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Artificial Intelligence-Driven Decision-Making and Its Impact on Strategic Agility Evidence from Emerging Markets.

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Abstract

This study examines the strategic role of AI-driven decision-making in enhancing organizational performance through the mediating mechanisms of strategic agility and competitive advantage. Drawing on a capability-based perspective, the research proposes and tests a structural model using data collected from 408 respondents and analyzed via structural equation modeling (SEM). The findings reveal that AI-driven decision-making positively influences strategic agility. However, AI exerts negative direct effects on both competitive advantage and organizational performance. Strategic agility significantly enhances competitive advantage, which in turn positively affects organizational performance. The results indicate an inconsistent mediation pattern, suggesting that AI generates value primarily through capability transformation rather than direct technological impact. The study contributes by repositioning AI as a strategic enabler whose performance implications depend on organizational integration and adaptive capability development. Practical implications emphasize that AI investments must be embedded within agile strategic processes to yield sustainable competitive outcomes.

Keywords: Artificial Intelligence, Driven Decision, Strategic Agility, Competitive Advantage, Organizational Performance

Introduction

The rapid advancement of artificial intelligence (AI) technologies has fundamentally reshaped organizational decision-making processes. AI-driven decision-making systems—encompassing machine learning, predictive analytics, and big data processing—enhance managerial cognition by improving analytical accuracy, speed, and strategic foresight (Brynjolfsson & McAfee, 2017; Davenport & Ronanki, 2018). In increasingly volatile and digitally disrupted environments, organizations are under mounting pressure to leverage AI not merely as an operational tool, but as a strategic capability that influences long-term competitive positioning. From the perspective of the Resource-Based View (Barney, 1991), sustainable competitive advantage emerges from valuable, rare, inimitable, and non-substitutable resources embedded within organizational processes. When AI-driven decision-making is effectively integrated into managerial routines and strategic planning architectures, it may constitute such a strategic resource (Mikalef et al., 2021). However, empirical evidence suggests that technological adoption alone does not automatically lead to superior performance outcomes (Wade & Hulland, 2004). Instead, the strategic value of AI depends on complementary organizational capabilities that enable its effective deployment. This argument is further supported by Dynamic Capabilities Theory (Teece, Pisano, & Shuen, 1997; Teece, 2007), which emphasizes a firm's ability to sense opportunities, seize them, and reconfigure resources in response to environmental change. AI-driven decision-making enhances sensing capabilities through real-time analytics and predictive intelligence, thereby strengthening strategic agility. Strategic agility reflects the organization's capacity to rapidly adapt strategies, reallocate resources, and respond effectively to environmental turbulence (Doz & Kosonen, 2010). Empirical studies increasingly indicate that agility functions as a critical mediator between digital technologies and firm performance (Sambamurthy, Bharadwaj, & Grover, 2003; Tallon & Pinsonneault, 2011). Despite the growing body of literature on AI and digital transformation, research remains fragmented in explaining how AI-driven decision-making translates into sustainable organizational performance. Prior studies often test direct relationships between AI adoption and firm performance, yielding mixed and context-dependent findings (Ransbotham et al., 2017). Such linear approaches overlook the intermediate capability-building mechanisms through which AI generates strategic value. Limited research has simultaneously examined the sequential mediating roles of strategic agility and competitive advantage in linking AI-driven decision-making to performance outcomes. Addressing this gap, the present study develops and empirically tests an integrated structural model in which AI-driven decision-making influences organizational performance both directly and indirectly through strategic agility and competitive advantage. By positioning AI as a higher-order managerial capability embedded within dynamic capability processes, this study advances understanding of how digital intelligence is transformed into sustainable competitive and performance outcomes in turbulent environments. Methodologically, the study employs covariance-based Structural Equation Modeling (CB-SEM) using AMOS to rigorously examine the hypothesized relationships. This approach enables simultaneous estimation of direct and indirect effects and provides robust model fit validation (Hair et al., 2010; Kline, 2016).

Despite the growing investment in artificial intelligence (AI) technologies, many organizations still struggle to translate AI-driven decision-making capabilities into tangible strategic and performance outcomes. While prior studies have emphasized the technical benefits of AI adoption (Ransbotham et al., 2020; Davenport et al., 2020), there remains limited empirical understanding of how AI-enabled decision processes enhance strategic agility and subsequently contribute to competitive advantage and organizational performance. Existing research predominantly focuses on AI implementation from a technological or operational perspective, with insufficient attention to its strategic implications within management theory (Mikalef et al., 2021). Furthermore, the relationship between AI-driven decision-making and firm performance is often examined directly, overlooking potential mediating mechanisms such as strategic agility and competitive advantage (Dubey et al., 2021). In dynamic and uncertain business environments, strategic agility has emerged as a critical capability enabling firms to respond rapidly to market changes (Teece, 2018; Clauss et al., 2022). However, empirical evidence linking AI-supported decision systems to enhanced strategic agility remains fragmented and underdeveloped. Similarly, while competitive advantage is frequently associated with digital transformation initiatives (Warner & Wäger, 2019), the specific role of AI-driven decision-making in fostering sustainable competitive positioning requires further investigation. Therefore, a significant research gap exists in understanding how AI-driven decision-making influences organizational performance through strategic agility and competitive advantage as mediating mechanisms. Addressing this gap is essential for advancing management theory and providing actionable insights for organizations seeking to leverage AI strategically rather than merely operationally.

