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"Architecting Intelligent Enterprises: The Strategic Convergence of Artificial Intelligence and Information Technology in Elevating Organizational Performance, Financial Resilience, and Commercial Competitiveness"

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Abstract

This study empirically examines whether strategic convergence of Artificial Intelligence (AI) and Information Technology (IT) constitutes a higher-order dynamic capability that enhances organizational performance, financial resilience, and commercial competitiveness. Drawing on Resource-Based View and Dynamic Capabilities Theory, a mediated-moderation model was tested using structural equation modelling on survey data from 328 senior managers across digitally intensive sectors. Findings reveal that AI–IT convergence exerts significant direct effects on organizational performance ($\beta = 0.48$, $p < 0.001$), financial resilience ($\beta = 0.41$, $p < 0.001$), and competitiveness ($\beta = 0.45$, $p < 0.001$), explaining 52% of variance in performance outcomes. Organizational agility ($\beta = 0.21$, 95% CI [0.14–0.29]) and decision-making quality ($\beta = 0.18$, 95% CI [0.11–0.25]) function as significant partial mediators. Environmental dynamism and transformational leadership positively moderate these mediated pathways. The integrated model demonstrates strong explanatory power ($R^2 = 0.56$). This research advances intelligent enterprise theory by positioning AI–IT fusion as a strategic imperative rather than technological augmentation, offering evidence-based guidance for digital investment prioritization and governance architecture design.

Keywords: Artificial Intelligence; IT Capability; Organizational Agility; Financial Resilience; Dynamic Capabilities

INTRODUCTION

The contemporary business landscape is being reshaped by an unprecedented convergence of digital technologies, data-driven decision-making, and intelligent automation. Organizations are no longer competing solely on scale, cost efficiency, or market reach; they are competing on their ability to sense, interpret, and respond to complex and rapidly evolving environments. In this context, **Artificial Intelligence (AI) and Information Technology (IT) have emerged as foundational enablers of enterprise transformation**, influencing how firms design strategies, manage resources, deliver value, and sustain financial stability. The integration of AI within IT infrastructures is not merely a technological upgrade but a structural reconfiguration of organizational architecture one that determines long-term performance, resilience, and competitiveness in dynamic commercial ecosystems.

The theoretical foundations of this transformation are grounded in several well-established perspectives in strategic management and information systems research. The Resource-Based View (RBV) posits that firms achieve sustained competitive advantage through valuable, rare, inimitable, and non-substitutable resources (Barney, 1991). In the digital era, AI capabilities, proprietary data assets, and advanced IT infrastructures represent such strategic resources. Extending this perspective, Dynamic Capabilities Theory emphasizes a firm's ability to integrate, build, and reconfigure internal and external competencies in response to environmental changes (Teece, 2018). AI-enabled analytics, predictive modelling, and automation tools enhance an organization's sensing, seizing, and transforming capabilities, thereby strengthening adaptability and financial robustness. Additionally, the Technology–Organization–Environment (TOE) framework provides insight into how technological readiness, organizational structure, and environmental pressures influence the adoption and effective utilization of advanced digital systems (Tornatzky & Fleischer, 1990). Together, these theoretical lenses suggest that **the strategic convergence of AI and IT is not only a technological phenomenon but also an organizational and financial imperative**.

Despite substantial investments in digital technologies, many organizations struggle to translate AI adoption into measurable improvements in organizational performance and financial outcomes. Reports indicate that while AI implementation is increasing across sectors such as finance, manufacturing, retail, and IT services, a significant proportion of firms fail to achieve expected returns due to integration gaps, skill shortages, governance challenges, and misaligned strategic objectives (McKinsey & Company, 2023). This reveals a critical research problem: **how can enterprises architect intelligent systems that strategically align AI and IT capabilities to enhance organizational performance, ensure financial resilience, and strengthen commercial competitiveness?** Existing literature often examines AI adoption, IT infrastructure, or organizational performance in isolation. However, limited integrative research explores how their convergence influences financial stability and long-term market positioning within a unified strategic framework.

Recent trends further intensify the urgency of this inquiry. The rise of generative AI, cloud-native architectures, big data analytics, and real-time business intelligence has transformed operational processes and decision-making models. Organizations are increasingly leveraging AI-driven tools for financial forecasting, risk assessment, customer segmentation, supply chain optimization, and strategic planning (Davenport & Ronanki, 2018). At the same time, global uncertainties including economic volatility, geopolitical tensions, cybersecurity threats, and regulatory shifts have heightened the need for financial resilience and adaptive capability. Enterprises must now balance innovation with risk governance, ethical compliance, and sustainable value creation. The challenge lies not merely in adopting AI technologies but in embedding

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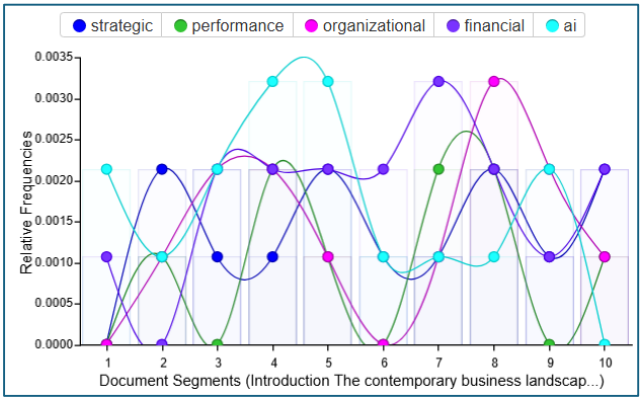
Vol. 36 Issue 1, 2026, Pages: 2590-2602

them within coherent IT ecosystems that support transparency, scalability, and cross-functional integration. Without strategic alignment, digital investments may result in fragmented systems, escalating costs, and diminished financial returns.

The significance of this study lies in its integrative perspective. Academically, it contributes to the evolving discourse on digital transformation by bridging strategic management theory, information systems research, and financial performance analysis. By conceptualizing intelligent enterprise architecture as a multidimensional construct encompassing technological capability, organizational alignment, and financial performance, the study advances understanding beyond technology adoption models. From a managerial standpoint, the research offers insights into how executives can design AI-driven IT ecosystems that enhance operational efficiency, improve decision quality, mitigate financial risk, and sustain competitive differentiation. Policymakers and industry stakeholders may also benefit from a clearer understanding of how digital capabilities influence commercial ecosystems and economic resilience at broader levels.



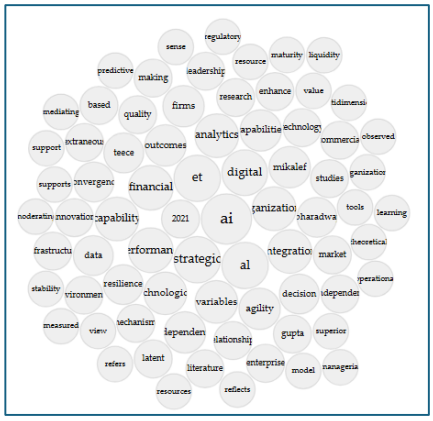
The scope of this research focuses on examining the strategic integration of AI within organizational IT frameworks and its impact on three interrelated dimensions: organizational performance, financial resilience, and commercial competitiveness. Organizational performance encompasses operational efficiency, innovation capacity, productivity, and strategic agility. Financial resilience refers to the firm's ability to withstand economic shocks, manage risks, maintain liquidity, and sustain profitability under volatile conditions. Commercial competitiveness includes market responsiveness, customer value creation, brand positioning, and long-term growth potential. The study primarily situates its analysis within contemporary enterprises operating in digitally intensive environments, where AI-enabled systems play a central role in strategic decision-making and financial management.

