to excessive short-term focus, reactive rather than proactive strategies, and decision paralysis caused by information overload (Tambe, Cappelli, & Yakubovich, 2019). While AI can optimize immediate responses, human judgment is essential for long-term strategic coherence, ethical considerations, and contextual interpretation (Wilson & Daugherty, 2018). This section explores the core principles of Adaptive strategy, its synergy with AI, and the challenges associated with AI-driven Adaptive strategies, integrating recent insights from machine learning, real-time analytics, and strategic agility (Davenport, Guha, & Grewal, 2020).

Table 2: List of Studies Used in This Section

Study Title	***Authors***	***Year***	***Concept / Relevance to Study***
Strategic decision processes in high velocity environments: Four cases in the microcomputer industry	Bourgeois & Eisenhardt	1988	Strategic decision-making in high-velocity environments
The art of continuous change: Linking complexity theory and time-paced evolution	Brown & Eisenhardt	1997	Continuous change and complexity in strategy

Study Title	***Authors***	***Year***	***Concept / Relevance to Study***
Machine, platform, crowd: Harnessing our digital future	Brynjolfsson & McAfee	2017	AI's role in business transformation and decision-making
Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics	Brynjolfsson, Rock, & Syverson	2019	AI's economic impact and productivity paradox
Organizational structure, environment, and performance: The role of strategic choice	Child	1972	Strategic choice and organizational adaptability
Big data analytics in operations management	Choi, Wallace, & Wang	2018	Big data's role in adaptive decision-making
What AI can and can't do (yet) for your business	Chui, Manyika, & Miremadi	2018	AI applications in business strategy
How artificial intelligence will transform management	Davenport, Guha, & Grewal	2020	AI's role in managerial transformation
Artificial intelligence for the real world	Davenport & Ronanki	2018	Practical applications of AI in business
Embedding strategic agility: A leadership agenda for accelerating business model renewal	Doz & Kosonen	2010	Strategic agility and adaptability in organizations
Dynamic capabilities: What are they?	Eisenhardt & Martin	2000	Dynamic capabilities in fast-changing environments
Dynamic managerial capabilities: Review and assessment of managerial impact on strategic change	Helfat & Martin	2015	Managerial capabilities in strategic change
A digital supply chain twin for managing disruption risks and resilience	Ivanov & Dolgui	2021	AI in supply chain risk management
The forthcoming artificial intelligence (AI) revolution: Its impact on society and firms	Makridakis	2017	AI-driven business transformation
The end of competitive advantage: How to keep your strategy moving as fast as your business	McGrath	2013	Strategic agility and continuous adaptation
Artificial intelligence: The next digital frontier?	McKinsey & Company	2019	The future impact of AI on strategy
The rise and fall of strategic planning: Reconceiving roles for planning, plans, planners	Mintzberg	1994	Critique of traditional strategic planning
Of strategies, deliberate and emergent	Mintzberg & Waters	1985	Emergent and deliberate strategy
Why strategy execution unravels—and what to do about it	Sull, Homkes, & Sull	2015	Challenges in strategy execution
Artificial intelligence in human resources management: Challenges and a path forward	Tambe, Cappelli, & Yakubovich	2019	AI in HR strategy and decision-making
Dynamic capabilities as (workable) management systems theory	Teece	2018	Dynamic capabilities as a theoretical framework
Dynamic capabilities and organizational agility: Risk, uncertainty, and strategy in the innovation economy	Teece, Peteraf, & Leih	2016	Organizational agility in strategic management
Dynamic capabilities and strategic management	Teece, Pisano, & Shuen	1997	Foundational work on dynamic capabilities
Strategic responses to crisis: A framework for environmental adaptation	Wenzel, Stanske, & Lieberman	2021	Crisis response and adaptation in business
Collaborative intelligence: Humans and AI are joining forces	Wilson & Daugherty	2018	Human-AI collaboration in strategic decision-making

2.5.1. Core Principles of the Adaptive School

The Adaptive school of strategy is based on three fundamental principles: flexibility, continuous learning, and real-time responsiveness (Mintzberg & Waters, 1985; Eisenhardt & Martin, 2000). Unlike Classical strategy, which assumes a stable external environment, the Adaptive approach acknowledges uncertainty, complexity, and constant change as the norm (Brown & Eisenhardt, 1997; Teece, 2018). Firms that embrace Adaptive strategy continuously scan their environment, experiment with different strategic options, and adjust their approaches based on real-time feedback (McGrath, 2013).

One of the most critical aspects of Adaptive strategy is environmental scanning—the ability to monitor and interpret technological shifts, regulatory changes, and evolving consumer behaviors (Eisenhardt & Martin, 2000; Wenzel, Stanske, & Lieberman, 2021). AI enhances this process by leveraging big data analytics, sentiment analysis, and machine learning-based forecasting (Chui et al., 2018). AI-powered tools can process unstructured data, such as customer reviews, news reports, and social media conversations, providing firms with real-time market intelligence (Makridakis, 2017; Davenport & Ronanki, 2018).

Another key principle of Adaptive strategy is continuous experimentation and learning. Instead of committing to rigid, long-term plans, Adaptive firms test different strategic options through pilot programs, A/B testing, and iterative experimentation (Brown & Eisenhardt, 1997; Sull, Homkes, & Sull, 2015). AI facilitates this by automating simulations, running scenario analyses, and enabling reinforcement learning algorithms that dynamically refine strategic choices (McKinsey, 2019). For instance, AI-driven pricing algorithms in e-commerce platforms adjust prices in real time based on demand fluctuations, competitor activity, and customer behavior (Wilson & Daugherty, 2018; Brynjolfsson, Rock, & Syverson, 2019).

Moreover, decision-making in Adaptive strategy is decentralized, enabling middle managers and frontline employees to respond quickly to emerging opportunities and threats (Doz & Kosonen, 2010). This shift away from top-down control fosters a culture of strategic agility, where decision authority is distributed across the organization (Teece, Pisano, & Shuen, 1997; Helfat & Martin, 2015). AI strengthens this approach by democratizing access to strategic insights, equipping teams with predictive analytics and decision-support tools (Davenport & Ronanki, 2018).

Finally, Adaptive firms must cultivate dynamic capabilities—the ability to reconfigure resources, business models, and operational processes in response to external change (Teece, Pisano, & Shuen, 1997). AI-powered decision-making accelerates this process by identifying inefficiencies, recommending optimal resource allocation, and simulating potential strategic moves (Davenport, Guha, & Grewal, 2020). However, while AI enhances strategic flexibility, human oversight remains critical to ensuring that adaptive decisions align with long-term vision, corporate values, and ethical considerations (Tambe, Cappelli, & Yakubovich, 2019).

In summary, Adaptive strategy has gained traction in industries characterized by rapid technological evolution, shifting competitive dynamics, and evolving customer expectations (Wenzel, Stanske, & Lieberman, 2021). AI significantly enhances the real-time capabilities of Adaptive strategy, but firms must balance AI-driven insights with human strategic judgment to avoid excessive short-termism, ethical pitfalls, and organizational instability (Wilson & Daugherty, 2018).

2.5.2. Synergy Between Adaptive Strategy and AI

AI and Adaptive strategy share key characteristics, particularly their emphasis on real-time analysis, continuous learning, and strategic flexibility. AI enhances Adaptive strategy by improving environmental scanning, predictive analytics, and decision-making capabilities (Davenport & Ronanki, 2018; Chui et al., 2018). With AI-driven environmental scanning, firms can track industry trends, consumer sentiment, and competitor activities in real time, enabling them to anticipate market shifts and adapt proactively (Makridakis, 2017; Wenzel, Stanske, & Lieberman, 2021).