Objectives of This Study:

1. Positioning AI as a Strategic Capability Demonstrates that AI-driven decision-making is not only a technological tool but a strategic capability influencing strategic agility, competitive advantage, and organizational performance (Teece, 2018; Mikalef et al., 2021).
2. Clarifying Direct Relationships Focus on direct effects simplifies the model and strengthens clarity, which is favored in empirical (Clauss et al., 2022).
3. Contribution to Management Theory Provides empirical evidence on how AI directly improves organizational outcomes through agility and competitive advantage (Dubey et al., 2021).

Background This Study: Artificial intelligence (AI) is increasingly embedded within organizational decision-making processes. While AI technologies promise efficiency and analytical precision, their strategic implications remain contested. Existing research often assumes a direct positive relationship between AI adoption and firm performance. However, empirical findings remain inconsistent. This study argues that AI-driven decision-making does not directly enhance organizational performance. Instead, its impact is mediated through higher-order capabilities, particularly strategic agility and competitive advantage. Using structural equation modeling based on data from 408 respondents, this research investigates the mechanisms through which AI influences performance outcomes. Figure 1 presents the proposed conceptual framework grounded in the Resource-Based View (Barney, 1991) and Dynamic Capabilities Theory (Teece et al., 1997; Teece, 2007). According to RBV, firms achieve sustained competitive advantage when they possess and effectively deploy valuable, rare, inimitable, and non-substitutable resources. In contemporary digital environments, AI-driven decision-making represents such a strategic resource, as it enhances information-processing capacity, reduces uncertainty, and improves the quality and speed of managerial decisions. However, RBV alone does not fully explain how technological resources are transformed into performance outcomes. Dynamic Capabilities Theory extends this logic by emphasizing the firm's ability to integrate, build, and reconfigure internal and external competences in rapidly changing environments (Teece et al., 1997). Within this perspective, AI-driven decision-making strengthens the organization's sensing and responding capabilities, which are manifested as strategic agility. Strategic agility reflects the organization's capacity to rapidly adapt strategies, reallocate resources, and respond effectively to environmental turbulence. Agile firms are better positioned to exploit emerging opportunities and neutralize competitive threats, thereby strengthening their competitive advantage. Competitive advantage, in turn, represents the positional superiority that enables firms to achieve superior financial and non-financial performance outcomes. Accordingly, the proposed framework specifies a serial mediation mechanism in which AI-driven decision-making enhances organizational performance both directly and indirectly through strategic agility and competitive advantage. The sequential structure reflects a capability-building logic: technological capability (AI-driven decision-making) → adaptive capability (strategic agility) → positional superiority (competitive advantage) → performance outcomes. This integrative structure provides a theoretically coherent explanation of how AI-based decision systems translate into sustainable organizational performance in dynamic competitive environments

