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Methodological Approaches, AI-Driven Market Leadership, and Nigerian SMEs: A PLS-SEM Validation of the Contextualized AI-Capability-to-Market Leadership Framework.

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Abstract

Purpose: Existing strategic management literature frequently exhibits technological determinism, assuming a direct link between artificial intelligence acquisition and firm performance while ignoring the infrastructural realities of emerging markets. This study addresses this gap by empirically validating the Contextualized AI Capability to Market Leadership Framework. Grounded in the Resource-Based View and Dynamic Capability Theory, the research investigates how technology adoption translates into sustained competitive advantage through internal capability building and external environmental boundary conditions.

Design/Methodology/Approach: The study adopted a quantitative, cross-sectional survey design. Primary data were gathered from 167 owners and senior managers of small and medium enterprises operating across diverse sectors in Nigeria. The conceptual model was rigorously evaluated using Partial Least Squares Structural Equation Modeling (PLS SEM). The analysis included specific indirect effect calculations for mediation, the orthogonal two-stage approach for moderation, and a Multi-Group Analysis to test for sectoral equivalence.

Findings: The empirical results confirm that AI-enabled dynamic capabilities significantly and complementarily mediate the relationship between AI use intensity and market leadership outcomes. Crucially, the moderation analysis revealed a significant negative buffering effect regarding institutional support. This demonstrates that severe infrastructural deficits compel enterprises to engage in necessity-driven innovation, utilizing AI tools to aggressively build internal capabilities that compensate for external systemic failures. Furthermore, ethical risk perception did not significantly moderate, indicating that pragmatic operational survival currently overrides algorithmic transparency concerns in early adopting markets.

Originality/Value: This research shifts the analytical focus from simplistic technology performance models to complex, capability-driven pathways. It contributes a novel perspective to emerging market literature, providing empirical evidence that environmental hostility and infrastructure deficits can paradoxically accelerate, rather than merely stifle, internal digital maturity.

Practical Implications: Enterprise leaders must abandon isolated IT software investments in favor of a deliberate redesign of organizational processes. For policymakers, the findings underscore the need to prioritize foundational digital infrastructure alongside proactive data governance frameworks, ensuring that current necessity-driven digital advancements evolve into sustainable global competitiveness.

1. Introduction

Artificial intelligence represents a fundamental technological shift that is redefining the competitive landscape for small and medium enterprises globally. Within African markets, and Nigeria specifically, the adoption of digital tools has accelerated rapidly as firms seek new avenues for operational efficiency and customer engagement (Ewuga et al., 2023; Rahmon et al., 2025; Tapera et al., 2026). However, the

prevailing strategic management literature examining this phenomenon suffers from two critical limitations. First, existing empirical models are overwhelmingly calibrated for developed economies characterized by robust digital infrastructure, mature regulatory environments, and high institutional support (Di Thuan et al., 2025; Achieng and Malatji, 2025). Second, much of the current literature exhibits technological determinism, assuming a direct and isolated relationship between the acquisition of artificial intelligence and immediate firm performance (Chen et al., 2022). This simplistic view overlooks the complex internal mechanisms required to transform digital tools into sustained competitive advantage, particularly in environments fraught with infrastructural deficits and resource constraints (Olalekan, 2025; Asa et al., 2026).

This study addresses these theoretical and contextual gaps by empirically validating the Contextualized AI Capability to Market Leadership Framework. Grounded in the Resource-Based View and Dynamic Capability Theory (Chaudhuri et al., 2022; Jamil et al., 2025), this research posits that artificial intelligence adoption is merely a strategic catalyst rather than a standalone solution. Basic digital tools can be easily acquired or imitated by competitors, rendering them insufficient for durable market dominance (Dzreke, 2025). Therefore, this study investigates how the intensity of artificial intelligence use translates into embedded organizational routines, specifically AI-enabled dynamic capabilities such as rapid resource reconfiguration and adaptive learning (Michael et al., 2025; Pu et al., 2025). These dynamic capabilities are hypothesized to serve as the critical transmission mechanism that ultimately drives market leadership outcomes.

Furthermore, this research challenges the assumption that digital transformation operates in a vacuum. The study integrates two distinct boundary conditions specific to the emerging market context. It evaluates the moderating role of institutional support to understand how systemic infrastructure deficits influence the capability-building process (Omonzejele & Okogun, 2025). Simultaneously, it examines the moderating effect of ethical risk perception, questioning whether nascent concerns regarding algorithmic bias and data privacy attenuate the market advantages of digital capabilities in early-stage adoption economies (Sánchez et al., 2025; Soudi & Bauters, 2024).

The empirical findings of this study offer profound contributions to the literature on strategic digital transformation. The analysis validates the mediating role of dynamic capabilities, confirming that internal agility is the true driver of competitive advantage. More significantly, the study reveals a counterintuitive negative buffering effect regarding institutional support. The data demonstrates that severe infrastructural deficits compel Nigerian SMEs to engage in necessity-driven innovation, accelerating their internal digital maturity to compensate for external systemic failures. Additionally, the research provides a critical contextual boundary for global discussions of technological ethics, showing that practical market delivery currently overrides concerns about algorithmic transparency in the emerging market investigated. Ultimately, this study provides a robust roadmap detailing how small businesses can navigate environmental hostility to transform digital tools into enduring market leadership.

The remainder of this paper is structured as follows. Section 2 reviews the extant literature and develops the theoretical underpinnings of the Contextualized AI Capability to Market Leadership Framework, culminating in the formulation of the study's hypotheses. Section 3 details the research methodology, including the cross-sectional survey design, sampling techniques, and the robust validation of the measurement instrument. Section 4 presents the empirical results from the Partial Least Squares Structural Equation Modeling analysis, including mediation, moderation, and multi-group analyses. Section 5 discusses the theoretical and practical implications of the findings, contextualizing the paradox of necessity-driven innovation within the Nigerian enterprise ecosystem. Finally, Section 6 concludes the study and outlines key limitations and recommendations for future academic inquiry.

2. Literature Review

2.1 Pathways from AI Adoption to Market Leadership

Emerging evidence from Nigeria and comparable SME contexts indicates that artificial intelligence adoption contributes to market leadership through a set of interrelated organizational pathways rather than through direct performance effects (Orizu and Agbionu, 2026; Agbaakin, 2025). Studies focused on Nigerian SMEs consistently show that firms using AI tools record improvements in operational efficiency, decision quality, innovation outcomes, and customer engagement, all of which are recognized drivers of competitive positioning in small business markets (Olalekan, 2025; Omonzejele & Okogun, 2025; Ola Oluwa, 2024; Michael et al., 2025; Pu et al., 2025; Bature & Ngozi, 2025).

One prominent pathway operates through decision quality and organizational agility. AI-supported analytics and machine learning applications enhance firms' ability to process large volumes of market and customer data, enabling faster and more informed strategic and operational decisions. Empirical studies report positive associations among data-driven decision-making, adaptability, and the sustainability of SME performance, particularly in volatile, resource-constrained environments such as Nigeria (Olalekan, 2025; Michael et al., 2025; Pu et al., 2025; Shahid et al., 2025). These capabilities enable SMEs to respond more quickly to shifts in demand and competitive pressures, thereby strengthening their leadership potential.