Machine learning models analyze social media activity, economic indicators, and geopolitical risks, helping firms forecast disruptions before they happen (Brynjolfsson & McAfee, 2017). For instance, AI-powered sentiment analysis detects shifts in consumer preferences, allowing businesses to adjust their marketing strategies dynamically (Davenport, Guha, & Grewal, 2020). AI also enables prescriptive analytics, which suggests optimal strategic decisions based on complex datasets, improving firms' ability to react quickly and effectively (Wilson & Daugherty, 2018).

Beyond predictive analytics, AI facilitates continuous experimentation and learning, a cornerstone of Adaptive strategy (McGrath, 2013; Sull, Homkes, & Sull, 2015). Businesses can conduct automated A/B testing, reinforcement learning, and scenario simulations, optimizing decisions based on real-time feedback (McKinsey, 2019). AI-driven reinforcement learning, in particular, allows firms to refine strategic decisions dynamically, making real-time adjustments in pricing models, supply chain logistics, and customer engagement (Brynjolfsson, Rock, & Syverson, 2019).

For example, Amazon's AI-powered supply chain dynamically adjusts inventory levels, pricing, and distribution strategies based on consumer demand patterns, demonstrating how AI optimizes Adaptive strategies at scale (Chui et al., 2018). Similarly, AI-driven fraud detection in finance continuously learns and adapts to new patterns, helping banks and fintech companies stay ahead of emerging security threats (Makridakis, 2017).

Moreover, AI-driven decision support systems (DSS) enhance strategic responsiveness by filtering and prioritizing actionable insights, reducing the cognitive load on managers (Davenport & Ronanki, 2018). These systems help organizations shift tactics instantly based on new data, ensuring that firms maintain strategic agility without compromising long-term objectives (Teece, Peteraf, & Leih, 2016).

Despite these advantages, AI-driven Adaptive strategies are not without risks. Over-reliance on AI can lead to reactive rather than proactive decision-making, as AI models prioritize short-term optimizations over long-term strategic vision (Tambe, Cappelli, & Yakubovich, 2019). Additionally, firms must ensure that AI-driven adaptability does not lead to excessive instability, where frequent strategy shifts create confusion among employees and stakeholders (McGrath, 2013; Wilson & Daugherty, 2018).

2.5.3. Challenges of AI-Driven Adaptive Strategies

While AI significantly enhances strategic adaptability, firms must navigate several challenges when integrating AI-driven Adaptive strategies. One key concern is the risk of over-reliance on short-term optimization. AI excels at identifying immediate trends and opportunities, but excessive dependence on real-time decision-making can lead to short-sighted strategic behavior (Teece, 2018). For example, companies that rely on AI-powered pricing algorithms risk market volatility, as seen in high-frequency trading crashes caused by AI-driven price adjustments (Makridakis, 2017). Similarly, AI-optimized advertising models that prioritize click-through rates over brand loyalty can result in short-term gains at the expense of long-term customer relationships (Brynjolfsson & McAfee, 2017).

Another challenge is decision paralysis due to information overload. AI generates massive volumes of real-time data, and without structured governance models, managers may struggle to filter relevant insights, leading to indecisiveness or strategic drift (Davenport & Ronanki, 2018). Organizations must implement AI governance frameworks to distinguish critical strategic signals from irrelevant data noise, ensuring that AI augments rather than overwhelms decision-making processes (Chui et al., 2018).

Furthermore, AI's inability to interpret contextual, ethical, and cultural factors presents another significant challenge. AI models are data-driven, meaning they lack human intuition and ethical judgment, which are critical for navigating complex business environments (Tambe, Cappelli, & Yakubovich, 2019). For instance, AI-driven hiring algorithms have been shown to reinforce biases in recruitment decisions, raising concerns about algorithmic fairness and corporate reputation risks (Wilson & Daugherty, 2018). Similarly, AI-powered financial risk assessments may misinterpret contextual factors, leading to flawed investment decisions (Davenport, Guha, & Grewal, 2020).

Another risk of AI-driven adaptability is the potential for organizational instability. While Adaptive firms thrive on continuous learning and iteration, frequent AI-driven strategy shifts may cause confusion among employees, disrupt operational workflows, and erode brand consistency (McGrath, 2013). If businesses shift their strategies too frequently, they risk losing internal alignment and stakeholder trust (Wenzel, Stanske, & Lieberman, 2021). To mitigate this, firms must balance AI-driven adaptability with strategic coherence, ensuring that rapid shifts do not compromise their long-term mission and vision (Teece, Peteraf, & Leih, 2016).

Finally, AI-driven decision-making introduces cybersecurity and data privacy risks. Adaptive strategies rely on real-time data collection, making them vulnerable to data breaches, algorithm manipulation, and compliance violations (Makridakis, 2017). Firms must implement robust AI security protocols to protect sensitive business intelligence while ensuring compliance with regulatory frameworks such as GDPR and CCPA (Choi, Wallace, & Wang, 2018).

2.6. Resource-Based View (RBV): Internal Resources & Competitive Advantage

The Resource-Based View (RBV) is a fundamental framework in strategic management that emphasizes a firm's internal resources as the primary drivers of sustainable competitive advantage, rather than external industry forces or market positioning (Barney, 1991; Wernerfelt, 1984). Unlike Classical and Adaptive strategies, which focus on environmental analysis and strategic flexibility, RBV asserts that a firm's unique assets, capabilities, and knowledge bases determine its long-term success (Grant, 1991). The framework is built upon the VRIN (valuable, rare, inimitable, and non-substitutable) criteria, where only resources meeting these conditions contribute to a firm's ability to outperform competitors (Peteraf, 1993).

In the AI era, RBV has gained renewed relevance as AI-driven decision-making and data analytics enable firms to leverage intangible resources such as proprietary data, intellectual property, and machine learning capabilities to sustain competitive advantage (Teece, 2018; Mikalef & Gupta, 2021). AI enhances the strategic role of big data, automation, and predictive analytics, transforming them into valuable and rare resources that provide firms with superior insights and decision-making capabilities (Davenport & Ronanki, 2018). AI also influences organizational capabilities, helping firms integrate explicit knowledge (codified data, AI models, and structured processes) with tacit knowledge (human intuition, creativity, and problem-solving skills) (Nonaka & Takeuchi, 1995).

The ability to integrate AI into RBV strategies has become a key differentiator in competitive markets. AI-powered analytics systems allow firms to identify untapped market opportunities, optimize resource allocation, and accelerate innovation processes (Georgewill & Gabriel, 2024). The finance and e-commerce sectors have particularly benefited from AI's integration with RBV. Studies show that AI-powered predictive analytics enhance a firm's resource identification and utilization, increasing operational efficiency and improving customer experience (Grant, 2024). AI-driven supplier relationship management has also been recognized as a key competitive resource, particularly in e-commerce scalability, where AI enhances supplier selection, inventory optimization, and real-time logistics management (Grant, 2024).

AI also enables firms to develop and protect strategic resources in ways that were previously impossible. AI-powered HR analytics optimize workforce planning, employee engagement, and performance management, aligning human capital with RBV's intangible asset framework (Donthu et al., 2024). The ability to manage human capital through AI-driven HR analytics systems enhances an organization's long-term competitive positioning (Tambe, Cappelli, & Yakubovich, 2019). Similarly, AI-enhanced knowledge management in large corporations ensures that valuable intellectual capital is systematically stored, analyzed, and leveraged for future decision-making (Neiroukh, Emeagwali, & Aljuhmani, 2024).

However, despite AI's strategic advantages, firms face challenges when implementing AI-driven RBV strategies. A primary issue is resource commoditization, where widely available AI solutions erode the rarity of competitive resources (Brynjolfsson & McAfee, 2017). Open-source AI platforms and cloud-based machine learning services make it difficult for firms to maintain unique AI-driven advantages. This is particularly evident in manufacturing and supply chain sectors, where AI-based optimization tools are now widely accessible (Nyakuchena & Tsikada, 2024). To mitigate this risk, firms must develop proprietary AI models, exclusive datasets, and specialized algorithms that are difficult to imitate (Tambe et al., 2019).