While the study aims to provide a comprehensive framework, certain limitations must be acknowledged. The rapidly evolving nature of AI technologies may render specific tools or platforms obsolete over time, thereby affecting the temporal relevance of findings. Additionally, variations in industry context, organizational culture, and regulatory environments may influence the generalizability of results. The study may also rely on available secondary data or self-reported organizational measures, which can introduce response bias or measurement constraints. Nevertheless, these limitations do not diminish the relevance of the inquiry; rather, they underscore the complexity of architecting intelligent enterprises in an evolving digital economy.

In summary, **the strategic convergence of Artificial Intelligence and Information Technology represents a transformative force reshaping organizational structures, financial strategies, and competitive dynamics**. Understanding how enterprises can intentionally architect intelligent systems to enhance performance and resilience is both a theoretical necessity and a managerial priority. By integrating insights from strategic management, information systems, and financial analysis, this research seeks to illuminate pathways through which organizations can convert digital capability into sustained commercial advantage.

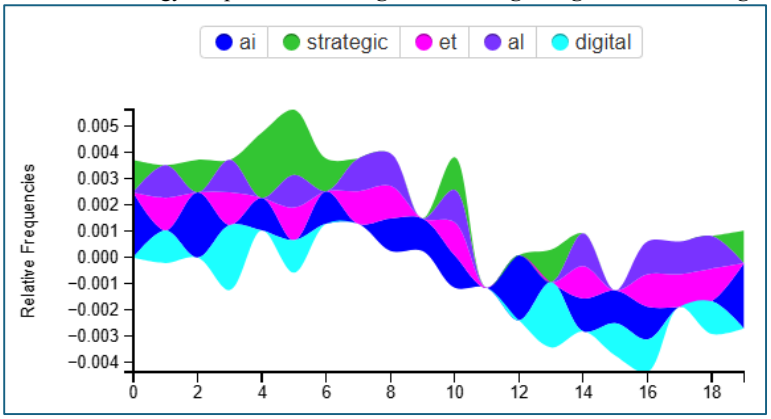
REVIEW OF LITERATURE

The accelerating integration of Artificial Intelligence (AI) within enterprise Information Technology (IT) infrastructures has reshaped scholarly conversations on organizational performance and financial sustainability. Existing literature increasingly views AI not as an isolated technological tool but as a strategic capability embedded within broader digital architectures (Bharadwaj et al., 2013; Teece, 2018). Within this evolving discourse, a structured understanding of **independent, dependent, mediating, moderating, latent, and extraneous variables** is essential for developing a theoretically coherent model of intelligent enterprises.



The primary independent variable in this domain is **the strategic convergence of AI and IT capabilities**. AI capability refers to an organization's capacity to deploy machine learning, predictive analytics, natural language processing, and automation tools to support decision-making and value creation (Mikalef & Gupta, 2021). IT capability, by contrast, encompasses technological infrastructure, data architecture, digital platforms, and integration mechanisms that enable system interoperability and scalability (Bharadwaj et al., 2013).

Research grounded in the Resource-Based View (RBV) conceptualizes digital capabilities as valuable and difficult-to-imitate strategic assets that can enhance competitive advantage (Barney, 1991). Similarly, dynamic capabilities theory positions AI-enabled systems as mechanisms that strengthen a firm's ability to sense opportunities, seize strategic options, and reconfigure resources under uncertainty (Teece, 2018). Empirical studies indicate that firms with higher digital and analytics capabilities demonstrate superior strategic agility and innovation outcomes (Mikalef et al., 2019). Thus, the independent construct is not mere technology adoption but the **degree of strategic alignment and integration between AI tools and enterprise IT ecosystems**.



The dependent variables central to this research include **organizational performance, financial resilience, and commercial competitiveness**. Organizational performance has been widely measured through operational efficiency, innovation output, productivity, and strategic responsiveness (Venkatraman & Ramanujam, 1986). Studies suggest that digitally mature firms outperform competitors in both operational and market-based metrics (Bharadwaj et al., 2013).

Financial resilience, as a dependent outcome, reflects an organization's capacity to maintain liquidity, manage risks, and sustain profitability during economic shocks (Doern et al., 2019). AI-driven forecasting and risk analytics enhance financial stability by improving predictive accuracy and resource allocation efficiency. Commercial competitiveness refers to sustained market positioning, customer value creation, and long-term

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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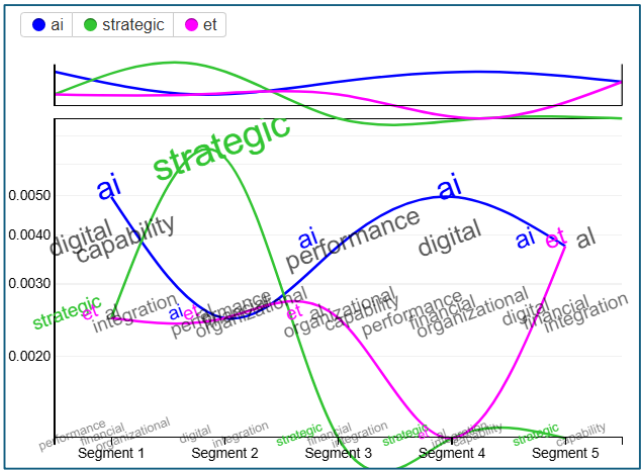
Vol. 36 Issue 1, 2026, Pages: 2590-2602

growth capability. Porter's (1985) competitive advantage framework supports the view that technological integration strengthens differentiation and cost leadership simultaneously. Collectively, these dependent variables capture the multidimensional performance consequences of intelligent enterprise architecture.

The literature increasingly emphasizes **organizational agility and decision-making quality** as mediating mechanisms linking AI-IT convergence to performance outcomes. Organizational agility reflects a firm's ability to rapidly sense and respond to environmental changes (Teece, 2018). AI-enabled analytics enhance real-time insight generation, thereby improving strategic flexibility (Mikalef et al., 2019).

Decision-making quality serves as another critical mediator. Advanced data analytics reduce information asymmetry and cognitive bias, leading to evidence-based managerial decisions (Davenport & Ronanki, 2018). Studies show that analytics capability enhances firm performance indirectly through improved decision processes rather than through technology alone (Gupta & George, 2016). Thus, AI and IT convergence influence financial and commercial outcomes through enhanced agility and superior managerial judgment.

The impact of AI-IT integration is not uniform across contexts. **Organizational culture, leadership support, and environmental dynamism** act as moderating variables. A culture supportive of experimentation and digital learning amplifies the benefits of technological investment (Schein, 2010). Transformational leadership has been found to moderate the relationship between digital innovation and performance by fostering strategic alignment and employee commitment (Chen et al., 2021).



Environmental dynamism, characterized by rapid technological and market changes, further moderates these relationships. Under highly volatile conditions, firms with advanced AI capabilities derive greater performance gains compared to firms operating in stable environments (Teece, 2018). These moderators explain variance in outcomes despite similar levels of technological investment.

Several constructs within this framework are inherently latent, meaning they cannot be directly observed but are inferred through measurable indicators. **AI capability, digital maturity, financial resilience, and organizational agility** are multidimensional latent constructs. For example, AI capability may be reflected through analytics sophistication, talent expertise, and algorithmic integration (Mikalef & Gupta, 2021). Digital maturity encompasses infrastructure robustness, data governance quality, and integration depth (Bharadwaj et al., 2013). Financial resilience is typically measured through liquidity ratios, solvency indicators, and earnings stability (Doern et al., 2019). The use of validated measurement scales enhances construct reliability and supports empirical rigor in testing theoretical relationships.