Efficiency and productivity gains form a second pathway. AI-enabled automation reduces reliance on manual routines, optimizes resource allocation, and lowers operational costs. Nigerian-based studies show that such efficiency gains translate into improved competitiveness and the capacity to scale operations, even when firms remain small (Omonzejele & Okogun, 2025; Ola Oluwa, 2024; Michael et al., 2025; Pu et al., 2025). Innovation represents a third mechanism. Evidence from logistics and service-oriented SMEs suggests that AI-related competencies, including digital infrastructure and a proactive technology orientation, significantly enhance product and process innovation, which serves as a proxy for emerging market leadership (Omonzejele & Okogun, 2025; Bature & Ngozi, 2025).

Customer engagement further mediates the relationship between AI leadership and the customer. AI-driven digital marketing tools and analytics support personalized communication, expanded market

reach, and improved customer retention, with documented effects on revenue growth and brand visibility among Nigerian SMEs (Olalekan, 2025; May et al., 2025; Magableh et al., 2024; Gupta, 2025).

Despite these pathways, adoption remains uneven. Many Nigerian SMEs engage with AI in fragmented or experimental ways, limiting the scale of competitive benefits achieved (Olalekan, 2025; Omonzejele & Okogun, 2025; Pu et al., 2025). Empirical work highlights the importance of mediating conditions such as data readiness, employee training, leadership commitment, and organizational preparedness in shaping outcomes (Omonzejele & Okogun, 2025; Michael et al., 2025; Sechabe & Malatji, 2025). Persistent barriers, including infrastructure deficits, high implementation costs, skills shortages, and digital illiteracy, continue to constrain deeper integration (Omonzejele & Okogun, 2025; Ola Oluwa, 2024; Pu et al., 2025; Cimino et al., 2025; Rahmon et al., 2025). Consequently, market leadership effects tend to emerge when AI is embedded strategically and supported by complementary capabilities, whereas superficial adoption yields limited, localized advantages.

2.2 Core Firm-Level Capabilities for Sustained Advantage

Evidence from Nigerian and closely related SME contexts converges on a central insight: artificial intelligence becomes a sustained source of competitive advantage only when it is embedded within firm-level capabilities that are difficult to replicate (Ferdiansyah et al., 2025). When treated as stand-alone tools, AI applications tend to yield short-term efficiency gains. Embedded within organizational systems, skills, and governance structures, they support durable advantage.

Foundational capability concerns data and technological readiness. Empirical studies in Nigeria show that the quality, timeliness, and accessibility of data strongly shape the effectiveness of AI-driven decision-making and performance outcomes among SMEs (Olalekan, 2025; Michael et al., 2025; Omonzejele & Okogun, 2025). Firms with reliable data infrastructure and interoperable information systems are better positioned to extract actionable insights from AI tools. Related work conceptualizes AI readiness as a bundled capability that combines infrastructure, system integration, and strategic alignment. Evidence from emerging market SMEs indicates that this bundle predicts AI-enabled innovation performance more strongly than any single technological input (Pooe et al., 2025; Jamil et al., 2025; Chaudhuri et al., 2022).

Human capital and organizational learning form a second capability domain. Nigerian studies consistently highlight employee training and technical competence as prerequisites for translating AI adoption into improved decision quality and operational outcomes (Olalekan, 2025; Ola Oluwa, 2024; Michael et al., 2025; Omonzejele & Okogun, 2025). Beyond individual skills, organizational learning capacity plays a decisive role. Firms that encourage experimentation, knowledge sharing, and continuous learning are more likely to sustain innovation and adapt AI applications over time (Ola Oluwa, 2024; Jamil et al., 2025; Chaudhuri et al., 2022; Pooe et al., 2025).

Leadership, strategy, and culture further condition whether AI capabilities yield a lasting advantage. Evidence suggests that top management support and AI-oriented leadership shape resource allocation, change management, and the strategic use of AI for frugal innovation and sustainability outcomes in SMEs (Ola Oluwa, 2024; Michael et al., 2025; Bindah et al., 2025; Ahmad et al., 2025; Song et al., 2025). Strategic flexibility and an innovative-oriented culture also influence whether AI capabilities translate into superior performance rather than isolated improvements (Pooe et al., 2025; Chen et al., 2022; Lanfranchi et al., 2025).

Finally, complementary resources and governance mechanisms reinforce sustainability. Proprietary data assets and embedded process knowledge reduce imitation risks and align with resource-based explanations of competitive advantage (Dzreke, 2025; Chen et al., 2022; Lanfranchi et al., 2025). At the same time, clear governance arrangements, ethical guidelines, and trust-enhancing practices support responsible AI use and legitimacy, which are increasingly central to sustaining AI-driven advantage over time (Ola Oluwa, 2024; Jöhnk et al., 2020; Kelley, 2022; Sánchez et al., 2025). See Table 2 for summarised insights.

2.3 External Conditions Shaping AI-Enabled Market Leadership in Nigeria

External conditions in Nigeria play a decisive role in determining whether artificial intelligence adoption can translate into market leadership for small and medium-sized enterprises. Evidence from Nigeria and comparable emerging economies shows that infrastructure quality, access to finance, policy clarity, and digital inclusion function as both enablers and bottlenecks, rather than as background conditions (Akinruwa et al., 2025).

Infrastructure and digital inclusion form the most immediate constraint. Limited and unreliable power supply, weak broadband coverage, and uneven access to appropriate digital tools increase the cost and operational complexity of AI use for Nigerian SMEs, reducing productivity gains and discouraging deeper integration (Omonzejele & Okogun, 2025; Ola Oluwa, 2024; Ewuga et al., 2023). Even where basic tools are available, digital illiteracy and shortages of AI-trained personnel constrain firms' ability to deploy, maintain, and scale AI systems (Omonzejele & Okogun, 2025; Olalekan, 2025; Bindah et al., 2025; Ola Oluwa, 2024). National digital economy initiatives and partnerships with global technology providers have begun to lower entry costs and expand access to locally adapted solutions, although empirical studies note that coverage remains uneven across regions and firm sizes (Omonzejele & Okogun, 2025; Ola Oluwa, 2024; Rahmon et al., 2025).

Policy and regulatory environments further condition outcomes. Comparative evidence across emerging markets shows that government incentives, skills programs, and public investment in digital infrastructure strengthen the link between AI automation and SME digitalization, effectively amplifying returns to adoption (Di Thuan et al., 2025; Sánchez et al., 2025; Díaz Arancibia et al., 2024; Rahmon et al., 2025). In Nigeria, however, regulatory uncertainty surrounding data protection, privacy, and compliance requirements has been shown to increase perceived risk and encourage cautious, limited AI use, particularly among smaller firms operating in Lagos and similar urban markets (Bindah et al., 2025;

Omonzejele & Okogun, 2025; Ola Oluwa, 2024). Support ecosystems, including enterprise agencies, technology hubs, and partnerships with global providers, partially offset these challenges by providing training, platforms, and implementation support that help raise SMEs to a competitive digital threshold (Olalekan, 2025; Omonzejele & Okogun, 2025; Ola Oluwa, 2024).

