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Artificial Intelligence Adoption, Financial Decision-Making, and Firm Growth: Evidence from Nigerian Micro, Small, and Medium Enterprises.

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Abstract

This study examines the mediating role of artificial intelligence (AI) adoption in the relationship between financial decision-making quality and firm growth among Nigerian micro, small, and medium enterprises (MSMEs). Adopting a positivist philosophy and a quantitative, cross-sectional survey design, the study collected primary data from 144 MSME owners and managers in Nigeria using a structured questionnaire. Hypothesised relationships were tested using partial least squares structural equation modelling (PLS-SEM) in SmartPLS 4, with bootstrapping (5,000 subsamples) used to estimate direct, indirect, and total effects. Independent-samples t-tests and one-way ANOVAs with Tukey HSD post-hoc comparisons examined group differences. Financial decision-making quality is positively and significantly associated with firm growth, both directly ($\beta = 0.218$, $p = .003$) and indirectly through AI adoption (indirect effect = 0.332, $p < .001$). AI adoption is strongly associated with firm growth ($\beta = 0.542$, $p < .001$). The variance accounted for (VAF) is 60.4%, indicating partial mediation: about 60% of the total association is transmitted through AI adoption. AI adoption differs significantly across sectors ($F(3, 140) = 4.28$, $p = .006$), with services and manufacturing firms reporting higher adoption than trade/retail and agro-processing. Financial decision-making quality differs significantly across educational levels ($F(3, 140) = 5.14$, $p = .002$). The model explains 48.2% of the variance in firm growth and 37.5% in AI adoption. The study extends an AI-finance literature dominated by banks to MSMEs, providing survey evidence on a mediation model in which AI adoption operationalises financial decision-making capabilities for firm growth, and documenting heterogeneity across sectors and education levels.

Keywords: Artificial intelligence adoption; financial decision-making; firm growth; MSMEs; Nigeria; PLS-SEM

JEL Classification: O33; G41; L25; L26; M15

1.0 Introduction

Artificial intelligence (AI) is reshaping business operations globally by enabling automated decision-making, real-time analytics, personalised customer services, and data-intensive operational optimisation (Iroh et al., 2026; Okoye, 2026). Machine learning, natural language processing, predictive analytics, and intelligent automation are now deployed across accounting, marketing, supply chain management, and financial management in firms of all sizes (Adedire-Ampitan et al., 2024; Akani et al., 2026). AI has therefore become not merely an auxiliary technology but a strategic capability that can alter how firms create value, allocate resources, and compete in increasingly digital markets (Oniye & Akinsode, 2026).

Nigeria provides a particularly consequential setting for examining this transformation. The rapid expansion of mobile and internet connectivity, FinTech platforms, electronic payments, and digital identity systems has increased both the volume of machine-readable business data and the demand for scalable digital services (CBN, 2021; Okoye, 2026). Nigerian banks have moved beyond basic digitisation and deployed AI-powered chatbots, fraud detection systems, and credit scoring models (Iroh et al., 2026; Oniye & Akinsode, 2026), while micro, small, and medium enterprises (MSMEs) are increasingly adopting AI tools for bookkeeping, customer relationship management, and market intelligence (Aju, 2026). A 2024 PwC Nigeria report found that over 60 per cent of Tier-1 banks have some form of AI integration in customer service, risk management, or analytics (PwC Nigeria, 2024), and a separate survey found that all sampled Nigerian deposit money banks had adopted AI for accounting functions (Salemcity et al., 2025). MSMEs, by contrast, have received far less empirical attention, despite contributing roughly half of Nigeria's gross domestic product (GDP) and the large majority of its employment, with exact shares varying by survey round (SMEDAN & NBS, 2021).

Yet this accelerating adoption occurs within an environment marked by uneven broadband and power infrastructure, fragmented data systems, limited specialist skills, high implementation costs, and evolving regulatory requirements (Okoye, 2026; Aju, 2026). The evidence on AI's actual adoption, operational value, and governance implications in Nigeria remains fragmented (Aju, 2026; Iroh et al., 2026). More critically, whether AI adoption improves financial decision quality and firm growth, as distinct from operational efficiency or customer experience, has received insufficient empirical attention (Iroh et al., 2026). Existing scholarship frequently examines isolated benefits, such as fraud detection or customer service, without relating them to the core financial decisions that determine firm performance: credit assessment, budgeting, cash-flow planning, investment allocation, and profitability optimisation (Aladeokin & Afolabi, 2025; Adeniji et al., 2025). Moreover, almost all of this evidence comes from banks, and little is known about whether the same mechanisms operate in the small, resource-constrained firms that dominate the Nigerian economy.