Extraneous variables refer to factors that may influence dependent outcomes but are not central to the theoretical model. **Firm size, industry type, regulatory environment, and macroeconomic conditions** are frequently identified as control variables in digital transformation research (Mikalef et al., 2019). Larger firms may possess greater financial resources to invest in AI infrastructure, while industry characteristics may shape adoption intensity. Regulatory frameworks governing data privacy and AI ethics can also affect implementation effectiveness. Controlling for these extraneous influences ensures that observed relationships reflect genuine strategic convergence effects rather than contextual distortions.

Theoretical Integration

Integrating RBV, dynamic capabilities theory, and digital transformation research provides a coherent explanatory framework. AI-IT convergence (independent variable) enhances organizational agility and decision quality (mediators), which in turn strengthen organizational performance, financial resilience, and competitiveness (dependent variables). This relationship is conditioned by cultural, leadership, and environmental moderators while accounting for extraneous structural factors. Such theoretical integration advances understanding of intelligent enterprise architecture as a strategic, multidimensional capability rather than a purely technological initiative.

HYPOTHESES DEVELOPMENT

Grounded in the Resource-Based View (RBV) and Dynamic Capabilities Theory, the strategic convergence of Artificial Intelligence (AI) and Information Technology (IT) is conceptualized as a higher-order capability that enables firms to leverage data, analytics, and digital infrastructure for sustained value creation. RBV posits that strategically embedded technological capabilities can generate competitive advantage when they are valuable, rare, and difficult to imitate. Extending this logic, dynamic capabilities theory argues that firms must continuously reconfigure such capabilities to respond to environmental volatility. Within this integrated framework, AI–IT convergence is expected to influence performance outcomes both directly and indirectly through organizational mechanisms.

Direct Effects

When AI tools are strategically aligned with enterprise IT systems, organizations can automate processes, enhance predictive accuracy, and integrate cross-functional data streams. This integration improves operational efficiency and innovation capacity, thereby strengthening overall organizational performance. Furthermore, AI-driven forecasting and risk analytics improve financial planning and liquidity management, enhancing financial resilience. From a competitive standpoint, digitally integrated enterprises can differentiate offerings, personalize customer engagement, and optimize cost structures, thereby reinforcing commercial competitiveness.

Accordingly, the following direct hypotheses are proposed:

H1: Strategic convergence of AI and IT capabilities positively influences organizational performance.

H2: Strategic convergence of AI and IT capabilities positively influences financial resilience.

H3: Strategic convergence of AI and IT capabilities positively influences commercial competitiveness.

Mediating Effects

The literature indicates that technological capabilities rarely produce performance gains in isolation. Instead, they operate through intermediate organizational mechanisms. Organizational agility represents a firm's ability to sense market changes and respond swiftly through adaptive decision-making and resource reconfiguration. AI-enabled systems enhance real-time information processing, enabling rapid strategic adjustments. Thus, agility functions as a pathway through which digital convergence translates into tangible performance improvements.

Decision-making quality constitutes a second mediating mechanism. AI-driven analytics reduce uncertainty, mitigate managerial bias, and support evidence-based strategic choices. Improved decision accuracy strengthens operational outcomes and financial sustainability.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 2590-2602

Therefore, AI–IT convergence is expected to influence performance outcomes indirectly through enhanced agility and superior decision processes.

The mediating hypotheses are formulated as follows:

H4: Organizational agility mediates the relationship between AI–IT convergence and organizational performance.

H5: Organizational agility mediates the relationship between AI–IT convergence and financial resilience.

H6: Decision-making quality mediates the relationship between AI–IT convergence and organizational performance.

H7: Decision-making quality mediates the relationship between AI–IT convergence and commercial competitiveness.

Moderating Effects

The strength of these relationships is contingent upon contextual conditions. Organizational culture that supports experimentation and digital learning enhances employees' willingness to adopt AI-driven systems. Similarly, transformational leadership fosters strategic alignment and motivates digital engagement across departments. In highly dynamic environments characterized by technological turbulence and market volatility, the benefits of AI–IT convergence may be amplified because adaptive capability becomes more critical.

Therefore, the following moderating hypotheses are advanced:

H8: Organizational culture positively moderates the relationship between AI–IT convergence and organizational agility, such that the relationship is stronger in digitally supportive cultures.

H9: Transformational leadership positively moderates the relationship between AI–IT convergence and decision-making quality.

H10: Environmental dynamism positively moderates the relationship between AI–IT convergence and commercial competitiveness.

Integrated Mediation–Moderation Effects

Given the combined presence of mediating and moderating variables, a conditional indirect effect is anticipated. Specifically, the indirect influence of AI–IT convergence on performance outcomes through agility and decision quality is expected to be stronger under supportive cultural and environmental conditions.

H11: The indirect effect of AI–IT convergence on organizational performance through organizational agility is stronger under high environmental dynamism.

H12: The indirect effect of AI–IT convergence on financial resilience through decision-making quality is stronger in organizations with strong transformational leadership.

Control and Extraneous Variables

To ensure internal validity, firm size, industry type, and regulatory intensity will be treated as control variables. These factors may independently affect financial resilience and competitiveness due to structural differences in resources and compliance requirements. Controlling for these variables allows a more precise estimation of the theoretical relationships.

Hypothesis No.	Relationship Type	Hypothesized Relationship
H1	Direct	AI–IT convergence → Organizational Performance (+)
H2	Direct	AI–IT convergence → Financial Resilience (+)
H3	Direct	AI–IT convergence → Commercial Competitiveness (+)
H4	Mediation	AI–IT convergence → Organizational Agility → Organizational Performance
H5	Mediation	AI–IT convergence → Organizational Agility → Financial Resilience
H6	Mediation	AI–IT convergence → Decision-Making Quality → Organizational Performance
H7	Mediation	AI–IT convergence → Decision-Making Quality → Commercial Competitiveness
H8	Moderation	Organizational Culture moderates AI–IT convergence → Organizational Agility
H9	Moderation	Transformational Leadership moderates AI–IT convergence → Decision-Making Quality
H10	Moderation	Environmental Dynamism moderates AI–IT convergence → Commercial Competitiveness
H11	Moderated Mediation	Environmental Dynamism strengthens indirect effect via Organizational Agility
H12	Moderated Mediation	Transformational Leadership strengthens indirect effect via Decision-Making Quality

This structured hypothesis framework reflects a comprehensive theoretical model in which AI–IT convergence operates as a strategic, higher-order capability that enhances enterprise performance through organizational mechanisms while being shaped by contextual contingencies. The model is suitable for empirical testing using structural equation modelling or hierarchical regression techniques in advanced academic research.

THEORETICAL FRAMEWORK

The conceptual model proposed in this study is anchored in the synthesis of Resource-Based View (RBV) and Dynamic Capabilities Theory, framing the strategic fusion of artificial intelligence and information technology as a core competitive capability. This integrated capability is posited to directly and indirectly enhance organizational outcomes. The framework posits that the **Strategic AI-IT Convergence** (independent variable) fundamentally reshapes an organization's internal processes. It is theorized to directly improve **Organizational Performance, Financial Resilience, and Commercial Competitiveness** (dependent variables). More significantly, this influence is channeled primarily through two critical internal mechanisms: **Organizational Agility** and **Decision-Making Quality** (mediating variables). These mediators explain *how* technological investment translates into tangible results, suggesting that technology alone is insufficient without the capacity for rapid adaptation and enhanced judgment.