Finance represents a final structural level. High upfront investment costs remain one of the most frequently reported barriers to AI adoption among Nigerian SMEs (Olalekan, 2025; Omonzejele & Okogun, 2025; Ola Oluwa, 2024). At the same time, the expansion of fintech and AI-enabled financial services across Africa has reduced credit constraints through alternative credit scoring, mobile lending, and digital wallets, supporting working capital access and enabling gradual AI investment and scaling (Wah, 2025; Sánchez et al., 2025; Ewuga et al., 2023). Market leadership effects therefore emerge most clearly where infrastructure reliability, inclusive finance, supportive policy, and ecosystem support align, while fragmented contexts limit AI's competitive impact.

2.4 Social, Ethical, and Organizational Risks Shaping the Sustainability of AI-Led Market Leadership

Evidence from Nigeria indicates that adopting artificial intelligence in small and medium-sized enterprises introduces social, ethical, and organizational risks that can undermine trust and erode the foundations of sustained market leadership if left unmanaged (Afokoghene et al., 2025; Nasiru et al., 2025). These risks do not negate AI's competitive potential, but they shape whether early gains translate into a durable advantage.

Concerns around data privacy, security, and misuse feature prominently in Nigerian SME studies. Firms operating in Lagos and other commercial centers report uncertainty about data protection obligations, weak enforcement clarity, and exposure to cyber risks, all of which heighten customer distrust and perceived legal vulnerability (Bindah et al., 2025; Omonzejele & Okogun, 2025; Oyeyemi et al., 2025; Ogundele et al., 2025). Closely related are risks of algorithmic bias and unfair outcomes. Empirical and conceptual work highlights how biased datasets can lead to discriminatory credit, pricing, or customer segmentation decisions, reinforcing existing regional and socioeconomic inequalities in Nigeria (Oyeyemi et al., 2025; Abhulimen & Ejike, 2024). Challenges with transparency and accountability further complicate these issues. The use of opaque or poorly understood AI systems limits explainability, weakens accountability, and raises legitimacy concerns for firms facing customers, regulators, and partners (Oyeyemi et al., 2025; Sánchez et al., 2025; Abhulimen & Ejike, 2024; Soudi & Bauters, 2024).

Organizational risks interact with these ethical concerns. Studies document worker anxiety and resistance linked to fears of job displacement and loss of autonomy, particularly where AI is introduced without consultation or reskilling pathways (Omonzejele & Okogun, 2025; Ola Oluwa, 2024; Cubric, 2020). In some cases, systems intended to support productivity evolve into tools of monitoring and control, contributing to declining morale, lower engagement, and reduced innovative behavior (Wu et al., 2025; Monod et al., 2024; Ola Oluwa, 2024). The absence of responsible AI governance structures within SMEs

intensifies these risks. Limited attention to fairness, transparency, and inclusion exposes firms to reputational damage and future compliance challenges as regulatory scrutiny increases (Sánchez et al., 2025; Soudi & Bauters, 2024). Weak change management further constrains outcomes, with skill gaps, fear, and limited employee participation increasing the likelihood of failed or underperforming AI initiatives (Bindah et al., 2025; Lu et al., 2022; Omonzejele & Okogun, 2025; Ola Oluwa, 2024; Štrukelj & Dankova, 2025). See Table 4.

Research increasingly points to ethical leadership, human-centered governance, explainable AI, and continuous ethics training as mechanisms through which SMEs can convert risk management into a source of trust and legitimacy (Chaudhuri et al., 2022; Suljic, 2025; Sánchez et al., 2025; Soudi & Bauters, 2024; Ogundele et al., 2025; Štrukelj & Dankova, 2025). For Nigerian SMEs, sustained market leadership depends not only on adopting AI, but on governing its social, ethical, and organizational consequences in ways that preserve confidence among workers, customers, and regulators.

2.5 Framework Development

The Contextualized AI Capability to Market Leadership Framework

The Contextualized AI Capability to Market Leadership Framework (CACMLF) explains how artificial intelligence adoption translates into sustained market leadership among Nigerian SMEs (Hossain et al., 2025). To capture the complexity of this process, the framework is theoretically grounded in two complementary perspectives: the Resource-Based View (RBV) and Dynamic Capability Theory (DCT).

Drawing from the RBV, the framework posits that treating AI as a stand-alone technological resource is insufficient for sustained competitive advantage, as basic digital tools can be easily acquired or imitated by competitors (Chen et al., 2022; Dzreke, 2025). Instead, AI becomes a valuable, rare, and inimitable resource only when it is deeply embedded within firm-specific processes, skills, and governance structures.

Building on this, DCT serves as the central transmission mechanism of the framework. DCT argues that in rapidly changing and volatile environments, firms must continuously integrate, build, and reconfigure internal competencies (Chaudhuri et al., 2022). Within this framework, AI Use Intensity does not directly dictate market dominance; rather, it serves as the catalyst for developing AI-Enabled Dynamic Capabilities, such as organizational agility, faster response times, and data-driven learning (Olalekan, 2025; Michael et al., 2025). It is these dynamic capabilities directly drive Market Leadership Outcomes, measured through customer preference, innovation, and competitive positioning.

Furthermore, the framework recognizes that this capability-building process is heavily context-dependent. The theoretical pathways are bounded by external and internal realities specific to emerging markets. Institutional and Infrastructure Support (IIS) shapes environmental conditions that determine how effectively AI tools can be leveraged to develop capabilities (Di Thuan et al., 2025; Rahmon et al.,

2025). Simultaneously, Ethical AI Risk Perception (EAIR) operates as a social boundary condition, recognizing that privacy concerns, algorithmic bias, and workforce resistance can erode trust and undermine the sustainability of AI-driven advantages if not governed responsibly (Sánchez et al., 2025; Oyeyemi et al., 2025). The complete theoretical pathways, including the core mediation and the contextual boundary conditions, are visually summarised in the conceptual model (see Figure 1).

Hypotheses Development

AI Use Intensity and AI-Enabled Dynamic Capabilities

The integration of artificial intelligence into routine business operations fundamentally alters how SMEs process information and execute tasks. Evidence from Nigerian contexts indicates that the intensive use of AI tools for data analytics, machine learning, and automation enhances a firm's ability to make rapid, informed strategic decisions (Olalekan, 2025; Michael et al., 2025). By reducing reliance on manual routines and optimizing resource allocation, AI adoption enables SMEs to develop critical organizational agility and adaptability, particularly in resource-constrained environments (Pu et al., 2025). Therefore, the intensity of AI use is posited as a foundational driver of dynamic organizational capabilities.