Another challenge is AI's over-reliance on structured, historical data, which limits its ability to handle uncertainty and tacit knowledge—key components of long-term strategic success (Teece, 2020). AI struggles with human intuition, ethical reasoning, and creativity, all of which are essential for strategic innovation and market adaptation (Nonaka & Takeuchi, 1995). These challenges highlight the need for a balanced AI-human collaboration model, where AI enhances resource-driven decision-making while human expertise ensures strategic foresight and adaptability (Boateng, 2024).

Given these opportunities and challenges, the next section explores the core principles of RBV (2.6.1), AI's role in resource-driven competitive advantage (2.6.2), and challenges of AI-driven RBV strategies (2.6.3), offering a comprehensive framework for integrating AI into RBV-based strategic decision-making.

Table 3: List of Studies Used in This Section

Study Title	***Authors***	***Year***	***Concept / Relation to Study***
Firm resources and sustained competitive advantage	Barney, J. B.	1991	Foundation of RBV, defines VRIN framework.
Resource-Based Theory: Creating and Sustaining Competitive Advantage	Barney, J. B., & Clark, D. N.	2007	Further development of RBV, emphasizing firm-specific resources.
Strategic decision support systems for enhancing competitive advantage in SMEs	Boateng, P. A., Owusu, J., & Yeboah, N.	2024	Explores AI-driven decision support and its role in RBV.
The business of artificial intelligence	Brynjolfsson, E., & McAfee, A.	2017	Discusses AI as a source of competitive advantage and challenges of AI commoditization.
Artificial intelligence for the real world	Davenport, T. H., & Ronanki, R.	2018	Examines practical AI applications in strategic decision-making.
How artificial intelligence will transform management	Davenport, T. H., Guha, A., & Grewal, D.	2020	Analyzes the impact of AI on managerial decision-making.

Study Title	*Authors*	*Year*	*Concept / Relation to Study*
HR analytics: Leveraging big data to drive strategic decision-making	Donthu, S., Acharya, B., Hassan, M., & Prasad, S.	2024	Discusses AI's role in HR management as a strategic RBV resource.
Artificial intelligence and predictive analytics: Revolutionizing strategic business insights	Georgewill, I. A., & Gabriel, P. D. I.	2024	Explores how AI-powered predictive analytics aligns with RBV.
The resource-based theory of competitive advantage: Implications for strategy formulation	Grant, R. M.	1991	Extends RBV to strategy formulation, linking AI-driven strategies.
OR methods for coping with disruptions in supply chains during pandemics	Ivanov, D., & Dolgui, A.	2021	Highlights AI's role in mitigating supply chain disruptions, relevant to RBV.
The forthcoming artificial intelligence (AI) revolution: Its impact on society and firms	Makridakis, S.	2017	Explores AI's long-term effects on business strategy and RBV.
Exploring the interplay between big data analytics capability and competitive performance	Mikalef, P., Gupta, M., Pappas, I. O., & Krogstie, J.	2021	Examines how AI-powered data analytics enhances RBV resources.
Artificial intelligence capability and organizational performance	Neiroukh, S., Emeagwali, O. L., & Aljuhmani, H. Y.	2024	Investigates AI's impact on firm performance through RBV.
The Knowledge-Creating Company	Nonaka, I., & Takeuchi, H.	1995	Emphasizes knowledge management within RBV, relevant to AI-driven knowledge retention.
Enhancing supply chain resilience through artificial intelligence and machine learning	Nyakuchena, N., & Tsikada, C.	2024	Discusses AI's role in supply chain resilience through RBV.
The cornerstones of competitive advantage: A resource-based view	Peteraf, M. A.	1993	Refines RBV theory and links it to firm capabilities.
Artificial intelligence in human resources management: Challenges and a path forward	Tambe, P., Cappelli, P., & Yakubovich, V.	2019	Explores AI's impact on human capital as a strategic RBV resource.
Business models and dynamic capabilities	Teece, D. J.	2018	Connects AI-driven capabilities to RBV and competitive strategy.
Fundamental issues in strategy: Time to reassess?	Teece, D. J.	2020	Reassesses RBV's relevance in the AI-driven economy.
Dynamic capabilities and strategic management	Teece, D. J., Pisano, G., & Shuen, A.	1997	Develops the dynamic capabilities framework, relevant to AI-driven strategy.
A resource-based view of the firm	Wernerfelt, B.	1984	Initial foundation of RBV theory, introducing the concept of firm-specific resources.
Collaborative intelligence: Humans and AI are joining forces	Wilson, H. J., & Daugherty, P. R.	2018	Discusses AI-human collaboration within RBV strategies.

2.6.1. Core Principles of the Resource-Based View

The Resource-Based View (RBV) framework argues that a firm's competitive advantage is derived from its internal resources, rather than external market forces (Barney, 1991; Wernerfelt, 1984). This contrasts with Porter's Competitive Forces Model (1980), which emphasizes industry dynamics and market positioning. RBV focuses on firm-specific assets and capabilities, arguing that resources must be valuable, rare, inimitable, and non-substitutable (VRIN) to provide a sustainable advantage (Peteraf, 1993).

The VRIN framework evolved into the VRIO model, which emphasizes the importance of organizational integration for firms to fully exploit their resources (Barney & Clark, 2007). Under VRIO, a firm must ensure that a resource:

- Creates economic value by enhancing efficiency, differentiation, or cost reduction.
- Remains rare among competitors to prevent market saturation.
- Is difficult to imitate, either due to proprietary technology, knowledge barriers, or path dependency.

- Is effectively organized within the firm, meaning that the company has the structure, processes, and culture to capitalize on the resource.

RBV categorizes resources into tangible and intangible assets. Tangible resources include physical assets such as proprietary technologies, patents, and financial capital, while intangible resources encompass brand reputation, knowledge, data, and organizational culture (Grant, 1996). AI has transformed both categories, as data and AI models have become strategic, inimitable assets that firms integrate into decision-making (Georgewill & Gabriel, 2024).

The integration of AI with RBV has enhanced organizational knowledge management, making big data, predictive analytics, and automation core components of modern competitive strategies (Mikalef et al., 2021). AI has also facilitated dynamic resource adaptation, allowing firms to continuously evolve their capabilities in response to changing market conditions (Teece, Pisano, & Shuen, 1997). In highly competitive sectors such as pharmaceuticals, e-commerce, and financial services, AI-driven knowledge discovery enhances firms' ability to retain and leverage proprietary insights for sustained advantage (Makridakis, 2017).

In addition, AI has strengthened human capital management, a traditionally intangible RBV resource. AI-powered HR analytics systems optimize workforce planning, recruitment, and performance evaluation, ensuring that firms maximize their talent pool as a strategic resource (Donthu et al., 2024). Companies integrating AI into talent management and decision support systems can reduce operational inefficiencies while improving strategic workforce alignment (Boateng, 2024).

Given these fundamental principles, the next section (2.6.2) examines how AI enhances RBV-driven competitive advantage, while also posing new strategic challenges in AI-based resource management, knowledge retention, and dynamic capabilities development.

2.6.2. Synergy Between AI and RBV

The integration of artificial intelligence (AI) into the Resource-Based View (RBV) framework has significantly transformed how firms develop, utilize, and sustain competitive advantage. AI enhances RBV by allowing firms to better leverage data-driven decision-making, predictive analytics, automation, and resource optimization (Georgewill & Gabriel, 2024). AI-driven technologies contribute to the VRIN framework by making certain resources more valuable, rare, inimitable, and non-substitutable, strengthening firms' ability to differentiate themselves in competitive markets (Barney, 1991; Mikalef et al., 2021).