This study addresses these gaps by posing three research questions. RQ1: Does financial decision-making quality have a significant positive association with firm growth among Nigerian MSMEs? RQ2: Does AI adoption mediate the relationship between financial decision-making quality and firm growth? RQ3: Does AI adoption differ across business sectors, and does financial decision-making quality differ across educational levels? The study analyses primary survey data from 144 MSME owners and managers using a mediation model estimated by partial least squares structural equation modelling (PLS-SEM), and interprets the results against the growing body of evidence from Nigerian banks (Adedire-Ampitan et al., 2024; Amaugo, 2025a; Adeniji et al., 2025; Salemcity et al., 2025; Iroh et al., 2026; Oniye & Akinsode, 2026).

The study contributes to the literature in three ways. First, it provides MSME-level survey evidence on a mediation model in which AI adoption operationalises financial decision-making capabilities for firm growth (Iroh et al., 2026). Second, it quantifies the extent to which the association between financial decision-making and growth is transmitted through AI adoption (60.4% in this sample). Third, it documents heterogeneity in AI adoption across sectors and in financial decision-making quality across education levels, which helps identify where support for MSMEs is most needed (Aladeokin & Afolabi, 2025).

The remainder of the paper proceeds as follows. Section 2 reviews the literature and develops the theoretical framework and hypotheses. Section 3 describes the methodology. Section 4 presents the results. Section 5 discusses

the findings in relation to theory and context. Section 6 concludes with theoretical contributions, practical recommendations, and directions for future research.

2.0 Literature Review and Theoretical Framework

2.1 AI Adoption in Nigerian Businesses

AI adoption in Nigerian businesses is real but selective, uneven, and less empirically mature than the rhetoric of transformation suggests (Aju, 2026; Okoye, 2026). Fraud detection, cybersecurity, customer-service automation, and predictive analytics show the clearest operational uptake, whereas explainable credit scoring, generative AI, and enterprise-wide integration remain emergent (Okoye, 2026). Chatbots such as UBA's Leo and Zenith Bank's Ziva use natural language processing to provide round-the-clock customer support, scale easily, and reduce pressure on human agents (Iroh et al., 2026; Smutný & Schreiberová, 2026). AI-powered fraud detection systems at Zenith Bank and Access Bank monitor transactions in real time, identify anomalies, and learn from evolving fraud tactics (Akani et al., 2026; Adedire-Ampitan et al., 2024). GTBank's QuickCredit uses AI to pre-qualify salaried individuals and disburse funds within minutes without human intervention, expanding credit access to underbanked segments (Auya & Jamiu, 2026).

The evidence base extends beyond the largest banks. Adedire-Ampitan et al. (2024) provide evidence from Guaranty Trust Bank showing that AI adoption, AI-driven credit scoring, and AI-based fraud detection each have a significant positive impact on risk management, while noting that Nigerian banks' AI efforts have focused more on infrastructure upgrades than on advanced decision-making. Amaugo (2025a) examines Fidelity Bank and reports that AI enhances decision efficiency by 40%, reduces human error by 35%, and improves risk assessment. Auya and Jamiu (2026) study selected deposit money banks in Abuja and find that automated credit scoring significantly enhances financial performance by improving credit appraisal efficiency, reducing default rates, and strengthening loan portfolio quality, while predictive risk analytics shows a strong positive effect through early risk detection and proactive credit monitoring. Research covering Zenith, UBA, Fidelity, and Union Bank in Port Harcourt further indicates that AI adoption improves organisational performance across deposit money banks (Amaugo, 2025a). Studies of document management across branches of Fidelity, GTB, Polaris, Stanbic, and Eco Bank suggest that AI substantially enhances document-management effectiveness (Amaugo, 2025b; Smutný & Schreiberová, 2026). At the industry level, AI disclosure across 12 Nigerian deposit money banks between 2015 and 2024 is positively associated with profitability and market valuation, with strategic and operational disclosures exerting the strongest effects (Galani et al., 2026).

However, adoption is constrained by high implementation costs, lack of technical expertise, infrastructure deficits, and regulatory uncertainty surrounding data privacy and cybersecurity (Okoye, 2026; Aju, 2026). A systematic review of 89 records found that AI adoption in Nigerian digital banking is accelerating but predominantly function-specific, and that benefits relating to efficiency and risk detection are inseparable from data-protection, bias, cybersecurity, model-risk, skills, and infrastructure constraints (Aju, 2026). Nigeria's open banking rollout has exposed missing AI guardrails: experts warn that without clear rules governing AI, open banking could introduce new risks related to bias, transparency, and accountability (Okoye, 2026). The Central Bank of Nigeria (CBN) became the first African regulator to issue a formal open banking framework in 2021 (CBN, 2021), followed by operational guidelines in 2023 and infrastructure development in 2025. The Nigeria Data Protection Act (2023) provides a foundational data-protection framework, but algorithmic bias, explainability, automated decision-making, and third-party technological responsibility remain insufficiently addressed (Okoye, 2026).