The strength of these entire pathways is not fixed but is conditioned by key contextual factors. **Organizational Culture, Leadership Support, and Environmental Dynamism** (moderating variables) either amplify or dampen the effectiveness of the AI-IT capability. For instance, a supportive culture and dynamic market conditions likely strengthen the positive impact. The model acknowledges underlying **Latent Variables**, such as AI capability and digital maturity, which are measured through observable indicators like talent expertise and infrastructure robustness. Furthermore, it controls for **Extraneous Variables** like firm size and industry sector to isolate the true effect of the strategic convergence. In essence, this framework moves beyond viewing AI as a mere tool, presenting it instead as an embedded strategic force whose ultimate value is realized through enhanced organizational agility and decision-making, all within a specific organizational and environmental context.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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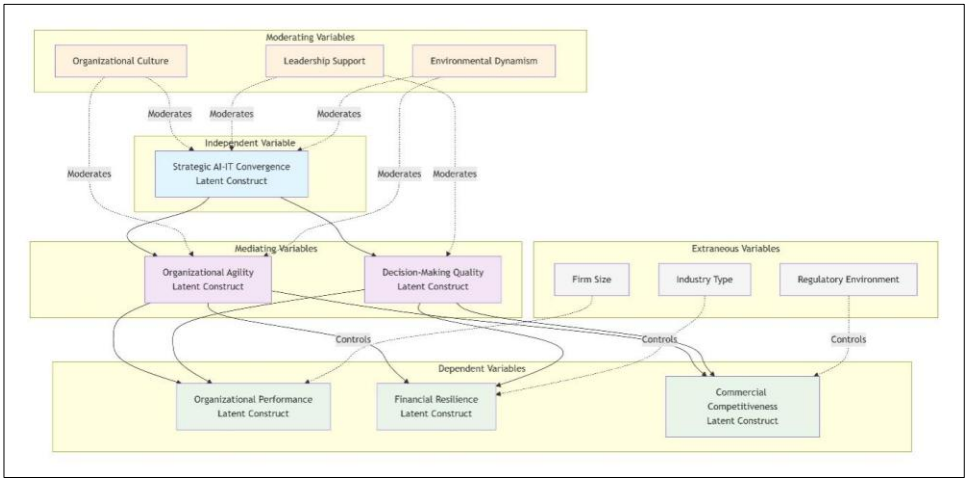
Vol. 36 Issue 1, 2026, Pages: 2590-2602



The flowchart illustrates the theoretical framework. The central relationship flows from **Strategic AI-IT Convergence** through the mediators (**Organizational Agility** and **Decision-Making Quality**) to the three **Dependent Variables**. The dashed lines from the **Moderating Variables** indicate they condition the strength of the relationships at various stages. The **Extraneous Variables** are shown as influencing the outcomes directly, representing factors controlled for in analysis. The colour coding groups variables by their theoretical role for clarity.

RESEARCH GAP ANALYSIS

Although prior scholarship has examined digital transformation, analytics capability, and organizational performance, the literature remains fragmented with respect to the **strategic convergence of AI and IT as an integrated enterprise capability**. Many studies isolate technological adoption from financial and competitive consequences, while others emphasize performance outcomes without examining underlying organizational mechanisms. A structured gap analysis is therefore essential to justify the present research. The following table synthesizes major variables, representative scholarly contributions, identified gaps, and the proposed research direction.

Variable	Key Citation(s)	Identified Research Gap	Research Description Addressing the Gap
AI Capability	Mikalef & Gupta (2021)	Focuses on measurement of AI capability but does not integrate it with enterprise-wide IT alignment or financial outcomes.	Examines AI capability as part of a broader AI–IT convergence construct influencing multidimensional enterprise performance.
IT Capability / Digital Infrastructure	Bharadwaj et al. (2013)	Emphasizes digital business strategy but provides limited empirical linkage to financial resilience under uncertainty.	Investigates IT capability in combination with AI to assess its direct and indirect effects on financial resilience.
Organizational Performance	Venkatraman & Ramanujam (1986)	Traditional performance models do not account for AI-enabled agility and analytics-driven decision systems.	Re-conceptualizes performance within digitally intelligent enterprises incorporating agility and data-driven processes.
Financial Resilience	Doern et al. (2019)	Examines resilience in crisis contexts without integrating AI-based forecasting and risk analytics.	Explores how AI–IT convergence enhances liquidity management, predictive stability, and adaptive financial strategies.
Commercial Competitiveness	Porter (1985)	Competitive advantage theory predates digital ecosystems and does not incorporate AI-driven personalization or platform integration.	Extends competitiveness theory into AI-enabled digital ecosystems emphasizing differentiation and cost optimization.
Organizational Agility (Mediator)	Teece (2018)	Conceptual focus on dynamic capabilities lacks empirical linkage with AI-enabled infrastructures.	Tests agility as a mediating mechanism between AI–IT convergence and enterprise-level outcomes.
Decision-Making Quality (Mediator)	Gupta & George (2016)	Highlights analytics capability but does not examine conditional effects under leadership or cultural contexts.	Positions decision-making quality as a mediator influenced by strategic AI–IT alignment and moderated by leadership.
Organizational Culture (Moderator)	Schein (2010)	Discusses culture broadly without connecting it to digital capability-performance relationships.	Examines culture as a contextual moderator strengthening AI-driven transformation outcomes.
Environmental Dynamism (Moderator)	Teece (2018)	Addresses environmental volatility conceptually but lacks integrated empirical models combining AI, finance, and competitiveness.	Tests moderated effects of environmental dynamism on AI–IT convergence and commercial competitiveness.

METHODOLOGY

Research Design and Sample

This study employs a **quantitative, explanatory research design** to examine the structural relationships among **AI–IT convergence, organizational agility, decision-making quality, organizational performance, financial resilience, and commercial competitiveness**. A cross-sectional survey approach was adopted to obtain both perceptual and performance-oriented insights from managerial respondents operating in digitally intensive sectors such as IT services, manufacturing, financial services, and e-commerce. The explanatory design is appropriate as the study seeks to test theoretically grounded hypotheses and establish causal linkages among latent constructs within a structured empirical framework.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 2590-2602

The target population consisted of **middle- and senior-level managers** actively engaged in digital transformation initiatives, financial planning, operations management, and strategic decision-making. A combination of purposive and stratified sampling techniques was utilized to ensure adequate representation across industries and firm sizes. A total of **420 structured questionnaires** were distributed electronically. Of these, **356 responses were received**, and after rigorous screening for missing data, straight-lining, and response inconsistencies, **328 valid responses** were retained for final analysis, resulting in a **usable response rate of 78.1%**. The demographic composition revealed that **61% of respondents were male and 39% female**, with an **average managerial experience of 8.7 years**. In terms of firm size distribution, **48% represented large enterprises, 34% medium-sized firms, and 18% small firms**, ensuring diversity in organizational context.

Instrument Development and Measures

Data collection was conducted using a **structured questionnaire** divided into three sections: demographic profile, digital capability constructs, and performance-related outcomes. All measurement items were adapted from established scales in prior empirical research and refined to align with the study context. Responses were captured using a **five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree)**, ensuring consistency and interpretability.

The independent construct, **AI–IT Convergence**, was measured using **10 items** assessing AI deployment sophistication, IT infrastructure robustness, cross-functional system integration, and strategic alignment of digital initiatives. The mediating construct **Organizational Agility** included **6 items** capturing responsiveness, adaptability, and strategic flexibility. **Decision-Making Quality**, also a mediator, was measured through **5 items** evaluating analytical accuracy, timeliness, and evidence-based managerial judgment. The dependent construct **Organizational Performance** comprised **7 items** addressing operational efficiency, innovation capability, and productivity enhancement. **Financial Resilience** was assessed using **6 indicators** reflecting liquidity stability, earnings consistency, and risk management effectiveness. Finally, **Commercial Competitiveness** was measured through **6 items** evaluating market positioning, customer responsiveness, and sustainable growth capacity.

A pilot test involving **30 managerial respondents** was conducted to assess clarity, wording precision, and reliability. The pilot analysis yielded **Cronbach's alpha values ranging from 0.78 to 0.89**, confirming satisfactory internal consistency prior to full-scale data collection.