- **H1:** *Artificial Intelligence Use Intensity (AIUI) significantly and positively influences the development of AI-Enabled Dynamic Capabilities (AIDC) in Nigerian SMEs.*

AI-Enabled Dynamic Capabilities and Market Leadership Outcomes

According to dynamic capability theory, the ability to reconfigure resources and respond swiftly to market shifts is the primary engine of competitive advantage (Held et al., 2025). Studies focused on logistics, retail, and service-oriented SMEs in emerging markets suggest that capabilities such as continuous process learning and adaptive decision-making directly enhance product innovation and customer engagement (Omonzejele & Okogun, 2025; Bature & Ngozi, 2025). Firms that can leverage AI-driven agility to personalize communication and expand market reach consistently record improvements in brand visibility, revenue growth, and overall market leadership (May et al., 2025; Magableh et al., 2024).

- **H2:***AI-Enabled Dynamic Capabilities (AIDC) significantly and positively influence Market Leadership Outcomes (MLO).*

The Mediating Role of AI-Enabled Dynamic Capabilities

While early empirical studies often sought a direct link between technology adoption and firm performance, recent literature highlights that AI adoption remains fragmented and experimental in many SMEs, limiting direct competitive benefits (Olalekan, 2025). To achieve sustained advantage, AI must be coupled with firm-level routines (Chen et al., 2022; Chaudhuri et al., 2022). AI tools generate immediate efficiency gains, but translating these tools into deeply embedded organizational learning and strategic flexibility drives long-term market leadership (Pooe et al., 2025; Jamil et al., 2025). Thus, capabilities act as a crucial bridge.

- **H3:***AI-Enabled Dynamic Capabilities mediate the relationship between AI Use Intensity and Market Leadership Outcomes.*

The Moderating Role of Institutional and Infrastructure Support

The external operating environment serves as a critical bottleneck or enabler for digital transformation in Nigeria. Limited power supply, weak broadband, and a lack of digital enterprise support increase the operational complexity of AI, theoretically constraining a firm's ability to translate AI use into fluid dynamic capabilities (Omonzejele & Okogun, 2025; Ola Oluwa, 2024; Ewuga et al., 2023). Conversely, supportive policy environments, access to training hubs, and reliable infrastructure are expected to amplify the returns on AI adoption, allowing SMEs to scale their capabilities more effectively (Sánchez et al., 2025; Rahmon et al., 2025).

- **H4:** *Institutional and Infrastructure Support (IIS) positively moderates the relationship between AI Use Intensity and AI-Enabled Dynamic Capabilities.*

The Moderating Role of Ethical AI Risk Perception

The deployment of AI introduces profound social and organizational vulnerabilities. In Nigerian commercial centers, concerns about data privacy, cyber risks, and algorithmic bias heighten customer distrust and perceived legal exposure (Bindah et al., 2025; Oyeyemi et al., 2025). Furthermore, internal risks such as worker anxiety and opaque governance can stifle innovative behavior (Wu et al., 2025; Monod et al., 2024). Even if an SME successfully builds AI-enabled dynamic capabilities, high perceptions of ethical risk can erode the legitimacy and trust required to convert those capabilities into sustained customer preference and market leadership (Sánchez et al., 2025; Soudi & Bauters, 2024).

- **H5:***Ethical AI Risk Perception (EAIR) negatively moderates the relationship between AI-Enabled Dynamic Capabilities and Market Leadership Outcomes.*

3. Methodology

3.1 Research Design

This study adopts a quantitative, cross-sectional survey research design to examine the relationships among artificial intelligence adoption, AI-enabled organizational capabilities, contextual conditions, ethical risk, and market leadership among Nigerian SMEs. A cross-sectional approach is highly appropriate for this investigation, as it captures current patterns of AI use and their associated organizational outcomes across firms operating in dynamic environments at a specific point in time (Saunders et al., 2019).

3.2 Study Area and Population

The study is conducted across Nigeria as a whole, capturing diverse SME contexts ranging from major commercial and technology hubs to emerging regional ecosystems. The target population comprises owners, managers, and senior decision makers of registered and informal SMEs operating across distinct business sectors. These individuals were selected because they possess the strategic oversight required to accurately assess organizational capabilities and market performance within their respective enterprises.

3.3 Sampling Technique and Sample Size

Due to the absence of a comprehensive national SME sampling frame, a multi-stage sampling approach was employed (Sekaran & Bougie, 2016). First, SMEs were purposively selected based on having active business operations and demonstrable baseline exposure to digital tools. Subsequently, respondents were identified through convenience and snowball sampling, leveraging industry networks to maximize reach across both formal and informal sectors. The final sample size yielded 167 valid responses. This sample size comfortably exceeds the minimum threshold for Partial Least Squares Structural Equation Modeling (PLS SEM) and provides adequate statistical power to detect significant path coefficients in a model with five latent constructs (Hair et al., 2021).

3.4 Data Collection Instrument

Primary data were collected using a structured, self-administered questionnaire designed on a five-point Likert scale ranging from strongly disagree to strongly agree. The survey measured the study's core latent constructs, all of which are anchored in established literature. Specifically, indicators for Artificial Intelligence Use Intensity were adapted to reflect active deployment levels and integration within business routines in developing economies (Smallbone et al., 2022). All items were worded positively to enhance clarity and ensure ease of comprehension for respondents with diverse educational backgrounds.

The survey was shared via WhatsApp to ensure respondent convenience and broad geographic accessibility across various locations in Nigeria. Researchers acknowledge a possible limit to the survey's reach, as this online distribution method inherently restricts participation to respondents with active internet access and a baseline level of digital literacy, potentially excluding highly traditional or offline enterprises.

3.5 Data Analysis Technique

Data analysis was conducted using the R statistical computing environment. Prior to model estimation, the data were screened for missing values. Minor missing data, ranging from 5.5% to 6.8%, was detected for specific indicators. To preserve sample size and data integrity, these missing values were imputed using the mean replacement method, a statistically sound procedure when missing data accounts for less than 10% of the dataset (Hair et al., 2021).

The analysis proceeded in two distinct stages. First, the measurement model was evaluated for reliability and validity. Indicator reliability was confirmed via outer loadings, and internal consistency was established using Composite Reliability and Average Variance Extracted that exceeded the standard thresholds (Hair et al., 2021). To establish discriminant validity, the Heterotrait-Monotrait ratio was used (Henseler et al., 2015). Specific items exhibiting severe cross-loading were systematically deleted during iterative refinement. This rigorous trimming process successfully reduced the HTMT ratio to a defensible level, preserving the minimum three-indicator threshold for construct robustness while ensuring empirical distinctiveness.