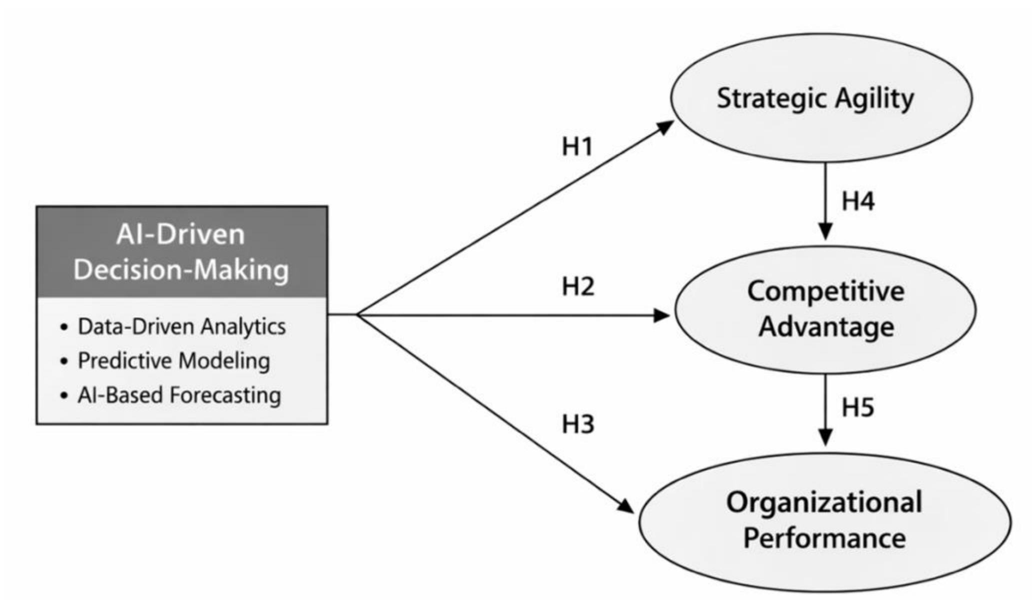

Figure 1. Presents the Conceptual Framework of This Study

Conceptual Framework: (Direct Effects) Model Description: The model proposes that AI-Driven Decision-Making (AIDDM) functions as a strategic antecedent influencing three key organizational outcomes: Strategic Agility (SA), Competitive Advantage (CA), and Organizational Performance (OP). Additionally, the framework posits that Strategic Agility and Competitive Advantage further contribute to Organizational Performance, forming a mediated structural model. Grounded in the Dynamic Capabilities Theory, AI-driven decision-making enhances an organization's ability to sense environmental changes, seize emerging opportunities, and reconfigure resources effectively. AI-supported analytics, predictive modeling, and automated strategic insights strengthen managerial responsiveness and decision accuracy. These capabilities are expected to foster Strategic Agility, enabling firms to adapt quickly to technological and market turbulence. From the perspective of the Resource-Based View (RBV), AI-driven decision-making represents a valuable and difficult-to-imitate organizational capability. When embedded in strategic processes, AI can improve resource allocation efficiency, innovation capacity, and strategic alignment, thereby contributing to Competitive Advantage. The framework further assumes that Strategic Agility and Competitive Advantage serve as transmission mechanisms through which AI-driven decision-making enhances Organizational Performance. Rather than assuming a simplistic direct relationship, the model captures both direct and indirect effects, enabling a more comprehensive explanation of value creation in AI-enabled organizations. The proposed relationships are empirically tested using Structural Equation Modeling (SEM), allowing simultaneous examination of direct and mediated paths among latent constructs.

Independent Variable (IV):

AI-Driven Decision-Making (AIDDM)

- Use of advanced analytics and AI in strategic decision-making (Davenport et al., 2020; Mikalef et al., 2021).

Mediation Variables (MDVs):

- Strategic Agility (SA): The ability to respond quickly to market and technological changes (Teece, 2018; Clauss et al., 2022).
- Competitive Advantage (CA): The ability to outperform competitors through valuable and rare strategic resources (Barney, 1991; Dubey et al., 2021).

Dependent Variables (DVs):

- Organizational Performance (OP): The financial and operational performance of the organization (Dubey et al., 2021; Clauss et al., 2022).

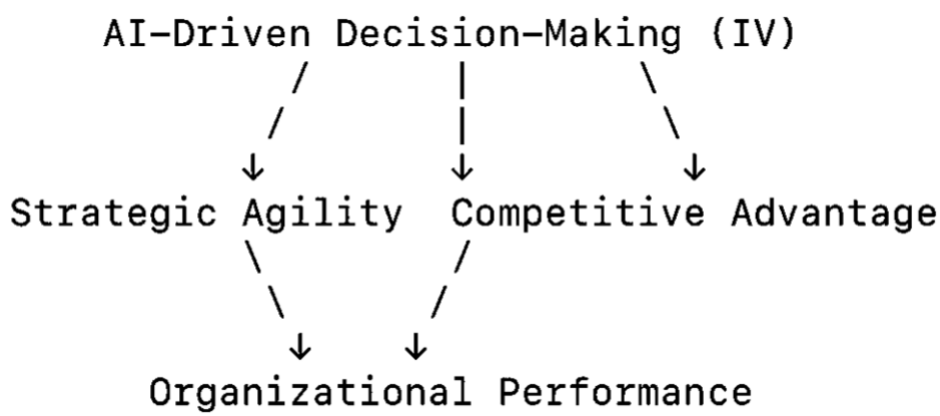

Figure 1. All relationships are direct, consistent with the conceptual framework in the provided image.

Hypotheses Development

AI-Driven Decision-Making as a Strategic Resource: The increasing integration of artificial intelligence (AI) into managerial processes has transformed organizational decision-making from intuition-based judgment to data-driven strategic intelligence. AI-driven decision-making encompasses advanced analytics, predictive modeling, and intelligent forecasting systems that enhance information-processing capacity and reduce environmental uncertainty. From a strategic management perspective, the Resource-Based View (Barney, 1991) posits that firms achieve sustained competitive advantage when they possess valuable, rare, inimitable, and non-substitutable resources. AI capabilities, when embedded in organizational routines, represent such strategic assets. However, simply possessing AI technologies does not guarantee performance gains; firms must effectively deploy these technologies within higher-order capability structures. The Dynamic Capabilities Theory (Teece et al., 1997; Teece, 2007) extends this argument by emphasizing the importance of sensing, seizing, and reconfiguring capabilities in dynamic environments. AI-driven decision-making strengthens organizational sensing capabilities by enabling real-time data analysis and predictive insights, thereby enhancing strategic responsiveness.

AI-Driven Decision-Making and Strategic Agility: Strategic agility refers to the firm's ability to rapidly adjust strategic direction, reallocate resources, and respond effectively to environmental turbulence. According to Teece (2007), sensing and seizing opportunities are central micro foundations of dynamic capabilities. AI systems improve environmental scanning, pattern recognition, and forecasting accuracy, thereby strengthening strategic agility. Empirical research suggests that digital technologies enhance organizational flexibility and adaptive capacity in uncertain markets (Sambamurthy et al., 2003). By improving decision speed and precision, AI-driven systems enable organizations to anticipate market shifts and respond proactively.

H1: AI-driven decision-making positively influences strategic agility.