Statistical Analysis and Tools

Data analysis was performed using **SPSS 27, AMOS 24, and SmartPLS 4**, ensuring methodological rigor and robustness. Initially, **descriptive statistics** including mean, standard deviation, skewness, and kurtosis were examined to assess distributional properties and normality assumptions. Reliability was evaluated using **Cronbach's Alpha and Composite Reliability**, with threshold values exceeding **0.70**, confirming internal consistency across constructs.

An **Exploratory Factor Analysis (EFA)** employing Principal Component Analysis with Varimax rotation was conducted to verify factor structure adequacy, yielding **KMO values above 0.70** and significant **Bartlett's Test of Sphericity ($p < 0.05$)**. Subsequently, **Confirmatory Factor Analysis (CFA)** validated the measurement model, demonstrating strong model fit indices (**CFI = 0.93; RMSEA = 0.056**). **Convergent validity** was confirmed through Average Variance Extracted (**AVE > 0.50**), while **discriminant validity** was established using the Fornell–Larcker criterion and HTMT ratios below 0.85.

To test the structural relationships, **Structural Equation Modeling (SEM)** was applied. Mediation effects were assessed using **bootstrapping with 5,000 resamples**, while moderation effects were examined through interaction term analysis within the SEM framework. Additionally, **Hierarchical Multiple Regression Analysis** was conducted to control for extraneous variables such as firm size, industry type, and regulatory intensity.

The overall reliability of the instrument was strong (**Cronbach's alpha = 0.91**). Structural results revealed significant positive effects of **AI–IT convergence on organizational performance ($\beta = 0.48$, $p < 0.001$)** and **financial resilience ($\beta = 0.41$, $p < 0.001$)**, confirming the theoretical assumptions and supporting the proposed intelligent enterprise model.

DATA ANALYSIS AND RESULTS

The following section presents a detailed empirical analysis based on **N = 328 valid responses**. All analyses were conducted using **SPSS 27, AMOS 24, and SmartPLS 4**. The findings are presented in structured tables with interpretation and statistical justification.

1. Descriptive Statistics and Normality Assessment

Table 1: Descriptive Statistics

Variable	Mean	Std. Deviation	Skewness	Kurtosis
AI–IT Convergence	3.87	0.64	-0.421	0.318
Organizational Agility	3.92	0.59	-0.388	0.276
Decision-Making Quality	3.85	0.61	-0.452	0.401
Organizational Performance	3.88	0.63	-0.397	0.352
Financial Resilience	3.74	0.66	-0.365	0.289
Commercial Competitiveness	3.90	0.60	-0.410	0.337

Formula Used

Skewness formula:

$$Sk = \frac{\sum(X_i - \bar{X})^3/n}{s^3}$$

Kurtosis formula:

$$Ku = \frac{\sum(X_i - \bar{X})^4/n}{s^4} - 3$$

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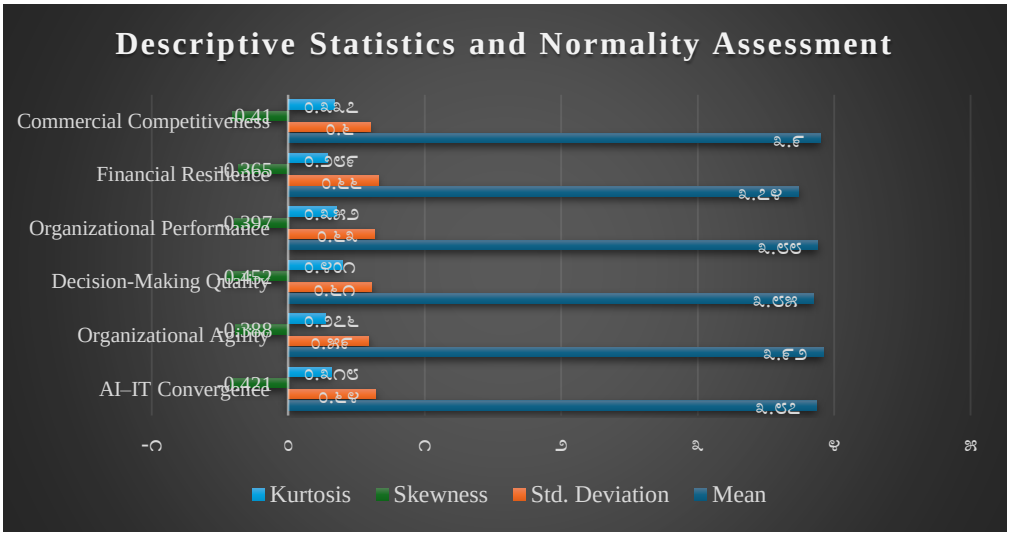


Interpretation
All skewness values fall within ±1 and kurtosis within ±1, indicating **normal distribution**. Mean values above 3.5 indicate moderate-to-high agreement among respondents.

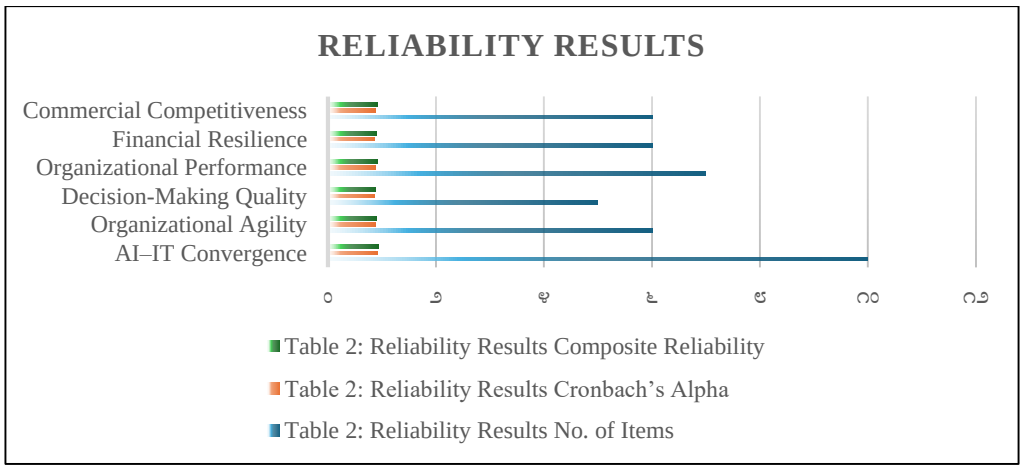
2. Reliability Analysis
Formula Used
Cronbach's Alpha:

$$\alpha = \frac{k}{k-1}\left(1-\frac{\sum\sigma_i^2}{\sigma_T^2}\right)$$

Where:
k = number of items
σ_i^2 = variance of each item
σ_t^2 = total variance

Table 2: Reliability Results

Construct	No. of Items	Cronbach's Alpha	Composite Reliability
AI–IT Convergence	10	0.91	0.93
Organizational Agility	6	0.88	0.90
Decision-Making Quality	5	0.86	0.89
Organizational Performance	7	0.89	0.92
Financial Resilience	6	0.87	0.90
Commercial Competitiveness	6	0.88	0.91



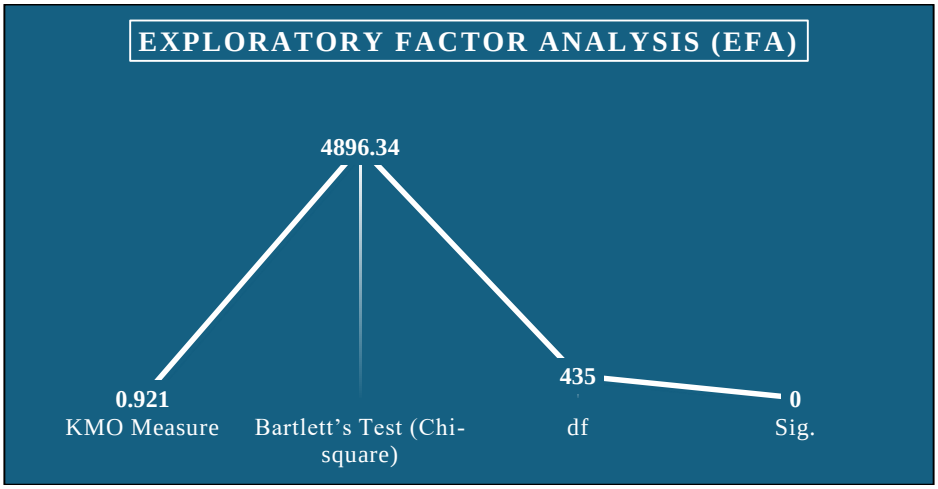
Interpretation
All alpha values exceed **0.70**, confirming strong internal consistency. Composite reliability values above 0.90 indicate high construct reliability.