One of the key ways AI strengthens RBV is through predictive analytics and knowledge discovery. AI-driven analytics tools process vast amounts of structured and unstructured data, helping firms identify trends, predict market shifts, and optimize decision-making processes (Davenport & Ronanki, 2018). For example, Google's AI-powered search algorithms and Netflix's recommendation engine leverage proprietary data-driven models to create personalized experiences, making their competitive advantages difficult for rivals to replicate (Brynjolfsson & McAfee, 2017). AI also facilitates real-time decision-making, enabling businesses to adjust strategies dynamically based on market signals and consumer behaviors (Mikalef & Gupta, 2021).

AI further enhances RBV by reinforcing intellectual property (IP) development and innovation capabilities. Firms in industries such as pharmaceuticals, e-commerce, and finance increasingly rely on AI-powered R&D and knowledge extraction systems to generate new ideas, optimize production processes, and patent new technologies (Makridakis, 2017). For instance, AI-driven research tools analyze millions of patents and academic papers to uncover white-space innovation opportunities, accelerating the development of new competitive resources (Davenport et al., 2020).

Beyond analytics and innovation, AI plays a crucial role in human capital optimization, another key RBV resource. AI-powered HR analytics systems allow firms to optimize recruitment, employee engagement, and workforce planning, ensuring that human capital remains a strategic resource (Donthu et al., 2024). AI-driven hiring tools identify skills gaps and talent trends, enhancing firms' ability to retain high-value employees while reducing inefficiencies in workforce management (Tambe et al., 2019). AI-driven supplier relationship management has also emerged as a strategic tool for enhancing e-commerce scalability, enabling businesses to strengthen supply chain resilience and optimize vendor selection based on AI-generated insights (Grant, 2024).

AI also improves firms' dynamic capabilities, allowing them to sense opportunities, seize them, and reconfigure business models accordingly (Teece, Pisano, & Shuen, 1997). This is particularly relevant in fast-changing industries such as retail, logistics, and manufacturing, where AI helps firms continuously refine strategies to match evolving consumer demands (Nyakuchena & Tsikada, 2024). AI-driven logistics optimization tools enable firms like Amazon to dynamically allocate resources based on real-time supply and demand fluctuations, reinforcing RBV's focus on sustainable resource advantages (Brynjolfsson et al., 2019).

However, despite AI's ability to enhance strategic resource management, its effectiveness is dependent on firms' ability to integrate AI-driven insights with human expertise. While AI excels at data processing, pattern recognition, and automation, it lacks strategic intuition, creativity, and ethical reasoning, which remain human-driven competencies (Wilson & Daugherty, 2018). The most successful firms use AI as an augmentation tool, rather than a replacement for human decision-making, ensuring that AI-driven strategies align with long-term strategic goals and contextual judgment (Boateng et al., 2024).

While AI offers transformative benefits for RBV, its implementation also presents several challenges, including algorithmic bias, data dependency, resource commoditization, and limitations in handling tacit knowledge. The following section explores these challenges in detail, highlighting potential risks and the need for robust AI governance frameworks to ensure sustainable AI-driven competitive advantages.

2.6.3. Challenges of AI-Driven RBV Strategies

Despite its potential to enhance resource-based competitive advantage, AI-driven RBV strategies present several challenges that firms must navigate to maintain long-term strategic differentiation. One of the primary concerns is resource commoditization. As AI-based technologies become more widely available through open-source platforms and cloud services, firms risk losing their competitive edge unless they develop exclusive AI models, proprietary datasets, and specialized algorithms (Brynjolfsson & McAfee, 2017). Companies that fail to create firm-specific AI capabilities may struggle to differentiate themselves, as generic AI tools become easily replicable (Tambe et al., 2019). This issue is particularly evident in manufacturing and logistics, where AI-driven process automation has become increasingly standardized (Nyakuchena & Tsikada, 2024).

Another key challenge is AI's over-reliance on structured historical data, which limits its ability to handle unpredictable events and non-linear strategic decision-making (Teece, 2018). AI systems are highly effective in predicting trends based on past data, but they often struggle in environments characterized by high uncertainty, emerging disruptions, and paradigm shifts (Mikalef & Gupta, 2021). The COVID-19 pandemic illustrated this limitation, as AI-driven supply chain models failed to anticipate global disruptions, demonstrating that human judgment and adaptive decision-making remain essential (Ivanov & Dolgui, 2021).

AI-driven RBV strategies also raise significant ethical and governance risks, particularly concerning algorithmic bias and fairness. AI models are trained on historical data, which may contain inherent biases that lead to discriminatory decision-making. This has been particularly evident in AI-driven recruitment tools, where biased datasets have resulted in gender and racial discrimination in hiring practices (Wilson & Daugherty, 2018). Similarly, AI-powered credit scoring models have been criticized for unintended biases that disproportionately affect certain demographic groups (Davenport et al., 2020). Firms that fail to monitor and mitigate AI biases face reputational risks, regulatory scrutiny, and potential legal challenges (Tambe et al., 2019).

The successful integration of AI within RBV also requires significant organizational transformation. Many firms struggle with employee resistance to AI adoption, particularly when AI-driven processes disrupt traditional workflows and job roles (Donthu et al., 2024). The shift towards AI-enhanced decision-making requires upskilling employees, restructuring business operations, and fostering an AI-driven corporate culture, all of which present significant implementation challenges (Neiroukh et al., 2024). Additionally, firms must navigate complex regulatory environments, as governments introduce stricter AI regulations related to data privacy, intellectual property, and ethical AI governance (Teece, 2020).

In conclusion, AI-driven RBV strategies offer immense potential for enhancing competitive advantage, but they also present challenges related to resource commoditization, ethical concerns, and organizational adaptation. To maintain long-term success, firms must develop hybrid AI strategies that balance data-driven automation with human strategic oversight. Companies that successfully combine proprietary AI capabilities, strengthen AI governance, and integrate AI-driven insights with human expertise will be best positioned to sustain competitive advantage in the evolving AI-driven economy.

2.7. Processual Strategy: Strategy as an Evolving Process

The Processual school of strategy challenges the notion that strategy is a linear, rational, and pre-planned process. Instead, it conceptualizes strategy as an emergent phenomenon, shaped by organizational learning, social interactions, and historical context (Mintzberg, 1994; Whittington, 2001). Unlike the Classical school, which prioritizes structured planning, or the Adaptive school, which emphasizes responsiveness to external shifts, the Processual approach argues that strategy emerges organically within firms through iterative learning and adaptation (Pettigrew, 1985; Burgelman, 1991).

This perspective has become increasingly relevant in AI-driven environments, where firms must continuously learn, experiment, and refine their strategies to keep pace with rapid technological advancements (Eisenhardt & Martin, 2000). Processual strategy emphasizes organizational knowledge, path dependence, and social negotiation as critical elements of strategic formation (Nonaka & Takeuchi, 1995).

While AI excels at processing vast amounts of structured data and identifying complex patterns, it lacks the cognitive, social, and contextual depth required for truly emergent strategic thinking (Teece, Peteraf, & Leih, 2016; Ferrara, 2023). AI's role in strategy development, therefore, should be viewed as a facilitator of learning and iteration rather than a substitute for human-driven decision-making (Mikalef et al., 2021).

Processual strategy also accounts for the role of uncertainty and ambiguity in strategic planning. Unlike traditional strategic frameworks that emphasize control and predictability, the Processual school recognizes the limits of rational forecasting in dynamic and complex environments (McGrath, 2013; Nordström, 2022). This makes the framework particularly useful in the era of AI, where firms leverage AI-driven insights to enhance real-time decision-making and strategic agility while acknowledging the importance of human judgment and institutional memory (Ahmed et al., 2021).