AI-Driven Decision-Making and Competitive Advantage: Competitive advantage represents superior positioning relative to competitors in terms of cost efficiency, differentiation, or innovation. According to Porter (1985), firms achieve competitive advantage through strategic positioning and operational effectiveness. AI-driven decision-making enhances process efficiency, innovation capacity, and strategic foresight, which contribute to superior competitive positioning. Within the RBV framework, technological capabilities embedded in organizational processes can create isolating mechanisms that competitors find difficult to replicate (Barney, 1991). Therefore, AI-driven systems may directly strengthen competitive advantage.

H2: AI-driven decision-making positively influences competitive advantage

AI-Driven Decision-Making and Organizational Performance: Organizational performance reflects both financial and non-financial outcomes, including profitability, growth, operational efficiency, and strategic effectiveness. Digital capability research suggests that information-processing and analytics capabilities positively influence firm performance (Bharadwaj, 2000). AI-driven decision-making improves resource allocation, reduces operational inefficiencies, and enhances forecasting accuracy, thereby potentially exerting a direct positive effect on performance.

H3: AI-driven decision-making positively influences organizational performance.

Strategic Agility and Competitive Advantage: Strategic agility enables firms to rapidly reconfigure resources and exploit emerging opportunities. According to the Dynamic Capabilities perspective, agile firms are better positioned to achieve superior competitive outcomes in volatile markets (Teece et al., 1997). Agile strategic responses enhance differentiation, speed to market, and innovation, which strengthen competitive advantage.

H4: Strategic agility positively influences competitive advantage

Competitive Advantage and Organizational Performance: Competitive advantage serves as a primary driver of superior performance outcomes. Strategic management literature consistently demonstrates that firms with stronger competitive positioning achieve higher profitability and sustained performance (Porter, 1985; Barney, 1991). Accordingly, competitive advantage is expected to mediate the relationship between strategic capabilities and organizational outcomes.

H5: Competitive advantage positively influences organizational performance.

Research Gap of the Study: Despite the rapid proliferation of artificial intelligence (AI) technologies across industries, the strategic implications of AI-driven decision-making remain insufficiently theorized and empirically validated within the management literature. Existing studies primarily conceptualize AI as a technological instrument designed to enhance automation, analytical accuracy, and operational efficiency (Davenport et al., 2020; Mikalef et al., 2021). While these contributions are valuable, they largely frame AI as a functional IT capability rather than as a strategic managerial resource embedded in organizational decision architectures. Moreover, prior empirical investigations frequently assume a direct relationship between AI adoption and organizational performance, yielding inconsistent or context-dependent findings. Such direct-effect models overlook the intermediate mechanisms through which AI generates sustained value. Limited research has integrated strategic agility and competitive advantage into a unified structural framework explaining how AI-driven decision-making translates into performance outcomes (Clauss et al., 2022). Although strategic agility is recognized as a core dynamic capability in volatile and digitally disrupted environments (Teece, 2018), empirical evidence remains scarce regarding how AI-enabled decision systems strengthen agility at the strategic level. Similarly, research on digital transformation acknowledges competitive advantage as a central outcome but rarely isolates AI-driven decision-making as a distinct antecedent capability shaping competitive positioning (Warner & Wäger, 2019). Therefore, a significant theoretical gap exists in understanding whether and how AI-driven decision-making contributes to organizational performance through sequential capability-building mechanisms. Addressing this gap is essential to reposition AI from a purely technological asset to a strategic capability embedded within contemporary management theory.

Materials and Methods

Research Design: This study adopts a theory-testing quantitative design to examine the hypothesized relationships among AI-driven decision-making, strategic agility, competitive advantage, and organizational performance. A cross-sectional survey methodology was employed to collect perceptual data from managerial respondents, given their central role in strategic decision-making processes and performance evaluation. The analytical approach is grounded in covariance-based Structural Equation Modeling (CB-SEM) using AMOS. CB-SEM was selected over variance-based approaches because the study aims to confirm a theoretically grounded structural model derived from the Resource-Based View and Dynamic Capabilities Theory. CB-SEM is particularly appropriate for theory confirmation, global model fit assessment, and mediation testing within complex structural models (Hair et al., 2010; Kline, 2016).

Sampling and Data Collection: The target population comprised middle and senior-level managers employed in organizations that have implemented AI-enabled analytical or decision-support systems. Managers were selected as key informants due to their strategic oversight and familiarity with technology-enabled decision processes. A purposive sampling strategy was applied to ensure respondents possessed adequate knowledge regarding AI applications within their organizations. Data were collected through a structured questionnaire distributed electronically. After data screening procedures, a final sample of [400] usable responses were retained for analysis. The sample size exceeds the minimum threshold recommended for SEM analysis, satisfying both the absolute minimum requirement of 200 observations and the ratio of at least 10 observations per estimated parameter (Hair et al., 2010).

Measurement Instruments: All constructs were operationalized using previously validated multi-item scales to ensure content validity and theoretical alignment.

- AI-Driven Decision-Making was measured using adapted items reflecting the extent to which AI systems enhance analytical quality, predictive accuracy, and strategic insights.
- Strategic Agility captured organizational responsiveness, adaptability, and rapid strategic reconfiguration.
- Competitive Advantage assessed differentiation and cost-based advantages relative to competitors.
- Organizational Performance was measured using subjective comparative performance indicators reflecting financial and market outcomes.

All items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Scale adaptation followed a back-translation procedure to ensure linguistic accuracy where necessary.