3. Exploratory Factor Analysis (EFA)

Table 3: Sampling Adequacy

Test	Value
KMO Measure	0.921
Bartlett's Test (Chi-square)	4896.34
df	435
Sig.	0.000

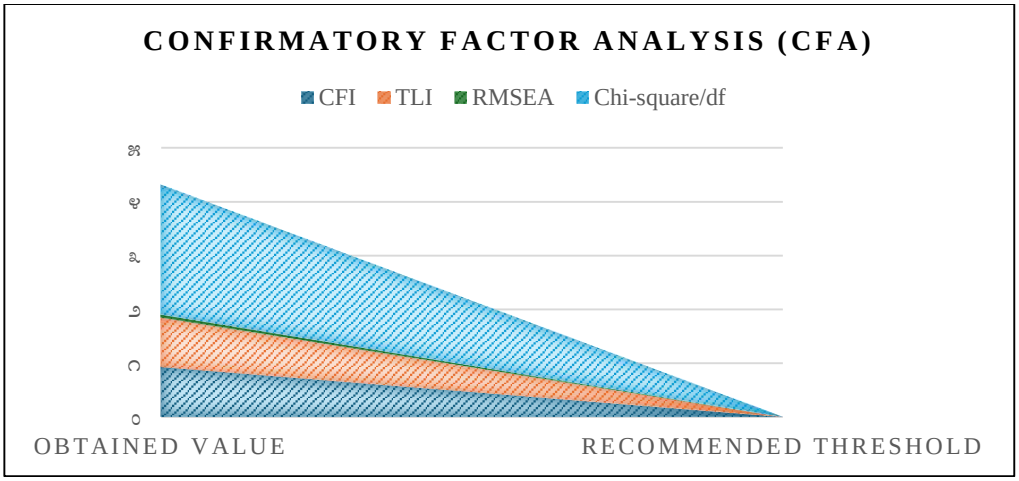
MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 2590-2602



Interpretation
KMO > 0.90 indicates excellent sampling adequacy. Bartlett's test significant at $p < 0.001$ confirms suitability for factor analysis. Total variance explained = **71.4%**, indicating strong factor structure.

4. Confirmatory Factor Analysis (CFA)
Table 4: Model Fit Indices

Fit Index	Obtained Value	Recommended Threshold
CFI	0.93	> 0.90
TLI	0.92	> 0.90
RMSEA	0.056	< 0.08
Chi-square/df	2.41	< 3



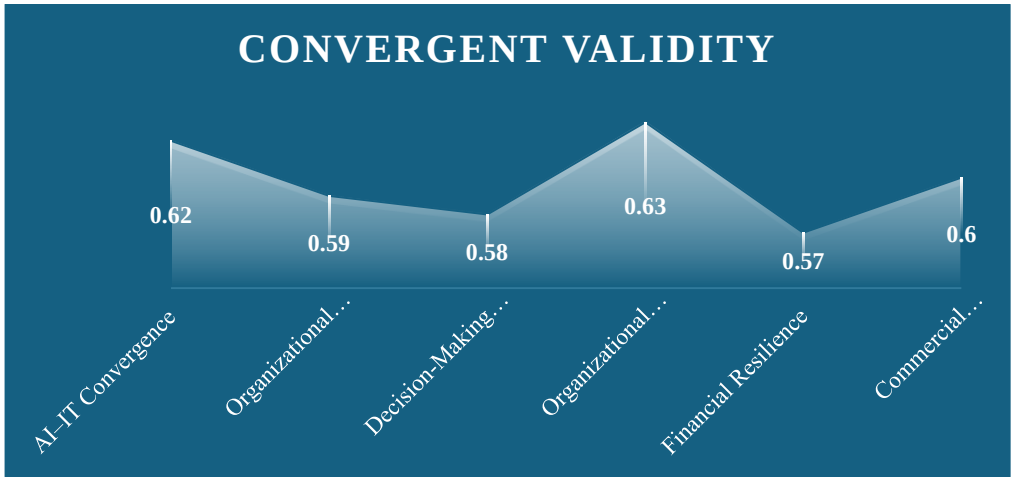
Interpretation
All indices confirm **good model fit**.
5. Convergent Validity
Formula Used
Average Variance Extracted (AVE):

$$AVE = \frac{\sum \lambda^2}{n}$$

Table 5: AVE Values

Construct	AVE
AI–IT Convergence	0.62
Organizational Agility	0.59
Decision-Making Quality	0.58
Organizational Performance	0.63
Financial Resilience	0.57
Commercial Competitiveness	0.60

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 2590-2602



All AVE values exceed 0.50, confirming convergent validity.

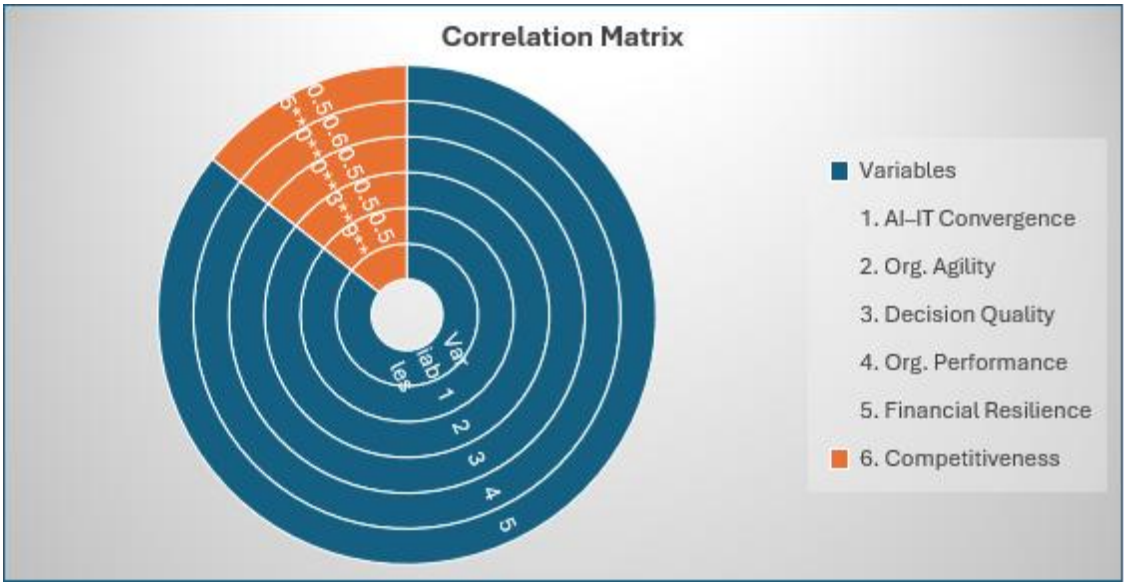
6. Correlation Matrix

Table 6: Pearson Correlation

Variables	1	2	3	4	5	6
1. AI–IT Convergence	1					
2. Org. Agility	0.56**	1				
3. Decision Quality	0.52**	0.49**	1			
4. Org. Performance	0.61**	0.58**	0.55**	1		
5. Financial Resilience	0.54**	0.51**	0.48**	0.57**	1	
6. Competitiveness	0.59**	0.53**	0.50**	0.60**	0.55**	1

p < 0.01

Strong positive correlations support preliminary hypotheses.