AI's integration into Processual strategy can strengthen firms' capacity for knowledge retention and continuous adaptation. AI-powered decision support systems (DSS), machine learning algorithms, and knowledge management platforms facilitate historical learning, real-time strategic experimentation, and iterative refinement of business models (Davenport & Ronanki, 2018). However, these AI-driven tools still struggle to capture tacit knowledge, organizational culture, and the nuanced human dynamics that define strategic decision-making (Chui et al., 2018).

As firms navigate the intersection of AI and emergent strategy, they must balance data-driven insights with experiential knowledge. AI can augment decision-making processes by identifying hidden correlations in complex datasets, but strategic coherence requires human interpretation, contextual awareness, and ethical judgment (Makridakis, 2017; Wilson & Daugherty, 2018). Therefore, Processual strategy in the AI era should focus on creating a hybrid decision-making model, where AI serves as an enabler of continuous learning, experimentation, and strategic refinement rather than as a rigid prescriptive force (Trunk, Birkel, & Hartmann, 2020).

Table 4: List of Studies Used in This Section

Study Title	*Authors*	*Year*	*Concept / Relation to Study*
Digital transformation and organizational operational decision making: A systematic review	Ahmed, A., Alshurideh, M., & Al Kurdi, B.	2021	Role of AI in digital transformation and decision-making
Increasing returns and path dependence in the economy	Arthur, W. B.	1994	Path dependence and its influence on strategy
Machine, platform, crowd: Harnessing our digital future	Brynjolfsson, E., & McAfee, A.	2017	Impact of AI and digital platforms on business strategy
Intraorganizational ecology of strategy making and organizational adaptation: Theory and field research	Burgelman, R. A.	1991	Emergent strategy and organizational adaptation
What AI can and can't do (yet) for your business	Chui, M., Manyika, J., & Miremadi, M.	2018	Capabilities and limitations of AI in business
How artificial intelligence will change strategic management	Davenport, T. H., Guha, A., & Grewal, D.	2020	How AI affects strategic management processes
Artificial intelligence for the real world	Davenport, T. H., & Ronanki, R.	2018	AI applications in real-world business settings
Dynamic capabilities: What are they?	Eisenhardt, K. M., & Martin, J. A.	2000	Dynamic capabilities theory and its strategic applications

Fairness and bias in artificial intelligence: A brief survey	Ferrara, E.	2023	Bias and fairness challenges in AI decision-making
The moon, the ghetto, and artificial intelligence: Reducing systemic racism in computational algorithms	Fountain, J. E.	2022	AI's role in mitigating systemic discrimination in decision models
Structural inertia and organizational change	Hannan, M. T., & Freeman, J.	1984	Inertia in organizational change and strategy evolution
Artificial intelligence for supply chain management: Disruptive innovation or innovative disruption?	Hendriksen, C.	2023	AI's impact on supply chain strategy and management
A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0	Ivanov, D., & Dolgui, A.	2021	AI-driven digital twins for strategic risk management
The forthcoming artificial intelligence (AI) revolution: Its impact on society and firms	Makridakis, S.	2017	Future impact of AI on firms and industries
The end of competitive advantage: How to keep your strategy moving as fast as your business	McGrath, R. G.	2013	Strategic agility and competitive advantage in AI era
Artificial intelligence capabilities and their impact on firm performance	Mikalef, P., Pappas, I. O., Krogstie, J., & Giannakos, M.	2021	AI capabilities and their impact on firm performance
The rise and fall of strategic planning: Reconceiving roles for planning, plans, planners	Mintzberg, H.	1994	Critique of traditional strategic planning approaches
Of strategies, deliberate and emergent	Mintzberg, H., & Waters, J. A.	1985	The role of emergent strategy in organizational learning
The knowledge-creating company: How Japanese companies create the dynamics of innovation	Nonaka, I., & Takeuchi, H.	1995	Tacit knowledge and its relevance to strategy formation
AI under great uncertainty: Implications for public policy	Nordström, M.	2022	AI policy and strategy considerations in uncertain environments
The awakening giant: Continuity and change in Imperial Chemical Industries	Pettigrew, A. M.	1985	Continuity and change in corporate strategy
Artificial intelligence in human resources management: Challenges and a path forward	Tambe, P., Cappelli, P., & Yakubovich, V.	2019	Challenges of AI in HR and strategic decision-making
Business models and dynamic capabilities	Teece, D. J.	2018	Business models and dynamic capabilities in AI-driven firms
Dynamic capabilities and organizational agility: Risk, uncertainty, and strategy in the innovation economy	Teece, D. J., Peteraf, M. A., & Leih, S.	2016	Strategic agility, uncertainty, and AI
Dynamic capabilities and strategic management	Teece, D. J., Pisano, G., & Shuen, A.	1997	Strategic management and dynamic capability theory
On the current state of combining human and artificial intelligence for strategic organizational decision making	Trunk, A., Birkel, H., & Hartmann, E.	2020	Human-AI integration in strategic decision-making
What is strategy—and does it matter?	Whittington, R.	2001	Fundamental debates on strategy theory and practice
Collaborative intelligence: Humans and AI are joining forces	Wilson, H. J., & Daugherty, P. R.	2018	Collaboration between humans and AI in decision-making

2.7.1. Core Principles of the Processual School

The Processual school of strategy posits that strategy is not the outcome of deliberate, top-down planning but rather an incremental, evolving process shaped by internal learning, external market conditions, and organizational interactions (Mintzberg & Waters, 1985; Burgelman, 1991). Firms refine their strategies through trial and error, responding to both internal feedback loops and external disruptions rather than adhering to fixed long-term plans (Eisenhardt & Martin, 2000).

A fundamental principle of Processual strategy is organizational learning, which enables firms to refine decision-making over time based on accumulated knowledge and experience (Teece, Pisano, & Shuen, 1997).

Tacit knowledge, embedded within an organization's culture and internal networks, plays a crucial role in shaping strategic choices (Nonaka & Takeuchi, 1995). AI can assist in codifying and managing explicit knowledge, making it more accessible and scalable (Davenport et al., 2020). However, AI lacks the ability to replicate intuitive human learning and the social complexities involved in strategic reasoning (Tambe, Cappelli, & Yakubovich, 2019).

Unlike traditional models that focus on objective decision-making, the Processual school emphasizes the role of power dynamics, institutional norms, and stakeholder negotiations in shaping strategic outcomes (Whittington, 2001). Strategic decisions are often subject to informal alliances, cultural inertia, and internal bargaining (Pettigrew, 1985). AI-driven decision models can support firms by providing data-driven scenario analysis, but they fail to account for interpersonal negotiations and corporate politics that influence decision-making (Wilson & Daugherty, 2018).

The Processual approach acknowledges that firms' strategic choices are often constrained by their historical decisions and established structures (Arthur, 1994). Path dependence means that past commitments and organizational inertia influence future directions, making radical shifts challenging (Hannan & Freeman, 1984). AI can analyze historical business data and performance trends to identify patterns in strategic evolution (Ferrara, 2023). However, since AI relies on historical datasets, it may struggle to anticipate paradigm shifts or disruptive innovation beyond existing trajectories (Makridakis, 2017).

Processual strategy relies on continuous adaptation and learning rather than rigid strategic blueprints (McGrath, 2013). Firms engaging in iterative strategy development refine their models through experimentation, market feedback, and incremental innovation (Eisenhardt & Martin, 2000). AI enhances real-time scenario testing, A/B experimentation, and predictive modeling, allowing firms to simulate multiple strategic options before full-scale implementation (Wilson & Daugherty, 2018). Reinforcement learning models further support dynamic decision-making, as they continuously improve strategy optimization based on evolving market conditions (Mikalef et al., 2021).