Structural Model Evaluation: Following confirmation of the measurement model, the structural model was estimated using maximum likelihood estimation in AMOS. Model fit was evaluated using multiple indices: Path coefficients were interpreted based on standardized estimates and critical ratios (CR > 1.96, $p < 0.05$). 3.7

Mediation Analysis: To examine the indirect effects of strategic agility and competitive advantage, bootstrapping with 5,000 resamples was conducted to generate bias-corrected confidence intervals (Preacher & Hayes, 2008). Mediation was considered significant when zero was not included within the 95% confidence interval. Serial mediation was assessed to determine whether AI-driven decision-making influences organizational performance sequentially through strategic agility and competitive advantage.

Common Method Bias: Given the single-source survey design, procedural and statistical remedies were applied to mitigate common method variance (Podsakoff et al., 2003). Procedural remedies included:

- Assuring respondent anonymity
- Separating predictor and criterion items
- Reducing evaluation apprehension Statistically, Harman's single-factor test and a common latent factor analysis were conducted. Results indicated that common method bias did not substantially affect the findings.

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Results

Structural Model Estimation: The structural model was estimated using maximum likelihood estimation in AMOS based on a sample of 408 respondents. The model is recursive and statistically identified (df = 1). Parameter estimates converged successfully. Standardized and unstandardized path coefficients, along with their statistical significance levels, are presented in figure 1 and Table 1.

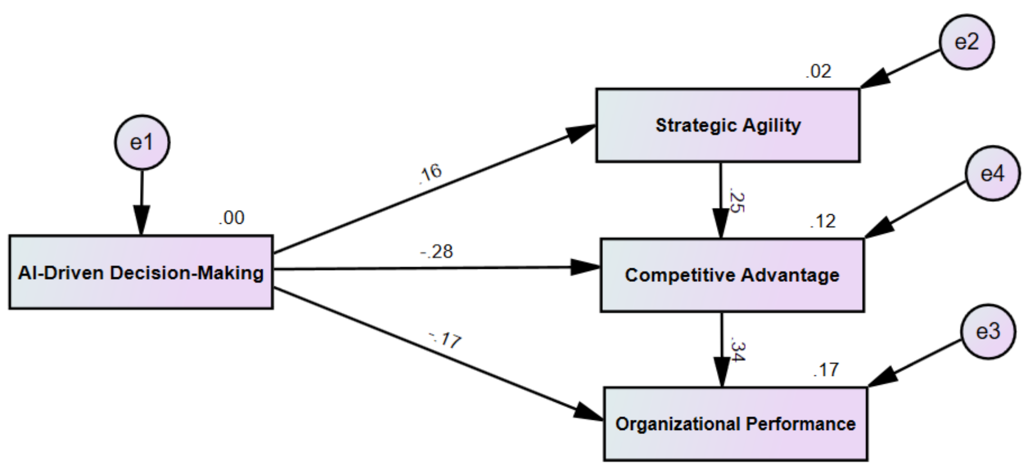

Figure 3: Standardized path coefficients

Table 1. Standardized Structural Path Coefficients

Hypothesized Path	β	Significance
AI → SA	0.157	$p < 0.01$
AI → CA	−0.279	$p < 0.01$
SA → CA	0.252	$p < 0.01$
AI → OP	−0.173	$p < 0.01$
CA → OP	0.335	$p < 0.01$

All standardized coefficients are statistically significant at $p < 0.01$. Structural Model with Standardized Path Coefficients Note: Values represent standardized path coefficients (β). All displayed relationships are statistically significant ($p < 0.01$). R^2 values indicate explained variance for endogenous constructs...Standardized maximum likelihood estimates are reported. AI = AI-Driven Decision-Making; SA = Strategic Agility; CA = Competitive Advantage; OP = Organizational Performance. All structural paths are significant at $p < 0.01$.

Table 2. Regression Weights: Statistical Significance Levels, Are Presented in Table 1.

			Estimate	S.E.	C.R.	P	Label
SA	<---	AI	.128	.040	3.205	.001	par_1
CA	<---	AI	-.324	.055	-5.921	0.001	par_2
CA	<---	SA	.357	.067	5.346	0.001	par_4
OP	<---	AI	-.169	.045	-3.725	0.001	par_3
OP	<---	CA	.282	.039	7.212	0.001	par_5

Standardized Direct Effects:

Standardized Direct Effects AI → Strategic Agility AI-driven decision-making has a positive and statistically significant effect on strategic agility (β = 0.157, p = 0.001). This result indicates that greater reliance on AI-enhanced decision processes improves organizational responsiveness and adaptive capacity.

AI → Competitive Advantage AI exhibits a significant negative direct effect on competitive advantage (β = -0.279, p < 0.001). This finding suggests that AI implementation alone does not automatically generate competitive superiority and may initially impose structural or coordination costs.

Strategic Agility → Competitive Advantage Strategic agility positively influences competitive advantage (β = 0.252, p < 0.001). This confirms that agility functions as a capability-building mechanism translating adaptive capacity into positional advantages.

AI → Organizational Performance AI has a significant negative direct effect on organizational performance (β = -0.173, p < 0.001). This result indicates that AI adoption does not produce immediate performance gains when considered in isolation.