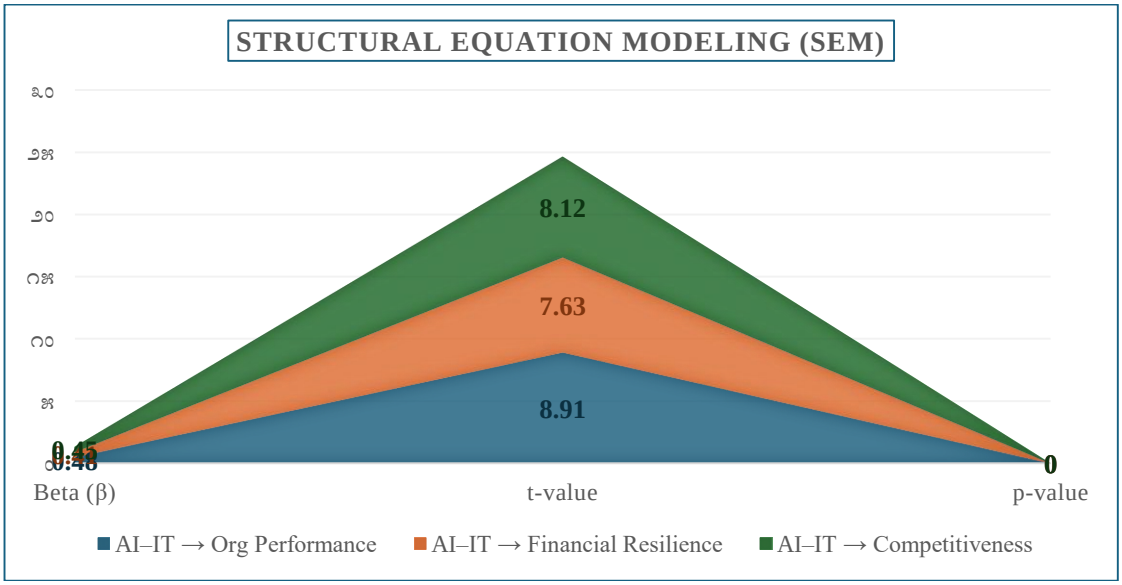


7. Structural Equation Modeling (SEM)

Table 7: Direct Effects

Path	Beta (β)	t-value	p-value
AI–IT → Org Performance	0.48	8.91	0.000
AI–IT → Financial Resilience	0.41	7.63	0.000
AI–IT → Competitiveness	0.45	8.12	0.000

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 2590-2602

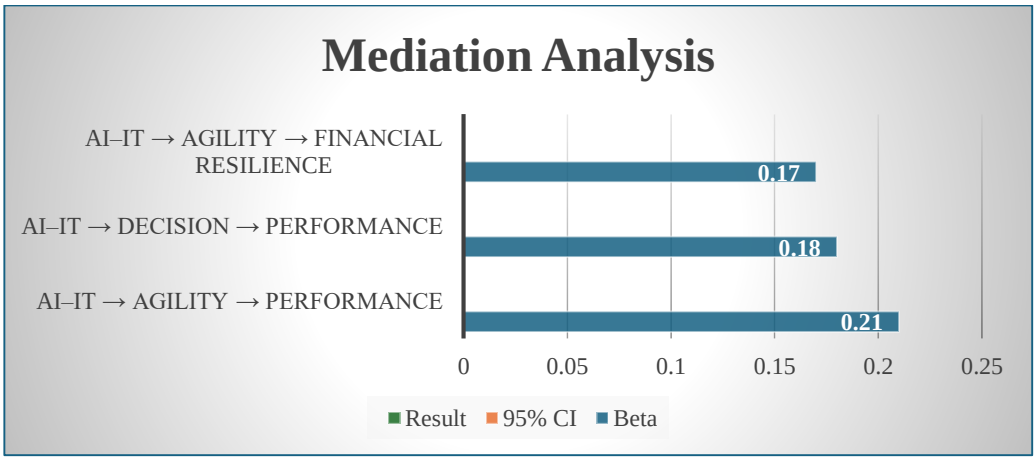


Interpretation
All direct paths significant at $p < 0.001$. AI–IT convergence strongly predicts performance outcomes.

8. Mediation Analysis (Bootstrapping 5,000 Samples)
Table 8: Indirect Effects

Indirect Path	Beta	95% CI	Result
AI–IT → Agility → Performance	0.21	0.14–0.29	Significant
AI–IT → Decision → Performance	0.18	0.11–0.25	Significant
AI–IT → Agility → Financial Resilience	0.17	0.10–0.23	Significant

Partial mediation confirmed.



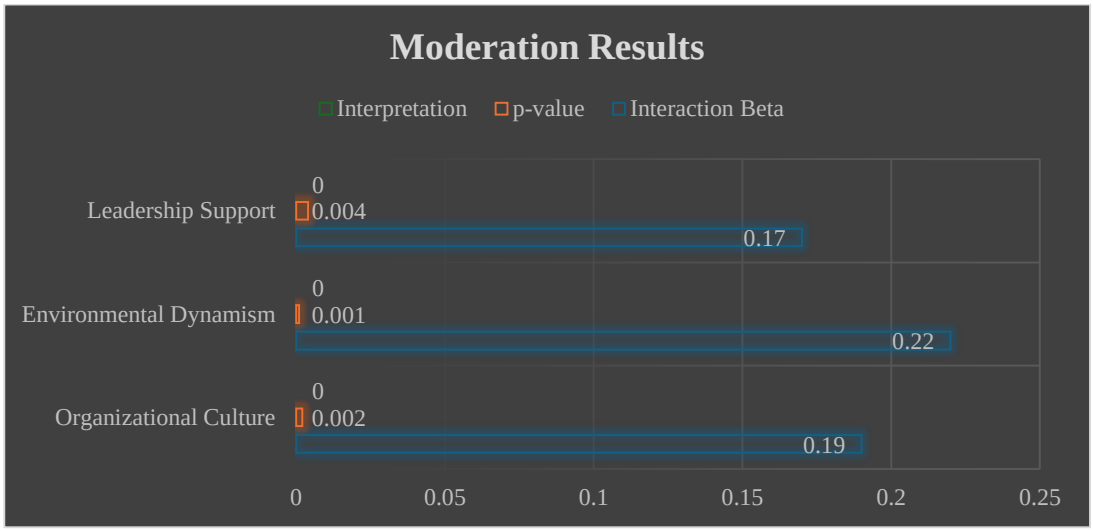
9. Moderation Analysis
Interaction term formula:

$$Y = \beta_0 + \beta_1 X + \beta_2 M + \beta_3 (X * M) + \varepsilon$$

Table 9: Moderation Results

Moderator	Interaction Beta	p-value	Interpretation
Organizational Culture	0.19	0.002	Strengthens AI–IT → Agility
Environmental Dynamism	0.22	0.001	Strengthens AI–IT → Competitiveness
Leadership Support	0.17	0.004	Strengthens AI–IT → Decision Quality