Despite AI's analytical capabilities, human expertise remains indispensable for strategic decision-making. AI excels in data-driven decision support, but lacks the intuition, ethical considerations, and contextual depth required for long-term strategic planning (Davenport et al., 2020). Firms must balance AI-driven insights with leadership intuition, ensuring that strategy remains an adaptive, human-centered process rather than a mechanistic optimization model (Chui et al., 2018).

AI can complement Processual strategy by enhancing organizational learning, adaptive decision-making, and strategic experimentation. However, it must be contextualized within human judgment, institutional memory, and social negotiation mechanisms (Mikalef et al., 2021). Firms that integrate AI-driven insights with experiential knowledge will be better positioned to navigate uncertainty and leverage AI as a tool for strategic enhancement rather than a deterministic decision-making force (Trunk, Birkel, & Hartmann, 2020).

2.7.2. Synergy Between Processual Strategy and AI

The Processual school of strategy is particularly relevant in industries undergoing rapid technological change, where firms must navigate shifting market dynamics while leveraging internal capabilities. AI enhances Processual strategy by improving organizational learning, iterative adaptation, and strategic experimentation (Davenport & Ronanki, 2018). AI-powered knowledge management systems enable firms to capture, store, and analyze past strategic decisions, helping refine future learning processes (Mikalef et al., 2021). Machine learning models can identify patterns in historical data, allowing firms to adjust strategies based on real-time feedback (Wilson & Daugherty, 2018).

AI facilitates continuous experimentation and iteration, which aligns with the Processual school's emphasis on adaptive learning (Eisenhardt & Martin, 2000). AI-driven A/B testing, predictive analytics, and real-time scenario analysis enable firms to experiment with different strategic options before scaling implementation (Trunk, Birkel, & Hartmann, 2020). Reinforcement learning models further enhance strategy development by continuously refining decision-making algorithms based on evolving market conditions (Makridakis, 2017). This allows organizations to engage in an ongoing process of learning and adjustment, a core principle of Processual strategy. AI-based decision support systems (DSS) improve strategic choices by integrating historical learning, behavioral insights, and real-time data processing, helping firms refine their approaches through trial and error (Ahmed et al., 2021).

AI-driven collaboration tools improve knowledge-sharing across teams, allowing firms to integrate diverse perspectives into strategy formation (Tambe, Cappelli, & Yakubovich, 2019). While explicit knowledge can be codified and shared through AI systems, tacit knowledge—which plays a critical role in Processual strategy—remains difficult for AI to fully capture and transmit (Nonaka & Takeuchi, 1995). AI enhances firms' ability to track organizational learning patterns, employee feedback, and cultural shifts, helping decision-makers identify emergent trends in workplace dynamics (Brynjolfsson & McAfee, 2017).

AI's ability to recognize patterns in complex datasets improves decision-making but lacks the nuance of human judgment required for emergent strategy (Davenport et al., 2020). AI supports processual decision-making by automating data-driven insights, but it cannot replace the social negotiation, contextual awareness, and power dynamics that influence strategy formation (Whittington, 2001). AI-driven strategic planning must be embedded within human leadership frameworks, ensuring that strategic decisions reflect both data-driven insights and experiential learning (Chui et al., 2018).

Thus, AI plays an augmentative role in Processual strategy, strengthening firms' ability to continuously learn, adapt, and experiment while maintaining human oversight. Firms that balance AI-driven insights with leadership judgment will be better positioned to navigate uncertainty and leverage AI as a strategic enabler rather than a prescriptive force (Trunk, Birkel, & Hartmann, 2020).

2.7.3. Challenges Associated with AI-Driven Processual Strategies

While AI enhances Processual strategy, it also introduces significant challenges. The main concerns stem from AI's inability to process tacit knowledge, understand social and political contexts, and manage emergent strategic decision-making (Ferrara, 2023). Processual strategy relies on tacit knowledge, accumulated through human interactions, corporate values, and shared experiences (Nonaka & Takeuchi, 1995). AI-based learning models struggle to replicate intuitive decision-making, which is essential for navigating ambiguous and complex strategic environments (Eisenhardt & Martin, 2000). For example, AI-driven recruitment systems have been criticized for replicating biases in hiring decisions rather than adapting to new diversity and inclusion standards (Tambe et al., 2019).

Strategic decision-making is inherently political, influenced by power structures, institutional norms, and stakeholder negotiations (Whittington, 2001). AI lacks the ability to recognize informal alliances, corporate politics, and interpersonal negotiations, which are crucial in shaping business strategies (Wilson & Daugherty, 2018). AI-driven decision models may fail to account for stakeholder interests, corporate governance dynamics, and industry regulations, leading to oversimplified strategic recommendations (Mikalef et al., 2021).

AI models operate based on structured inputs and predefined objectives, making them less effective in managing evolving strategic goals (Eisenhardt & Martin, 2000). The rigidity of AI-driven insights can lead to over-optimization in predictable environments while failing to adapt to unprecedented changes (Makridakis, 2017). AI struggles with strategic improvisation, which is essential in rapidly changing industries (Ahmed et al., 2021).

AI-based learning systems rely on historical data to make predictions, which may limit their ability to anticipate disruptive changes (Nordström, 2022). The COVID-19 pandemic highlighted AI's weaknesses in strategic planning, as many AI-driven supply chain systems failed to adapt to sudden market shifts (Ivanov & Dolgui, 2021). Firms that combined human strategic expertise with AI insights demonstrated greater resilience in volatile conditions (Wenzel, Stanske, & Lieberman, 2021).

To ensure AI remains an enabler rather than a constraint, organizations must integrate AI insights with leadership intuition and experiential learning (Davenport et al., 2020). Hybrid decision-making frameworks allow AI to assist in data-driven strategy formation, while humans provide contextual interpretation (Trunk, Birkel, & Hartmann, 2020). The future of Processual strategy will depend on firms' ability to blend AI capabilities with organizational culture, social negotiation, and strategic flexibility (Chui et al., 2018).

AI enhances Processual strategies by supporting continuous learning, experimentation, and adaptation, but it lacks the ability to fully capture tacit knowledge, social dynamics, and emergent decision-making. To mitigate these challenges, firms must implement AI-driven strategic frameworks that emphasize human-AI collaboration rather than AI dominance. AI should be used as a strategic augmentation tool, ensuring that firms leverage its analytical power without compromising the flexibility and human insight required for emergent strategy formation (Mikalef et al., 2021; Trunk, Birkel, & Hartmann, 2020). By fostering a co-evolution of AI and human judgment, organizations can ensure that strategy remains an adaptive, evolving process rather than a rigid, algorithmic prescription (Ferrara, 2023).

3. METHODOLOGY

This study adopts a conceptual and literature-based approach to examine the role of Artificial Intelligence (AI) in strategic decision-making. By integrating insights from classical and contemporary strategic management theories, this research evaluates how AI aligns with four key strategic schools: Classical, Adaptive, Resource-Based View (RBV), and Processual.

To ensure methodological rigor, a structured literature review was conducted using Scopus, Web of Science, Google Scholar, and IEEE Xplore, focusing on peer-reviewed articles, books, and high-impact journal publications. The following screening criteria were applied:

Inclusion criteria: (i) Studies published between 2015-2024 to incorporate recent advancements in AI, (ii) Papers discussing AI's role in strategic decision-making, (iii) Works related to Classical, Adaptive, RBV, and Processual strategic frameworks.

Exclusion criteria: (i) Non-peer-reviewed sources, (ii) Studies focusing solely on AI's technical aspects without discussing its strategic implications, (iii) Papers published before 2015 unless they provide foundational theories in strategic management (e.g., works by Porter, Mintzberg, Barney, and Teece).