Second, the structural model hypotheses were tested utilizing a bootstrapping procedure with 5,000 subsamples to generate highly robust standard errors and significant values (Hair et al., 2021). Specific indirect effects were calculated to definitively test the mediation pathways (Nitzl et al., 2016). The boundary conditions were tested using the orthogonal Two Stage approach to generate the interaction terms, which is the recommended method for testing moderation as it maximizes statistical power while minimizing multicollinearity (Becker et al., 2018). Finally, to test for contextual heterogeneity across business types, a PLS MGA was executed utilizing 1,000 bootstrap subsamples. The dataset was partitioned to compare the primary operating sector with all other aggregated sectors, enabling a rigorous statistical comparison of structural path differences across firm categories (Henseler et al., 2009).

3.6 Ethical Considerations

The research strictly adhered to standard ethical guidelines for social science research in Nigeria. Participation was entirely voluntary, and informed consent was obtained from all respondents prior to data collection. Participants were explicitly briefed on the study's purpose, and robust measures were implemented to ensure the confidentiality and anonymity of both individual respondents and their respective enterprises. All collected data were securely stored and utilized strictly for academic research purposes.

4. Results

4.1 Measurement Model Assessment

The evaluation of the measurement model focused on indicator reliability, internal consistency, convergent validity, and discriminant validity using the final comprehensive algorithm. Indicator reliability was assessed through the outer loadings. Internal consistency was firmly established, as Composite Reliability (rhoC) values for all constructs, including AI Use Intensity, AI Enabled Dynamic Capabilities, Market Leadership Outcomes, Institutional Support, and Ethical Risk Perception, comfortably exceeded the recommended 0.70 threshold (Hair et al., 2021).

Convergent validity was evaluated using the Average Variance Extracted (AVE). The AVE values for most constructs exceeded the 0.50 benchmark. The AVE for Institutional Support recorded 0.488, falling

marginally below the strict threshold. However, adequate convergent validity is established according to Fornell and Larcker (1981), who note that an AVE slightly below 0.50 is acceptable provided the corresponding Composite Reliability exceeds 0.60, which Institutional Support satisfies with a robust CR of 0.825.

To confirm discriminant validity, the Heterotrait Monotrait (HTMT) ratio of correlations was examined. Initial estimates indicated substantial conceptual overlap between AI Use Intensity and AI-Enabled Dynamic Capabilities. An iterative item-deletion strategy was employed, leading to the strategic removal of three indicators (daily_operations, explore_solutions, and adjust_operations), resulting in severe cross-loading. This rigorous refinement reduced the highest HTMT ratio to a defensible value of 0.902, which is acceptable for theoretically adjacent constructs while preserving empirical distinctiveness (Henseler et al., 2015). The final measurement properties and discriminant validity matrices are presented in Tables 1 and 2.

Table 1: Construct Reliability and Validity

AI Use Intensity (AIUI)		0.863	0.679
data_decisions	0.854		
predict_trends	0.777		
function_integration	0.839		
AI Enabled Dynamic Capabilities (AIDC)		0.871	0.628
respond_faster	0.703		
reconfigure_resources	0.830		
adaptive_decisions	0.816		
process_learning	0.815		
Market Leadership Outcomes (MLO)		0.901	0.646
market_leader	0.834		
customer_preference	0.833		
competitive_position	0.771		
early_innovator	0.795		
trend_setter	0.784		
Institutional Support (IIS)		0.825	**0.488***
reliable_internet	0.772		
adequate_power	0.658		
accessible_support	0.745		
government_incentives	0.559		
encouraging_environment	0.735		
Ethical Risk Perception (EAIR)		0.837	0.506
privacy_risks	0.676		
unintentional_bias	0.727		
lacking_guidelines	0.737		
reputation_harm	0.723		
ethical_limits	0.691		

Note. AIUI indicators 'daily_operations' and 'explore_solutions', and AIDC indicator 'adjust_operations' were removed to establish discriminant validity. CR = Composite Reliability; AVE = Average Variance

Extracted. *Adequate convergent validity established per Fornell and Larcker (1981) as CR > 0.60.

Table 2

Discriminant Validity (Heterotrait Monotrait Ratio - HTMT)

1. AI Enabled Dynamic Capabilities (AIDC)				
2. AI Use Intensity (AIUI)	0.902			
3. Ethical Risk Perception (EAIR)	0.569	0.602		
4. Institutional Support (IIS)	0.457	0.526	0.429	
5. Market Leadership Outcomes (MLO)	0.871	0.765	0.515	0.506

Note. HTMT values below the conservative 0.90 threshold (or marginally at the 0.90 boundary for theoretically adjacent constructs) establish discriminant validity.

4.2 Structural Model Assessment and Hypothesis Testing

The structural model hypotheses were tested utilizing a bootstrapping procedure with 5,000 subsamples to generate highly robust standard errors and significance values (see Table 3 below). The analysis demonstrated strong empirical support for the direct pathways. Artificial Intelligence Use Intensity significantly and positively predicts AI-Enabled Dynamic Capabilities ($\beta = 0.605$, $p < 0.001$), providing robust support for Hypothesis 1. Consequently, AI-enabled dynamic capabilities exert a significant positive effect on Market Leadership Outcomes ($\beta = 0.529$, $p < 0.001$), supporting Hypothesis 2. The overall structural model, detailing all path coefficients and their respective significance levels, is presented graphically in Figure 2.

To examine the mediation pathway, the specific indirect effect was calculated. The results confirmed that AI-enabled dynamic capabilities significantly mediate the relationship between AI Use Intensity and Market Leadership Outcomes ($\beta = 0.413$, $p < 0.001$), supporting Hypothesis 3. A significant direct path from AIUI to MLO ($\beta = 0.175$, $p = 0.031$) was also observed, indicating partial complementary mediation. This validates the core premise that technology adoption primarily drives competitive advantage when effectively translated into embedded organizational capabilities.

Table 3. *Structural Model Assessment and Hypothesis Testing*

Hypothesis	Structural Path	β	SD	t-value	p-value	Decision
Direct Effects						
H1	AIUI → AIDC	0.605	0.072	8.410	< 0.001	Supported
H2	AIDC → MLO	0.529	0.079	6.693	< 0.001	Supported
—	AIUI → MLO (Direct Effect)	0.175	0.082	2.135	0.031	Significant
Indirect / Mediation Effect						
H3	AIUI → AIDC → MLO	0.413	0.071	5.810	< 0.001	Supported
Moderation Effects						
H4	AIUI × IIS → AIDC	-0.091	0.038	-2.403	0.040	Supported (Negative Effect)
H5	AIDC × EAIR → MLO	-0.038	0.040	-0.944	0.349	Not Supported

Note. AIUI = AI Use Intensity; AIDC = AI Enabled Dynamic Capabilities; MLO = Market Leadership Outcomes; IIS = Institutional Support; EAIR = Ethical Risk Perception. Bootstrapping based on 5,000 subsamples. *H4 was hypothesized as a strengthening effect but resulted in a significant buffering (negative) effect.