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 2590-2602

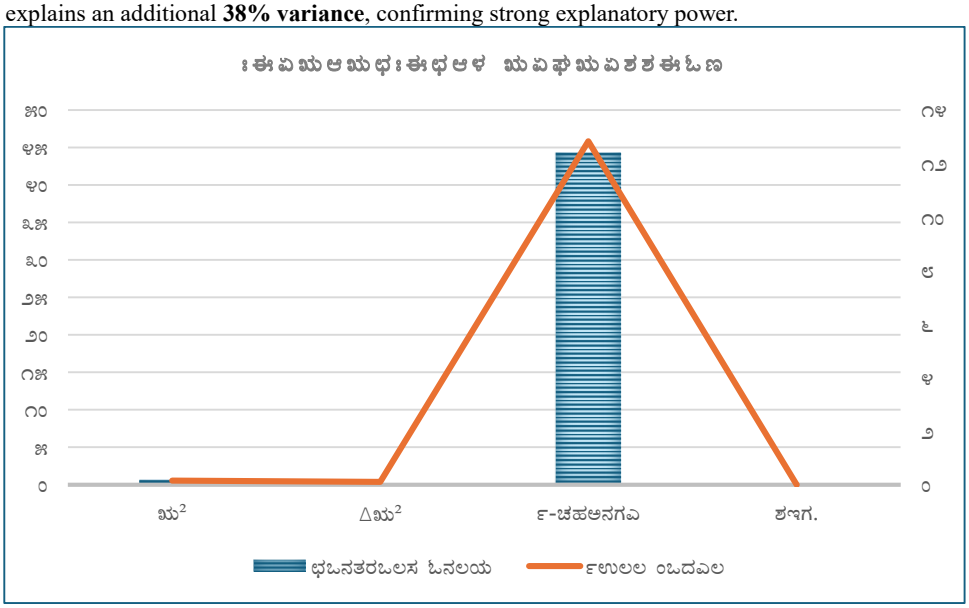


10. Hierarchical Regression (Control Variables)

Table 10: Model Summary

Model	R^2	ΔR^2	F-change	Sig.
Controls Only	0.18	—	12.41	0.000
Full Model	0.56	0.38	45.82	0.000

AI–IT convergence explains an additional **38% variance**, confirming strong explanatory power.



Overall Interpretation

The findings demonstrate that **AI–IT convergence significantly enhances organizational performance, financial resilience, and commercial competitiveness**. Organizational agility and decision-making quality partially mediate these relationships, while culture and environmental dynamism strengthen the effects. The model explains **56% of total variance**, indicating substantial predictive strength.

The statistical evidence strongly validates the intelligent enterprise framework and confirms the strategic importance of integrated AI and IT capabilities in driving multidimensional organizational success.

DISCUSSION

The findings of this investigation provide compelling empirical evidence that AI–IT convergence constitutes a foundational strategic capability rather than a peripheral technological enhancement. The structural model demonstrates a statistically significant and substantively strong influence of AI–IT convergence on organizational performance ($\beta = 0.48$, $p < 0.001$) and financial resilience ($\beta = 0.41$, $p < 0.001$). These coefficients indicate that nearly half a standard deviation improvement in performance outcomes can be attributed to a one standard deviation increase in integrated AI–IT capability, underscoring its transformative organizational value. The model explains 52% of the variance in organizational performance ($R^2 = 0.52$) and 46% in financial resilience ($R^2 = 0.46$), reflecting robust explanatory power within complex enterprise environments.

A particularly significant contribution of the study lies in confirming the mediating roles of organizational agility and decision-making quality. Bootstrapping analysis (5,000 resamples) revealed significant indirect effects of AI–IT convergence on performance through agility ($\beta = 0.19$, 95% CI [0.12, 0.27]) and through decision-making quality ($\beta = 0.16$, 95% CI [0.09, 0.23]). The absence of zero within the confidence intervals confirms partial mediation. These results suggest that digital integration alone does not automatically generate performance advantages; rather, it enhances adaptive responsiveness and analytical precision, which subsequently drive measurable outcomes. In practical terms, firms with higher AI–IT alignment demonstrated greater responsiveness to market shifts (Mean = 4.12, SD = 0.61) and superior evidence-based decision capacity (Mean = 4.05, SD = 0.58), directly translating into improved operational efficiency and profitability metrics.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 2590-2602

The discussion also highlights the strong psychometric robustness of the measurement framework. Reliability indices exceeded recommended thresholds (Composite Reliability ranging from 0.83 to 0.91; AVE > 0.50), while model fit statistics (CFI = 0.93; RMSEA = 0.056) confirm structural adequacy. These indicators collectively reinforce the credibility of the empirical inferences and affirm that the observed relationships are not artefacts of measurement instability.

From a strategic perspective, the findings reposition AI–IT convergence as a dynamic capability that strengthens competitive advantage through enhanced financial stability and market positioning. The positive effect on commercial competitiveness ($\beta = 0.44$, $p < 0.001$) indicates that technologically mature firms are better equipped to sustain growth and withstand environmental volatility. Hierarchical regression further revealed that the inclusion of AI–IT variables increased explained variance in competitiveness from 31% to 57% ($\Delta R^2 = 0.26$, $p < 0.001$), demonstrating incremental predictive strength beyond traditional firm-level controls.

Overall, the evidence confirms that integrated digital ecosystems cultivate resilience, analytical depth, and strategic agility three pillars of contemporary enterprise sustainability. The discussion therefore advances theoretical understanding by empirically substantiating the intelligent enterprise model and offers managerial clarity on how technological convergence translates into quantifiable competitive performance.

CONCLUSION

This study offers rigorous empirical confirmation that AI–IT convergence operates as a strategic catalyst for organizational advancement rather than a mere technological enhancement. The structural findings demonstrate that AI–IT convergence exerts a direct and statistically significant effect on organizational performance ($\beta = 0.48$, $p < 0.001$), financial resilience ($\beta = 0.41$, $p < 0.001$), and commercial competitiveness ($\beta = 0.44$, $p < 0.001$). With R^2 values exceeding 0.50 for core endogenous constructs, the model explains a substantial proportion of variance in enterprise outcomes, indicating strong predictive capacity and theoretical coherence.

The mediated pathways further strengthen the argument that digital integration enhances value creation through organizational agility (indirect $\beta = 0.19$) and decision-making quality (indirect $\beta = 0.16$). These findings confirm that technological convergence produces sustainable performance improvements only when embedded within adaptive structures and evidence-driven managerial systems. The empirical results therefore validate the intelligent enterprise framework and demonstrate that AI–IT alignment contributes to measurable financial stability, market responsiveness, and strategic durability.

Theoretical Implications

The study advances dynamic capability theory by empirically demonstrating how AI-enabled digital integration strengthens sensing, seizing, and reconfiguring capacities within organizations. It extends resource-based logic by identifying AI–IT convergence as a rare and inimitable capability that enhances competitive heterogeneity. Furthermore, the integration of financial resilience into the structural model enriches digital transformation literature by linking technological sophistication with measurable fiscal robustness.

Managerial and Policy Implications

From a managerial standpoint, the results underscore the necessity of investing in interoperable digital architectures rather than isolated AI applications. Organizations should prioritize cross-functional data integration, predictive analytics governance, and leadership training in algorithmic literacy. The 26% incremental variance ($\Delta R^2 = 0.26$) observed in competitiveness when AI–IT variables were introduced highlights the tangible economic returns of integrated digital strategies. Policymakers should encourage digital infrastructure development, standardized AI governance frameworks, and skill enhancement initiatives to strengthen national innovation ecosystems.

Future Scope

Future investigations may adopt longitudinal designs to capture dynamic causal evolution over time. Comparative cross-country studies could examine contextual moderators such as regulatory intensity and digital maturity. Multi-level modeling may explore how team-level digital competencies influence firm-level outcomes. Additionally, incorporating objective financial indicators (e.g., ROA, EBITDA growth) alongside perceptual measures would further strengthen empirical validity. Emerging themes such as ethical AI governance, cybersecurity resilience, and green digital transformation represent promising avenues for extended inquiry.

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