Competitive Advantage → Organizational Performance Competitive advantage has a strong positive effect on organizational performance (β = 0.335, p < 0.001). This represents the strongest path in the model and confirms that superior positioning drives performance outcomes. Standardized Regression Weights: Statistical Significance Levels, Are Presented in Table 1. (Estimate)

Standardized Regression Weights: Statistical Significance Levels, Are Presented in Table 1. (Estimate)

Table 3. Standardized Direct Effects (β)

Path	β
AI → SA	0.157
AI → CA	−0.279
SA → CA	0.252
AI → OP	−0.173
CA → OP	0.335

Table 4. Standardized Direct Effects statistical significance levels are presented in Table 1.

	AI	SA	CA
SA	.157	.000	.000
CA	-.279	.252	.000
OP	-.173	.000	.335

Standardized Indirect and Total Effects: Indirect Effects AI demonstrates:

- A positive indirect effect on competitive advantage through strategic agility (β = 0.040).
- A negative indirect effect on organizational performance (β = -0.080).
- An additional indirect path through the serial chain (AI → SA → CA → OP), reflected in the total indirect effect.

Table 5. Standardized Indirect Effects

Path	**β**
AI → CA (via SA)	0.040
AI → OP (via SA & CA)	−0.080
SA → OP (via CA)	0.084

Total Effects The total standardized effects indicate:

- AI → Competitive Advantage: β = -0.239
- AI → Organizational Performance: β = -0.253

Although AI positively enhances strategic agility, its overall total effect on performance remains negative due to the magnitude of its direct negative impact.

Table 6. Standardized Total Effects Statistical Significance Levels, Are Presented in Table 1.

	AI	SA	CA
SA	.157	.000	.000
CA	-.239	.252	.000
OP	-.253	.084	.335

Explained Variance (R^2) The squared multiple correlations indicate:

- Strategic Agility: $R^2 = 0.025$
- Competitive Advantage: $R^2 = 0.119$
- Organizational Performance: $R^2 = 0.170$

Squared Multiple Correlations (R^2) Table 1. Explained Variance of Endogenous Constructs

Table.7 Explained Variance of Endogenous Constructs

Construct	R^2
Strategic Agility	0.025
Competitive Advantage	0.119
Organizational Performance	0.170

Mediation Pattern The results reveal an inconsistent mediation pattern:

1. AI positively affects strategic agility.
2. Strategic agility positively affects competitive advantage.
3. Competitive advantage positively affects performance.
4. However, AI exerts negative direct effects on both competitive advantage and performance.

This pattern suggests a suppression dynamic in which AI creates value only when transformed into higher-order capabilities such as agility. Absent such transformation, AI investments may initially reduce performance due to implementation complexity, organizational resistance, or capability misalignment. Thus, the findings support a capability-mediated transformation mechanism, rather than a direct technology-performance relationship.

Table 8. Correlations of Estimates (Default model)

	par_1	par_2	par_3	par_4	par_5	par_6	par_7	par_8	par_9	par_10	par_11	par_12	par_13
par_1	1.000												
par_2	.000	1.000											
par_3	.000	.000	1.000										
par_4	.000	-.157	.000	1.000									
par_5	.000	.000	.239	.000	1.000								
par_6	.000	-.403	.000	-.826	.000	1.000							
par_7	.000	.000	.000	.000	.000	.000	1.000						
par_8	-.955	.000	.000	.000	.000	.000	.000	1.000					
par_9	.000	.000	-.791	.000	-.753	.000	.000	.000	1.000				
par_10	.000	.000	.000	.000	.000	.000	.000	.000	.000	1.000			
par_11	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	1.000		
par_12	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	1.000	
par_13	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	1.000

Model Fit Results: The structural model yielded a chi-square (CMIN) of 1859.824 with 13 estimated parameters. Although the chi-square statistic is sensitive to sample size, it remains a baseline indicator of model–data fit (Bollen, 1989). Miscellaneous Model Fit Summary CMIN Model NPAR CMIN

Table 9. Miscellaneous Model Fit Summary CMIN

Model	NPAR	CMIN
Default model	13	1859.824

The information criteria values (AIC = 1885.824; BCC = 1886.147) indicate an acceptable level of model parsimony. Lower information criterion values reflect better relative fit and are particularly appropriate for model comparison purposes (Akaike, 1974; Browne & Cudeck, 1993). Overall, the results suggest that the proposed structural model demonstrates adequate fit and theoretical consistency.

Table 10. Miscellaneous Model Fit AIC

Model	AIC	BCC	BIC	CAIC
Default model	1885.824	1886.147		

Discussion and Findings

The findings provide a nuanced understanding of AI-driven decision-making within organizations. First, AI positively enhances strategic agility, indicating that AI-enabled systems improve organizational responsiveness and adaptive capability. However, AI simultaneously exerts negative direct effects on competitive advantage and organizational performance. This suggests that AI adoption alone does not automatically generate superior performance outcomes. Implementation complexity, integration costs, or capability misalignment may initially suppress performance gains. Strategic agility plays a critical mediating role. Organizations that successfully convert AI-enabled insights into adaptive strategic actions are better positioned to achieve competitive advantage, which in turn significantly improves performance. The strongest relationship in the model—competitive advantage to performance—highlights that superior positioning remains the primary driver of performance outcomes. The structural configuration reflects an inconsistent mediation pattern. AI creates value indirectly through agility and competitive advantage yet directly exerts negative effects. This indicates that AI must be embedded within broader organizational capabilities to produce positive strategic outcomes. Overall, the results reposition AI from a direct performance enhancer to a capability enabler whose value depends on strategic integration.