4.3 Moderation Analysis

The study examined the contextual boundary conditions utilizing the orthogonal two-stage approach for interaction terms, a standard practice for robust moderation testing in PLS SEM (Becker et al., 2018). The analysis revealed that Institutional Support exerts a significant negative moderating effect on the relationship between AI Use Intensity and AI-Enabled Dynamic Capabilities (β = -0.091, p = 0.040). This points to a buffering effect rather than the initially hypothesized strengthening effect, supporting Hypothesis 4, albeit in the inverse direction. The specific nature of this buffering effect is illustrated by a simple slope analysis (see Figure 3), which shows that the capability-building advantage of AI is most pronounced in environments with lower institutional support, where SMEs are compelled to innovate internally to bridge external infrastructure gaps.

Conversely, Ethical Risk Perception did not significantly moderate the relationship between AI-Enabled Dynamic Capabilities and Market Leadership Outcomes (β = -0.038, p = 0.349). Therefore, Hypothesis 5 was not supported. This suggests that ethical apprehensions currently do not attenuate the market advantages derived from AI capabilities within the investigated emerging market context.

4.4 Multi-Group Analysis

To investigate potential context heterogeneity, a PLS Multi-Group Analysis (PLS MGA) was executed utilizing 1,000 bootstrap subsamples. The dataset was partitioned to statistically compare the primary operating sector (Sector 1, n = 73) against all other aggregated sectors (n = 95). The results revealed no statistically significant differences across the primary structural paths. The pathways from AI Use Intensity to Dynamic Capabilities ($p = 0.112$) and from Dynamic Capabilities to Market Leadership Outcomes ($p = 0.494$) demonstrated robust statistical equivalence. This analysis confirms that the internal mechanisms that map AI adoption to market leadership are highly generalizable and operate uniformly across different SME sectors in Nigeria.

5. Discussion

5.1 Overview and Theoretical Triangulation

This study set out to validate the Contextualized AI Capability to Market Leadership Framework (CACMLF) within the Nigerian SME ecosystem. The objective outlined in the conceptualization phase was to move beyond the simplistic technology performance paradigm to understand the internal mechanisms and external boundary conditions that make artificial intelligence a durable source of competitive advantage. The findings validate the framework, demonstrating that AI adoption is not a stand-alone solution. Instead, it serves as a strategic catalyst that must be embedded within firm-level routines to generate dynamic capabilities. Theoretical triangulation utilizing Resource-Based View and Dynamic Capability Theory provides a robust lens for interpreting these results. The structural model confirms that while tangible digital tools are readily acquired, the organizational agility and data-driven learning derived from them remain rare and difficult for competitors to replicate (Chen et al., 2022; Chaudhuri et al., 2022).

5.2 The Capability Engine: Mediating AI Use to Market Leadership

The results provide strong empirical support for Hypotheses 1, 2, and 3, confirming that AI-enabled dynamic capabilities serve as the central transmission mechanism between technology adoption and market dominance. The analysis revealed a highly significant positive relationship between AI Use Intensity and the development of dynamic capabilities (Appiah et al., 2026). This aligns with recent literature suggesting that intensive deployment of analytics and automation fundamentally alters how small businesses process information, allowing for faster response times and more adaptive resource configuration (Michael et al., 2025; Pu et al., 2025).

Consequently, these dynamic capabilities significantly predict Market Leadership Outcomes. The confirmation of complementary partial mediation underscores a critical reality for emerging-market SMEs. While there is a small direct performance benefit to adopting AI tools, the overwhelming majority of the competitive advantage is unlocked only when SMEs translate digital adoption into continuous organizational learning and agility (Pooe et al., 2025; Jamil et al., 2025). Firms that merely purchase

software experience marginal gains, whereas firms that utilize AI to structurally reconfigure their operational responses achieve sustained market leadership.

5.3 The Paradox of Infrastructure: A Survival Buffering Effect

The most striking theoretical revelation of this study involves the moderation of Institutional Support (Hypothesis 4). The framework initially hypothesized an amplifying effect, assuming that better infrastructure and government support would strengthen the capability-building process. The data, however, revealed a significant negative buffering effect. The simple slope analysis demonstrated that the positive relationship between AI use and capability development is much steeper for SMEs operating in environments with low institutional support.

This counterintuitive finding requires deep interpretation within the realities of the Nigerian commercial landscape. In regions lacking reliable power, broadband, or enterprise support, SMEs are forced to engage in necessity-driven frugal innovation. For these enterprises, artificial intelligence is not merely an operational upgrade; it is a survival imperative. SMEs facing severe environmental deficits stretch the utility of AI tools to internally compensate for the lack of external infrastructure, aggressively building capabilities to bridge the institutional gap (Ewuga et al., 2023; Omonzejele & Okogun, 2025). Conversely, firms in highly supported environments experience a flatter capability curve because they rely on existing external infrastructure rather than internal technological adaptation. This validates the CACMLF's contextual premise, demonstrating that environmental adversity can paradoxically accelerate internal digital maturity.

5.4 The Insignificance of Ethical Risk in Early-Stage Adoption

Hypothesis 5 proposed that Ethical Risk Perception would negatively moderate the translation of dynamic capabilities into market leadership. The structural analysis rejected this hypothesis, showing no statistically significant interaction. This finding contradicts Western-centric AI literature, which heavily emphasizes consumer backlash against algorithmic bias and data privacy violations (Soudi & Bauters, 2024; Sánchez et al., 2025).

Interpreting this within the Nigerian context suggests that the market is currently in an early, pragmatic stage of digital adoption. The immediate efficiency gains, service delivery improvements, and cost reductions delivered through AI-enabled capabilities currently overshadow nascent ethical concerns among consumers and partners (Bindah et al., 2025; Oyeyemi et al., 2025). Furthermore, the regulatory environment surrounding data protection remains highly fragmented. Until institutional enforcement matures, the perceived ethical risks of AI deployment are unlikely to manifest as tangible penalties that diminish market share or customer preference for SMEs.

5.5 Sectoral Equivalence and Framework Generalizability

The Multi Group Analysis fulfilled the methodological promise to test the framework across varying business sectors. The statistical equivalence found across the primary structural paths confirms that the

CACMLF is robust and highly generalizable. Whether a Nigerian SME operates in manufacturing, retail, or services, the fundamental rules of digital competition remain uniform. The translation of technology into capability and of capability into leadership represents a universal strategic pathway for emerging-market enterprises.

5.6 Theoretical Contributions

This research makes three distinct contributions to the literature on digital transformation and strategic management, directly satisfying the promises outlined in the study's objectives: First, it shifts the analytical focus from direct technology-performance links to capability-driven pathways. The empirical validation of the CACMLF provides researchers with a proven theoretical model that integrates the Resource-Based View with Dynamic Capability Theory, specifically for resource-constrained environments. Second, the discovery of the negative buffering effect of Institutional Support offers a novel perspective on the emerging market literature. It challenges the assumption that infrastructure deficits purely restrict innovation, providing empirical evidence that environmental hostility can drive accelerated, compensatory capability building through AI. Third, the rejection of ethical risk moderation provides a critical contextual boundary for global AI ethics discussions, demonstrating that, in early-stage digital economies, practical market delivery currently overrides algorithmic transparency concerns.