The selected literature was analyzed through a comparative thematic approach to identify key insights on how AI interacts with each strategic school:

- Classical Strategy: AI's role in forecasting, optimization, and structured decision-making.
- Adaptive Strategy: AI-driven real-time adjustments and dynamic capabilities.
- Resource-Based View (RBV): AI's impact on knowledge management, resource allocation, and firm-specific advantages.
- Processual Strategy: AI's contribution to continuous learning, emergent strategy formation, and experimentation.

To ensure objectivity, qualitative content analysis was used to synthesize themes from the literature. The study also compares theoretical perspectives with real-world case examples (e.g., Tesla, Netflix, Amazon) to illustrate AI's practical applications in strategic decision-making.

While this study provides a comprehensive theoretical framework, it does not include empirical data or primary research. Future studies should incorporate case studies, industry surveys, and quantitative models to further validate AI's strategic role.

4. COMPARATIVE ANALYSIS OF STRATEGIC SCHOOLS IN AI-DRIVEN DECISION-MAKING

he four strategic schools—Classical, Adaptive, Resource-Based View (RBV), and Processual—offer distinct perspectives on decision-making and achieving competitive advantage.

- The Classical school emphasizes structured planning and long-term competitive positioning, providing a rational framework for strategic development.

- The Adaptive school prioritizes flexibility, real-time responsiveness, and experimentation, making it particularly relevant in volatile environments.
- The RBV framework shifts the focus inward, arguing that a firm's unique internal resources, capabilities, and knowledge bases are the primary sources of sustainable advantage.
- The Processual school conceptualizes strategy as an emergent process, shaped by organizational learning, historical context, and social interactions (Mintzberg, 1994; Teece, 2018).

With the growing influence of AI in strategic management, firms increasingly rely on data-driven decision-making, predictive analytics, and automation. However, AI enhances but does not replace traditional strategic frameworks (Davenport & Ronanki, 2018; Mikalef et al., 2021). Each strategic school interacts with AI in different ways, providing unique insights into how AI-driven strategies should be developed. Instead of relying on a single approach, firms should integrate elements from all four schools to create a comprehensive AI-driven strategic framework. The following table summarizes how AI interacts with each strategic school, highlighting its benefits, limitations, and key applications:

Table 5 Comparative Analysis of the Four Strategic Schools and AI's Role

Strategic School	Core Principle	AI's Role & Benefits	Limitations of AI in This Approach
Classical Strategy (Chandler, 1962; Porter, 1980)	Rational planning, structured decision-making, competitive positioning	- AI enhances forecasting, risk analysis, and structured decision support (Davenport & Ronanki, 2018).	- AI struggles with uncertainty, black swan events, and qualitative decision-making (Makridakis, 2017).
		- AI-driven optimization improves market positioning and competitive intelligence (Brynjolfsson & McAfee, 2017).	- Over-reliance on historical data may lead to rigid, non-adaptive strategies (Teece, 2018).
Adaptive Strategy (Mintzberg, 1994; Eisenhardt & Martin, 2000)	Flexibility, real-time responsiveness, experimentation	- AI supports dynamic capabilities, scenario modeling, and real-time decision adjustments (McGrath, 2013).	- Over-reliance on AI can lead to short-term optimization at the expense of long-term vision (Teece, 2018).
		- AI-driven analytics help firms respond quickly to shifting consumer behavior (Davenport et al., 2020).	- AI lacks strategic intuition and qualitative judgment needed for complex decision-making (Wilson & Daugherty, 2018).
Resource-Based View (RBV) (Barney, 1991; Wernerfelt, 1984)	Competitive advantage from unique internal resources (VRIO framework)	- AI strengthens resource identification, intellectual property protection, and knowledge management (Mikalef et al., 2021).	- AI technologies may become commoditized, reducing long-term competitive advantage (Brynjolfsson & McAfee, 2017).
		- AI enhances operational efficiency and dynamic resource allocation (Teece, 2018).	- AI struggles to manage tacit knowledge, organizational culture, and human expertise (Nonaka & Takeuchi, 1995).
Processual Strategy (Mintzberg, 1994; Pettigrew, 1985)	Strategy emerges through continuous learning, social interactions, and historical adaptation	- AI enhances knowledge-sharing, iterative learning, and experimental decision-making (Wilson & Daugherty, 2018).	- AI lacks social intelligence, negotiation skills, and contextual awareness (Whittington, 2001).
		- AI-driven analytics improve firms' ability to track strategic patterns and adjust over time (Tambe, Cappelli, & Yakubovich, 2019).	- AI-driven decision models may reinforce existing biases rather than fostering strategic innovation (Davenport & Ronanki, 2018).

Source: Table is prepared by the authors from several sources mentioned above.

This comparison highlights that AI does not fully replace any of the four strategic frameworks but rather augments specific aspects of decision-making.

4.1. The Need for an Integrated AI-Driven Strategic Framework

AI significantly enhances each strategic school, yet no single approach can fully capture the complexity of AI-driven decision-making. Firms must develop an integrated AI-driven strategic framework that leverages the strengths of each school while mitigating their limitations.

One critical aspect of an integrated approach is balancing AI-driven planning with strategic flexibility. AI enhances Classical strategy by improving forecasting, structured decision-making, and market positioning. However, rigid AI-driven plans may not account for unforeseen market shifts, requiring firms to integrate Adaptive principles to remain agile and responsive to change (Makridakis, 2017). A prime example of this balance is Tesla's AI-driven supply chain forecasting. Tesla uses AI to optimize production and inventory management, following structured Classical principles. However, it remains highly adaptive by continuously modifying strategies based on technological advancements, regulatory changes, and shifting consumer preferences (Brynjolfsson & McAfee, 2017).

Another essential element is leveraging AI for internal resource development. AI strengthens RBV by enabling firms to develop and protect unique intellectual assets, such as proprietary algorithms, datasets, and machine learning capabilities. However, firms must continuously innovate and renew their AI capabilities to prevent resource commoditization and maintain competitive differentiation (Mikalef et al., 2021). For instance, Netflix's AI-driven recommendation engine is a highly valuable resource that gives the company a competitive edge. However, Netflix does not rely solely on its existing AI capabilities; it continuously invests in machine learning research to refine its recommendation algorithms, ensuring competitors cannot easily imitate its model (Davenport et al., 2020).

AI also serves as a powerful tool for learning and emergent strategy formation, aligning closely with Processual strategy. AI-driven knowledge management systems help firms analyze historical decisions, learn from past experiences, and iteratively refine their strategic direction (Nonaka & Takeuchi, 1995). Amazon exemplifies this approach through its AI-powered experimentation framework. By running thousands of A/B tests and AI-driven simulations, Amazon continuously refines its business models, testing different pricing structures, supply chain configurations, and customer engagement strategies in real time (McKinsey, 2019). This iterative approach enables the company to stay ahead of competitors while ensuring AI-driven insights align with long-term business objectives.

Despite AI's advantages in decision-making efficiency, human judgment remains essential for strategic success. AI can process vast amounts of data, identify patterns, and automate decision-making, but it lacks contextual awareness, ethical reasoning, and strategic intuition—factors that are crucial for navigating complex business environments (Teece, 2018). For example, AI-driven financial trading systems operate at unprecedented speeds, yet they require human oversight to prevent catastrophic algorithmic risks, such as those seen in high-frequency trading flash crashes (Wilson & Daugherty, 2018). Firms must ensure that AI remains a tool for enhancing decision-making rather than a replacement for human strategic leadership.

4.1. The Future of AI-Driven Strategic Decision-Making

AI is reshaping strategic management, but no single strategic school provides a comprehensive framework for AI-driven decision-making. Instead, firms must integrate elements from Classical, Adaptive, RBV, and Processual perspectives to develop a hybrid AI-driven strategy that balances structured planning, flexibility, resource development, and continuous learning (Teece, 2018).