A notable feature of this literature is its concentration on banks and other large financial institutions. Beyond Nigeria, evidence from other emerging markets suggests that SME AI adoption is constrained by similar factors-limited digital infrastructure, skills shortages, and financing constraints-but that mobile-first AI tools (e.g., mobile bookkeeping apps, WhatsApp-based customer service) can lower barriers to adoption. Comparative evidence from Kenyan SMEs, for example, indicates that AI-enabled mobile money analytics improve cash-flow forecasting and credit access. These findings suggest that the Nigerian MSME experience may be representative of broader patterns in African emerging markets, although contextual differences warrant further investigation. To the best of our knowledge, little peer-

reviewed survey evidence links AI adoption, financial decision-making, and firm growth in Nigerian MSMEs, which motivates the present study.

2.2 AI and Financial Decision-Making Outcomes

Financial decision-making in business encompasses credit assessment, loan repayment monitoring, risk management, investment allocation, budgeting, cash-flow planning, and profitability optimisation (Aladeokin & Afolabi, 2025; Leland & Pyle, 1977). AI-based systems are theorised to enhance these decisions through improved forecasting accuracy, decision speed, risk management effectiveness, investment decision quality, and operational efficiency (Adeniji et al., 2025; Iroh et al., 2026).

Empirical evidence from Nigeria is generally positive but contingent. Using a sample of 350 respondents across seven financial institutions, including Zenith Bank, GTCO, Access Bank, First Bank, UBA, ARM, and Leadway Assurance, Adeniji et al. (2025) find that automation significantly improves financial forecasting accuracy ($\beta = 0.721$, $p < .05$), predictive analytics has a strong positive impact on decision-making speed ($\beta = 0.684$, $p < .05$), AI-driven customer service enhances risk management effectiveness ($\beta = 0.702$, $p < .05$), AI-based fraud detection improves investment decision quality ($\beta = 0.763$, $p < .05$), and AI-powered decision support systems enhance operational efficiency ($\beta = 0.694$, $p < .05$). However, the relationship between AI and credit assessment is not straightforward. Aladeokin and Afolabi (2025), studying 220 credit officers, find that AI has a negative and significant direct influence on credit assessment ($B = -0.263$, $p < .001$) and a negative but marginal influence on loan repayment ($B = -0.146$, $p = .059$), although the interaction of AI with occupational capacity positively affects credit assessment ($B = 0.108$, $p < .001$) and repayment ($B = 0.022$, $p = .040$). This suggests that AI's success in credit operations is contingent on organisational characteristics and employee ability (Aladeokin & Afolabi, 2025).

At the aggregate level, Salemcity et al. (2025) report that AI investment contributes significantly to cost reduction, profitability, return on assets, and revenue growth across Nigerian deposit money banks (all $p < .01$), and that AI-driven automation and predictive analytics reduce operating costs while improving service delivery. Akani et al. (2026) find that AI-driven fraud detection has a positive and significant impact on return on investment at the 10 per cent level ($\beta = 0.222$, $p = .074$). Panel analysis of the FUGAZ banks (First Bank, UBA, GTCO, Access, and Zenith) over 2015-2024 shows that automated chatbot systems, deep learning models in credit risk management, and fraud detection each have a positive and statistically significant association with return on assets (Oniye & Akinsode, 2026).

2.3 Theoretical Framework

The study is underpinned by three complementary theories.

Technology Acceptance Model (TAM). Developed by Davis (1986), TAM emphasises perceived usefulness and perceived ease of use as central determinants of technology acceptance. In business, TAM helps explain how AI technologies are adopted to improve operational efficiency and risk mitigation, such as fraud detection and credit risk assessment (Adedire-Ampitan et al., 2024). However, TAM has been criticised for neglecting organisational culture, regulatory frameworks, and ethical concerns, including data privacy and algorithmic bias (Okoye, 2026). This study therefore complements TAM with firm-level and contextual factors (sector, education, and firm characteristics) that may shape how AI relates to financial decision quality and growth (Aladeokin & Afolabi, 2025).

Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT integrates performance expectancy, effort expectancy, social influence, and facilitating conditions to explain both intention and actual use of technologies (Venkatesh et al., 2003). Qualitative research with 36 Nigerian residents shows that the four UTAUT factors help explain how consumers engage with banking chatbots (Smutný & Schreiberová, 2026). UTAUT is particularly relevant in the Nigerian context, where facilitating conditions such as infrastructure reliability, digital competency, and institutional trust are unevenly distributed across firm sizes and geographies (Aju, 2026). UTAUT extends TAM by incorporating social influence and facilitating conditions, which are particularly relevant in the Nigerian MSME context where infrastructure and institutional trust are unevenly distributed (Venkatesh et al., 2003). TAM is retained as a foundational framework because its core constructs-perceived usefulness and ease of use-remain central to explaining AI adoption, while UTAUT provides a more comprehensive account of contextual moderators.