5.7 Practical Implications

For SME owners and senior managers, the findings offer a clear strategic directive. Investment in AI software must be matched with equal investment in organizational training and process redesign. Treating AI as an isolated IT project yields minimal returns; it must be utilized to build agile routines and data-driven cultures. For policymakers and enterprise support agencies in Nigeria, the results highlight a nuanced reality. While improving foundational infrastructure remains critical, policy should prioritize programs that teach business leaders how to embed AI into their core operations. Furthermore, the current insignificance of ethical risk serves as a warning. Policymakers must proactively develop transparent, SME friendly data governance frameworks before consumer trust is eroded, ensuring that the current wave of AI-driven market leadership remains sustainable in the long term.

6. Conclusion

The primary objective of this study was to empirically validate the Contextualized AI Capability to Market Leadership Framework within the Nigerian SME ecosystem. The findings conclusively demonstrate that artificial intelligence adoption does not automatically confer market dominance. Instead, AI serves as a powerful strategic catalyst that must be deliberately embedded in organizational routines. Drawing on the Resource-Based View and Dynamic Capability Theory, the research confirms that AI-enabled dynamic capabilities act as the indispensable bridge between basic technology use and sustained competitive advantage. SMEs that successfully leverage AI to respond faster, reconfigure resources, and enhance data-driven learning ultimately achieve market leadership.

Furthermore, this study fundamentally challenges prevailing assumptions regarding digital infrastructure in emerging markets. The discovery of a negative buffering effect reveals a compelling narrative of necessity-driven innovation. In environments characterized by severe institutional and infrastructural deficits, Nigerian SMEs do not passively stagnate; rather, they aggressively leverage AI tools to build internal capabilities that compensate for external systemic failures. This proves that environmental hostility can paradoxically accelerate internal digital maturity. Conversely, the non-significant role of ethical risk perception underscores a pragmatic reality. Nigerian SMEs currently operate in an early-adopter phase, where the immediate operational and survival benefits of AI heavily outweigh nascent concerns about algorithmic transparency and data privacy. Ultimately, this research provides a robust, contextually grounded roadmap for how small businesses in emerging economies can navigate infrastructural constraints to transform digital tools into enduring market leadership.

7. Limitations and Recommendations for Future Studies

While this study offers significant theoretical and practical contributions, it presents certain methodological limitations that provide clear avenues for future research.

First, the research adopted a cross-sectional survey design, which captures digital adoption patterns at a single point in time. Because capability building is inherently an evolutionary process, future research should employ longitudinal research designs. Tracking SMEs over an extended period would allow scholars to observe how AI-enabled dynamic capabilities mature over time and whether the buffering effect of institutional support changes as firms transition from early adoption to advanced digital integration.

Second, while the study captured diverse operational contexts across Nigeria, the distribution of the survey instrument via WhatsApp inherently restricted the sample to digitally connected enterprise leaders. This approach may have excluded highly traditional or informal SMEs that operate entirely offline. Future studies should incorporate stratified offline sampling to capture a broader range of digital exclusion and assess how the CACMLF applies to microenterprises taking their first steps toward digitalization.

Third, the measurement of Market Leadership Outcomes relied on self-reported perceptual data from SME owners and managers. Although perceptual measures are highly correlated with objective performance in strategic management literature, future studies could triangulate these findings by incorporating objective financial metrics, such as audited revenue growth, customer acquisition costs, or verified market share percentages, to further validate the economic impact of AI capabilities.

Finally, the study focused on institutional support and ethical risk as primary boundary conditions. As the artificial intelligence landscape rapidly evolves, future research must expand the framework to explore additional moderating variables. Investigating factors such as the CEO's digital mindset, access to specialized venture capital, and the specific type of AI architecture deployed (generative versus predictive algorithms) would yield deeper insights into the precise conditions under which emerging-

market SMEs can sustain global competitiveness. Cross-country comparative studies within the broader Sub-Saharan African region are also strongly recommended to test whether the necessity-driven buffering effect observed in Nigeria holds true across varying political and economic environments.

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Figures

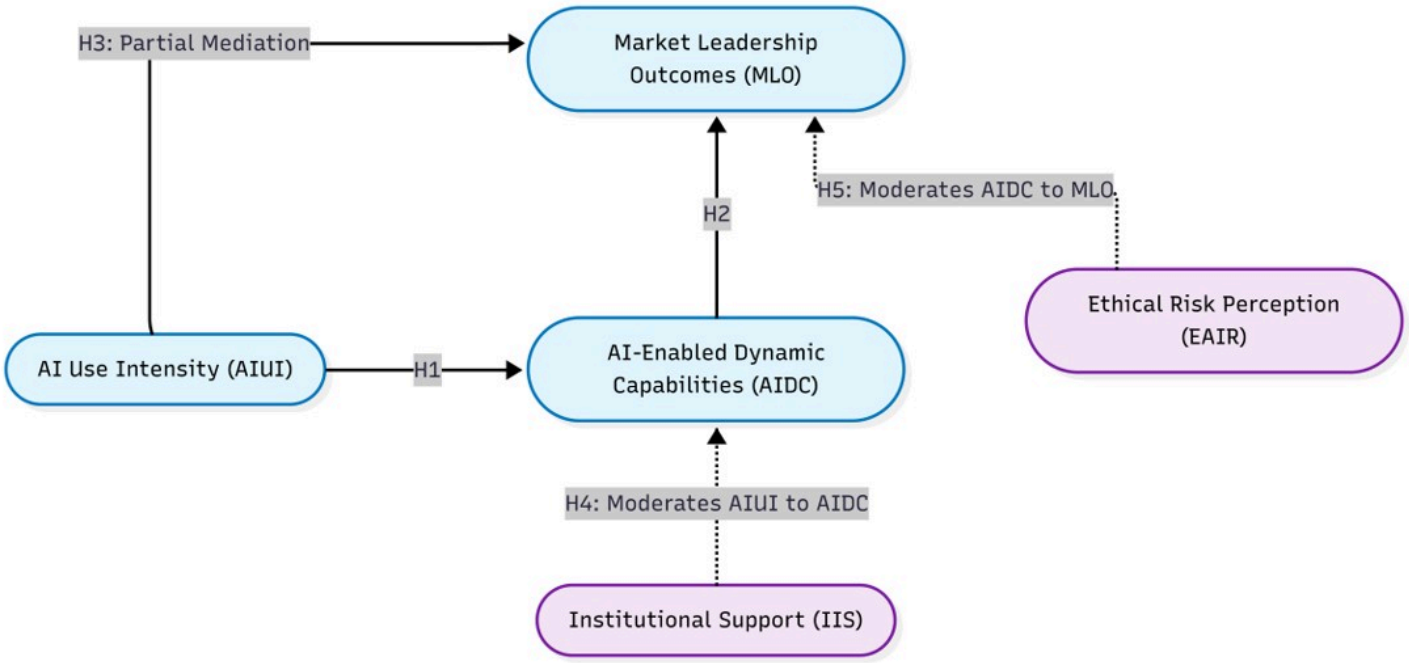


Figure 1

Conceptual Research Model for the Contextualized AI Capability to Market Leadership Framework (CACMLF)