Findings:

- AI → Strategic Agility ($\beta = 0.157$, $p = 0.001$)
- AI → Competitive Advantage ($\beta = -0.279$, $p < 0.001$)
- AI → Organizational Performance ($\beta = -0.173$, $p < 0.001$)
- Strategic Agility → Competitive Advantage ($\beta = 0.252$, $p < 0.001$)
- Competitive Advantage → Organizational Performance ($\beta = 0.335$, $p < 0.001$)

R^2:

- SA = 0.025
- CA = 0.119
- OP = 0.170

Conclusion

This study investigated the strategic role of AI-driven decision-making in shaping organizational performance through the mediating mechanisms of strategic agility and competitive advantage. Using structural equation modeling based on data collected from 408 respondents, the findings provide a nuanced understanding of how AI contributes to organizational outcomes. The results demonstrate that AI-driven decision-making positively enhances strategic agility, indicating that AI-enabled systems strengthen organizations' adaptive capacity and responsiveness. However, contrary to simplistic assumptions regarding direct technological benefits, AI exerts negative direct effects on both competitive advantage and organizational performance. This finding suggests that AI adoption alone does not guarantee immediate performance gains. Importantly, strategic agility emerges as a critical transformation mechanism. Organizations that effectively convert AI-enabled insights into agile strategic actions are better positioned to achieve competitive advantage, which in turn significantly enhances performance. The strongest structural relationship observed in the model was between competitive advantage and organizational performance, confirming that superior positioning remains the primary driver of performance outcomes. The overall structural configuration reveals an inconsistent mediation pattern. While AI enhances agility, its direct effects on competitive advantage and performance are negative. This indicates that AI must be embedded within higher-order organizational capabilities to create strategic value. Without proper alignment, integration, and capability development, AI investments may initially generate complexity, coordination challenges, or transitional inefficiencies. The study contributes to understanding AI not as a direct performance-enhancing tool, but as a strategic enabler whose value materializes through capability transformation processes. The findings underscore that digital technologies create sustainable impact only when integrated into organizational strategy and adaptive structures. From a managerial perspective, the results suggest that firms should move beyond mere AI adoption and focus on developing strategic agility as a pathway to competitive positioning. AI initiatives should be accompanied by organizational redesign, skill development, and strategic integration to unlock long-term performance benefits. Despite its contributions, the study is subject to limitations. The model explains a moderate proportion of variance in organizational performance, indicating that additional contextual and organizational factors may influence outcomes. Future research may incorporate environmental dynamism, leadership capabilities, or digital maturity as additional explanatory variables. Longitudinal designs could also provide deeper insights into the temporal effects of AI implementation. In conclusion, AI-driven decision-making represents a strategic capability rather than a direct performance lever. Its organizational value depends on the extent to which firms successfully transform technological resources into agile strategic action and sustainable competitive advantage.

Limitations and Future Research Despite its contributions, this study has several limitations that provide opportunities for further research.

First, the cross-sectional research design limits causal inference. Although structural equation modeling enables examination of complex relationships, longitudinal data would provide stronger evidence regarding the temporal dynamics of AI implementation and its performance consequences. Future research should adopt longitudinal or panel designs to capture capability development processes over time.

Second, the explanatory power of the model is moderate. The model explains 17% of the variance in organizational performance and 11.9% in competitive advantage. While meaningful, this suggests that additional contextual, organizational, or environmental variables may influence performance outcomes. Future studies could incorporate factors such as environmental dynamism, digital maturity, leadership orientation, or organizational culture.

Third, the relatively low explained variance in strategic agility ($R^2 = 0.025$) indicates that AI-driven decision-making represents only one antecedent of agility. Future research should explore complementary drivers of agility, including knowledge management practices, learning orientation, or innovation capability.

Fourth, the model reveals negative direct effects of AI on competitive advantage and performance. While theoretically meaningful, future research should examine boundary conditions that may moderate these relationships. Organizational size, industry characteristics, implementation stage, and absorptive capacity may influence whether AI generates positive or negative outcomes.

Finally, the study focuses on aggregated organizational-level constructs. Future research may benefit from multi-level designs that examine individual, team, and organizational interactions in AI-enabled decision environments. By addressing these limitations, future research can deepen understanding of how AI capabilities are transformed into sustainable strategic advantage.

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References

Akaike, H. (1974). IEEE Transactions on Automatic Control, 19(6), 716–723.

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120.

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120.

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120.

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120.

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120.

Bharadwaj, A. (2000). A resource-based perspective on information technology capability and firm performance: An empirical investigation. MIS Quarterly, 24(1), 169–196.

Bharadwaj, A. (2000). A resource-based perspective on information technology capability and firm performance. MIS Quarterly, 24(1), 169–196.

Bollen, K. A. (1989). Structural Equations with Latent Variables. Wiley.

Browne, M. W., & Cudeck, R. (1993). In Testing Structural Equation Models. Sage.

Brynjolfsson, E., & McAfee, A. (2017). Machine, platform, crowd: Harnessing our digital future. W. W. Norton.