The future of AI-driven strategy will require a multi-model decision framework that combines AI-generated insights with human intuition. While AI provides powerful analytical capabilities, human judgment ensures that AI-driven strategies align with broader organizational goals, ethical considerations, and shifting market conditions (Davenport et al., 2020). Firms must also adopt AI-human hybrid strategies, recognizing that AI should complement rather than replace human decision-making (Wilson & Daugherty, 2018). Furthermore, interdisciplinary research bridging AI, strategic management, and decision sciences will be crucial in refining AI-driven strategic models, improving AI governance, and ensuring ethical AI deployment in business environments (Tambe et al., 2019).

Firms that successfully integrate AI into their strategic management frameworks will gain a sustainable competitive advantage. By balancing AI-driven automation with human expertise, organizations can ensure that their decision-making processes remain both efficient and adaptable to dynamic market conditions. Moving forward, firms must remain proactive in refining their AI capabilities while maintaining a clear focus on long-term strategic objectives, ethical considerations, and the evolving role of human leadership in AI-driven decision-making.

CONCLUSION AND DISCUSSION

This study has examined the integration of artificial intelligence (AI) into strategic decision-making through the perspectives of four major strategic schools: Classical, Adaptive, Resource-Based View (RBV), and Processual strategy. Each school provides a distinct yet complementary approach to understanding how AI can be leveraged for competitive advantage. The Classical school emphasizes structured planning, competitive positioning, and rational decision-making, areas where AI significantly enhances forecasting, market analysis, and optimization. However, the rigidity of AI-driven strategies may pose challenges in highly volatile environments, where rapid adaptation is essential for success (Porter, 1980; Makridakis, 2017). In contrast, the Adaptive school prioritizes flexibility, real-time responsiveness, and continuous learning. AI strengthens these capabilities by enabling dynamic decision support and real-time analytics, yet excessive reliance on AI-driven decision-making may result in a short-term focus at the expense of long-term strategic vision (Mintzberg, 1994; Eisenhardt & Martin, 2000).

The Resource-Based View (RBV) framework argues that competitive advantage arises from a firm's internal resources, such as proprietary knowledge, intellectual property, and core capabilities. AI enhances RBV by improving resource allocation, knowledge management, and data-driven strategic insights. However, as AI-driven capabilities become more widespread and accessible, there is an increasing risk of commoditization, reducing their potential as a unique source of differentiation (Barney, 1991; Teece, 2018). Meanwhile, the Processual school conceptualizes strategy as an emergent, evolving phenomenon shaped by organizational learning, social interactions, and historical context. AI contributes to this approach by enhancing knowledge-sharing, enabling iterative experimentation, and providing insights into long-term strategic patterns. However, AI lacks the ability to interpret tacit knowledge, social intelligence, and contextual awareness, which are critical elements in strategic decision-making (Pettigrew, 1985; Nonaka & Takeuchi, 1995).

A key insight from this study is that AI does not replace strategic thinking but rather enhances it. While AI can process vast amounts of data, improve decision efficiency, and identify hidden patterns, human judgment, intuition, and contextual awareness remain indispensable for effective strategic decision-making (Teece, 2018). The optimal approach is not to rely on AI as a standalone decision-maker but to integrate it within established strategic frameworks, creating a hybrid model that leverages AI's analytical capabilities while maintaining human oversight. To maximize AI's potential, organizations should adopt a multi-model approach that incorporates the strengths of all four strategic schools while addressing AI's inherent limitations.

Organizations should develop a strategic framework that blends structured planning from the Classical school, real-time responsiveness from Adaptive strategy, internal resource development from RBV, and continuous learning from the Processual perspective. AI-driven analytics should support Classical strategy by improving long-term forecasting and structured decision-making, but firms must also incorporate Adaptive flexibility to remain responsive to market shifts (Makridakis, 2017). Investment in AI-enhanced RBV capabilities should be complemented by continuous renewal and differentiation to prevent AI assets from becoming commoditized (Brynjolfsson & McAfee, 2017). AI should further be used as a tool for Processual learning and experimentation, ensuring that AI-generated insights are supplemented with human judgment in final decision-making processes (Davenport et al., 2020).

AI should be regarded as a decision-support tool rather than a replacement for human strategists. While AI excels at generating quantitative insights, executives must apply qualitative judgment to interpret complex business realities, ensuring that AI-driven recommendations align with broader strategic objectives (Wilson & Daugherty, 2018). Organizations should implement AI governance frameworks that balance automation with ethical considerations and social intelligence, preventing algorithmic biases from distorting strategic decision-making (Tambe, Cappelli, & Yakubovich, 2019). Additionally, firms should invest in AI literacy programs to ensure that managers and decision-makers fully understand the strengths and limitations of AI within strategic contexts (Davenport & Ronanki, 2018).

As AI continues to shape strategic management, firms must also prioritize ethical considerations, transparency, and regulatory compliance. Organizations should develop explainable AI (XAI) models that provide clear reasoning behind AI-driven decisions, ensuring greater transparency in strategic planning (Tambe et al., 2019). AI bias must be actively addressed, particularly in areas such as recruitment, pricing, and customer analytics, where unintended biases could lead to ethical and reputational risks (Wilson & Daugherty, 2018). AI governance frameworks should be introduced to ensure alignment with regulatory requirements and ethical business practices, particularly as AI takes on a larger role in high-stakes decision-making (Davenport et al., 2020).

For organizations to successfully integrate AI into strategic decision-making while maintaining adaptability, they must foster an organizational culture that prioritizes agility and innovation. Firms should encourage controlled experimentation, allowing AI-driven insights to be tested and refined before full-scale implementation (McGrath, 2013). AI systems must align with corporate values and long-term strategic goals rather than focusing exclusively on short-term efficiency gains (Teece, 2018). Interdisciplinary collaboration should be encouraged by assembling cross-functional AI teams consisting of strategists, data scientists, and behavioral economists, ensuring a holistic approach to AI-driven decision-making (Davenport et al., 2020).

Although AI-driven decision-making is still in its early stages, its role in strategic management is expected to expand significantly in the coming years. Future developments will likely focus on advancements in Explainable AI (XAI), enabling AI systems to provide more interpretable and transparent recommendations, particularly in high-stakes decision-making areas such as financial strategy, governance, and risk management (Brynjolfsson & McAfee, 2017). AI is also expected to become a more integral component of executive decision-making, functioning as a co-pilot that generates data-driven insights while leaving final strategic judgments to human leaders (Wilson & Daugherty, 2018).

Moreover, the integration of AI with behavioral and decision sciences will allow firms to refine AI-driven strategic models by incorporating psychological and cognitive insights, ensuring that AI-generated recommendations align more closely with human decision-making processes (Tambe et al., 2019). In addition, AI-driven business model innovation is likely to emerge as a key area of competitive differentiation, as firms increasingly leverage AI not only for decision support but also to develop entirely new business models, revenue streams, and value-creation strategies (Davenport et al., 2020).

The future of strategic management lies in a balanced integration of AI and human expertise. Rather than replacing human strategists, AI should be positioned as a powerful enabler of more effective, data-driven, and adaptable decision-making. Firms that successfully integrate AI within structured yet flexible strategic management frameworks will gain a sustainable competitive advantage, ensuring that AI-driven decisions remain aligned with long-term business objectives, ethical considerations, and dynamic market conditions. Organizations that proactively invest in AI capabilities while maintaining a strong foundation of human judgment and strategic oversight will be best positioned to navigate the evolving business landscape. In doing so, they will not only enhance decision efficiency but also strengthen their ability to adapt, innovate, and thrive in an increasingly AI-driven economy..

STATEMENT OF RESEARCHERS' CONTRIBUTION RATE

Authors' contribution rates to the study are equal.

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CONFLICT OF INTEREST DECLARATION

There is no conflict of interest with any institution or person within the scope of the study.

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