Source: Author's conceptualization**.**

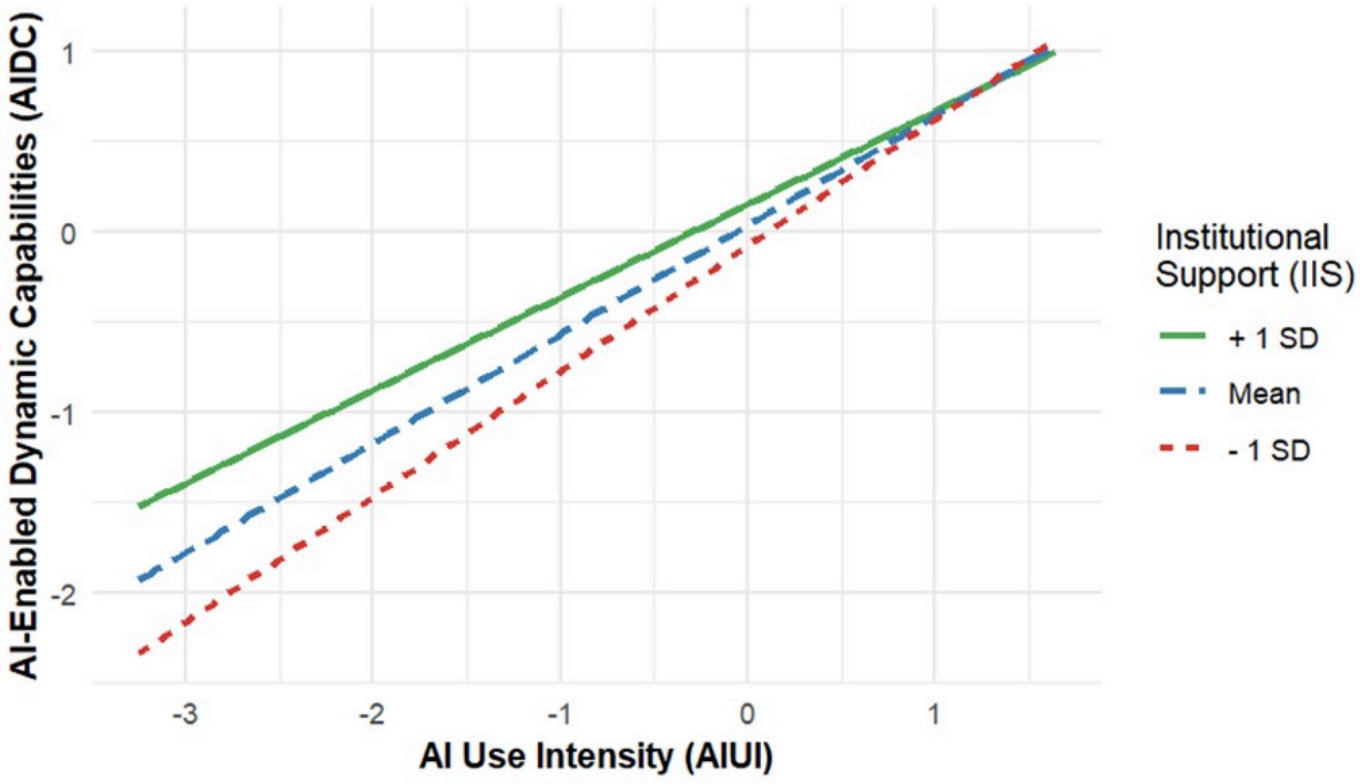


Figure 2

Estimated Structural Model with Path Coefficients

Source: Field survey data (2026).

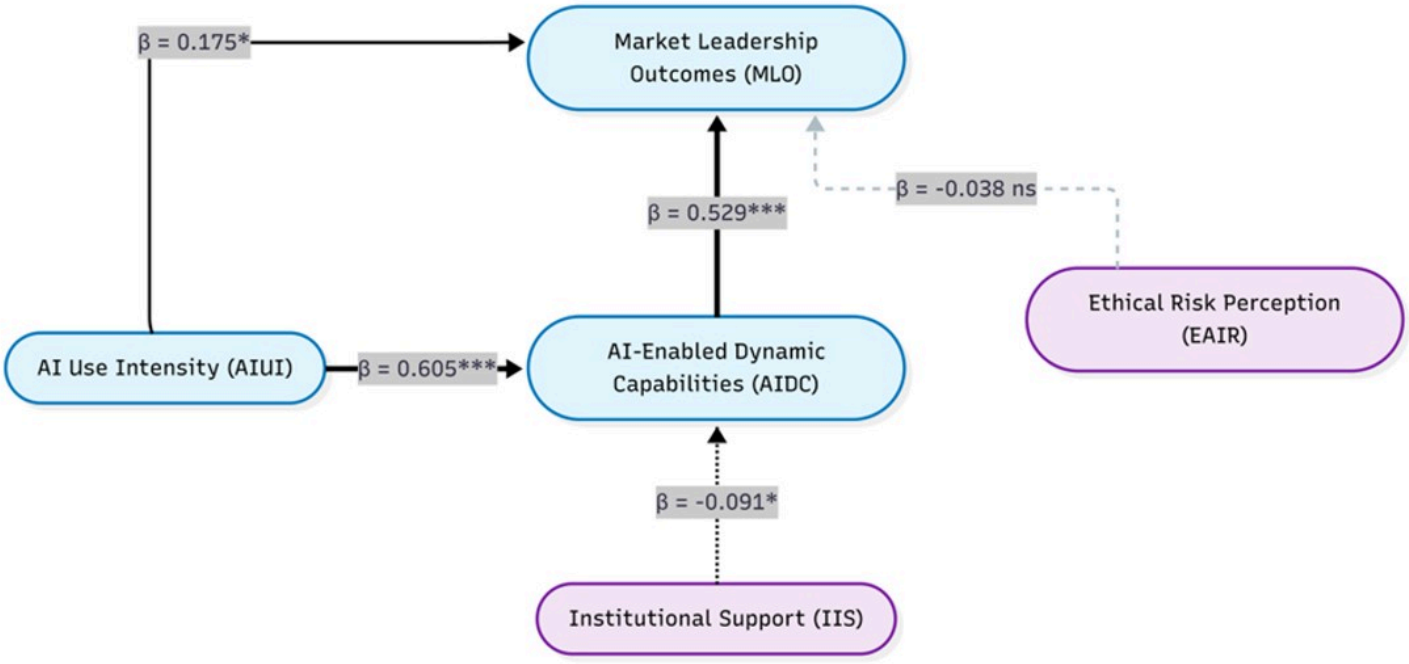


Figure 3

Interaction Plot - Moderating Effect of Institutional Support

Source: Field survey data (2026).