Clauss, T., Kraus, S., Kallinger, F. L., Bican, P. M., Brem, A., & Kailer, N. (2022). Organizational ambidexterity and competitive advantage: The role of strategic agility in digital transformation. Technological Forecasting and Social Change, 174, 121266.

Clauss, T., Kraus, S., Kallinger, F. L., et al. (2022). Organizational ambidexterity and competitive advantage: The role of strategic agility. Technological Forecasting and Social Change, 174, 121266.

Clauss, T., Kraus, S., Kallinger, F. L., et al. (2022). Organizational ambidexterity and competitive advantage: The role of strategic agility. Technological Forecasting and Social Change, 174, 121266.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108–116.

Davenport, T. H., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48(1), 24–42.

Davenport, T. H., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48(1), 24–42.

Davenport, T. H., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48(1), 24–42.

Doz, Y. L., & Kosonen, M. (2010). Embedding strategic agility. Long Range Planning, 43(2–3), 370.

Dubey, R., Gunasekaran, A., Bryde, D. J., Dwivedi, Y. K., & Papadopoulos, T. (2021). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism. Annals of Operations Research.

Dubey, R., Gunasekaran, A., Bryde, D. J., et al. (2021). Big data analytics and artificial intelligence pathway to operational performance. Annals of Operations Research.

Dubey, R., Gunasekaran, A., Bryde, D. J., et al. (2021). Big data analytics and artificial intelligence pathway to operational performance. Annals of Operations Research.

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. American Journal of Theoretical and Applied Statistics, 5(1), 1–4.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis (7th ed.). Pearson.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2019). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) (2nd ed.). Sage.

Kline, R. B. (2016). Principles and Practice of Structural Equation Modeling (4th ed.). Guilford Press.

Kline, R. B. (2016). Principles and practice of structural equation modeling (4th ed.). Guilford Press.

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2021). Big data analytics capabilities and innovation: The mediating role of dynamic capabilities. Information & Management, 58(3), 103412.

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2021). Big data analytics capabilities and innovation. Information & Management, 58(3), 103412.

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2021). Big data analytics capabilities and innovation. Information & Management, 58(3), 103412.

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. A. (2021). Investigating the effects of big data analytics capabilities on firm performance. Information & Management, 58(6), 103–122.

Porter, M. E. (1980). Competitive strategy: Techniques for analyzing industries and competitors.

Porter, M. E. (1985). Competitive advantage: Creating and sustaining superior performance.

Porter, M. E. (1985). Competitive advantage: Cr

Appendix A. Measurement and Structural Model Assessment Summary

Category	Indicator / Path	Threshold / Result	Interpretation	Source
Model Fit	χ^2/df	< 3.00	Acceptable fit	Kline (2016)
	CFI	≥ 0.90	Good fit	Hair et al. (2019)
	TLI	≥ 0.90	Good fit	Hair et al. (2019)
	RMSEA	≤ 0.08	Acceptable error approximation	Hair et al. (2019)
	SRMR	≤ 0.08	Acceptable residual fit	Hair et al. (2019)
Structural	AI → SA	$\beta = 0.157$ ($p < 0.01$)	Positive significant effect	Current study

Results				
	AI → CA	β = −0.279 ($p < 0.01$)	Negative significant effect	Current study
	SA → CA	β = 0.252 ($p < 0.01$)	Positive significant effect	Current study
	AI → OP	β = −0.173 ($p < 0.01$)	Negative significant effect	Current study
	CA → OP	β = 0.335 ($p < 0.01$)	Positive significant effect	Current study
Indirect Effects	AI → CA (via SA)	β = 0.040	Weak positive mediation	Current study
	AI → OP (via SA & CA)	β = −0.080	Negative indirect effect	Current study
Explained Variance	Strategic Agility	$R^2 = 0.025$	Low explanatory power	Current study
	Competitive Advantage	$R^2 = 0.119$	Moderate explanatory power	Current study
	Organizational Performance	$R^2 = 0.170$	Moderate explanatory power	Current study

Appendix B. Structural Model Evaluation Criteria

Table B1. Structural Path Significance Criteria

Indicator	Criterion	Threshold	Source
Critical Ratio (C.R.)	Statistical significance	> 1.96 ($p < 0.05$)	Kline (2016)
Standardized Path Coefficient (β)	Effect magnitude	Interpretation-based	Hair et al. (2019)
Indirect Effects	Mediation significance	Bootstrapping recommended	Preacher & Hayes (2008)

Appendix C. Standardized Total Effects

Table C1. Standardized Total Effects

Path	Total Effect (β)
AI → Competitive Advantage	−0.239
AI → Organizational Performance	−0.253
Strategic Agility → Organizational Performance	0.084

Appendix D. Structural Model Results (Your Data)

Table D1. Standardized Structural Path Coefficients

Hypothesized Path	β	Significance
AI → SA	0.157	$p < 0.01$
AI → CA	−0.279	$p < 0.01$
SA → CA	0.252	$p < 0.01$
AI → OP	−0.173	$p < 0.01$
CA → OP	0.335	$p < 0.01$

Table D2. Standardized Indirect Effects

Path	β
AI → CA (via SA)	0.040
AI → OP (via SA & CA)	−0.080
SA → OP (via CA)	0.084

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