Decision Theory and Financial Intermediation Theory. Decision Theory (von Neumann & Morgenstern, 1944) provides a framework for analysing decision-making under uncertainty and aligns with AI's capacity to provide data-driven insights for credit risk assessment and fraud detection (Adeniji et al., 2025). Financial Intermediation Theory (Leland & Pyle, 1977) emphasises information production and delegated monitoring in financial decisions; AI can strengthen these functions by reducing information asymmetries and improving monitoring efficiency (Iroh et al., 2026).

2.4 Conceptual Model and Hypothesis Development

Figure 1 presents the conceptual model. Financial decision-making quality (FDM) is the focal predictor, AI adoption is the mediator, and firm growth (FG) is the outcome.

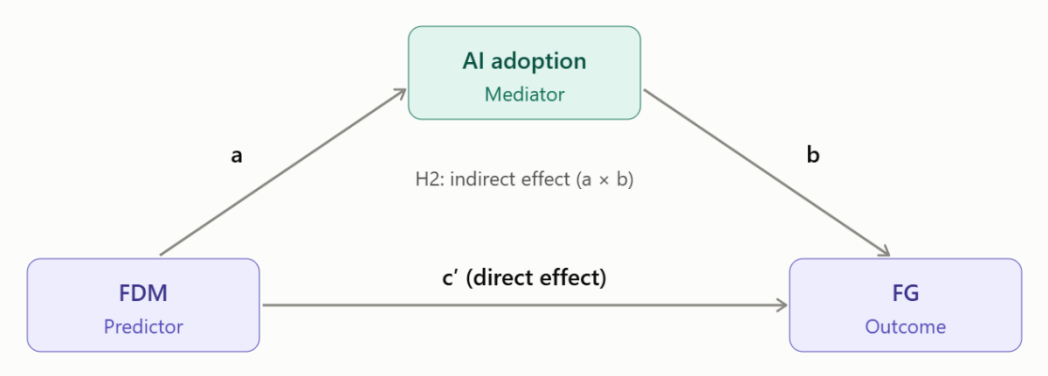


Figure 1. Conceptual model. H2 represents the indirect effect (a × b). Group comparisons (H4a and H4b) are examined separately and are not depicted as paths in the model.

Rationale for the mediating role of AI adoption. The reviewed studies, almost all conducted in banks, report positive associations between AI applications and the quality of financial decisions and performance (Adedire-Ampitan et al., 2024; Amaugo, 2025a; Adeniji et al., 2025; Auya & Jamiu, 2026; Salemcity et al., 2025; Iroh et al., 2026). Evidence on credit assessment is less consistent: Aladeokin and Afolabi (2025) report a negative direct effect of AI on credit assessment, whereas Auya and Jamiu (2026) report that automated credit scoring improves credit appraisal and portfolio quality. Two inferences follow. First, firms with disciplined budgeting, cash-flow planning, and investment appraisal are likely to have the data, routines, and absorptive capacity needed to use AI tools productively, consistent with the facilitating-conditions logic of UTAUT; AI adoption is therefore plausibly a channel through which financial decision-making capability is operationalised in firm growth (Iroh et al., 2026). Second, because the benefits of AI vary with organisational capacity (Aladeokin & Afolabi, 2025), heterogeneity across sectors and education levels warrants examination. Following Baron and Kenny (1986) and Hair et al. (2019), AI adoption is specified as a mediator because the research task is to explain how a predictor is related to an outcome, rather than to identify the conditions under which that relationship strengthens or weakens. Because the supporting evidence comes mainly from banks and direct tests of this chain in MSMEs are scarce, the model is exploratory. Sector and education are examined through group comparisons rather than modelled as moderators.

Building on the theories and evidence above, the following hypotheses are proposed:

H1: Financial decision-making quality is positively and significantly associated with firm growth among Nigerian MSMEs.

H2: AI adoption mediates the relationship between financial decision-making quality and firm growth (that is, financial decision-making quality is positively associated with AI adoption, and the indirect effect through AI adoption is significant).

H3: AI adoption is positively and significantly associated with firm growth.

H4a: AI adoption differs significantly across business sectors.

H4b: Financial decision-making quality differs significantly across educational levels.

Theoretical justification for H4a and H4b. Sectorial differences in AI adoption are expected because the nature of operations, data intensity, and digital maturity vary across sectors. Manufacturing and services firms typically generate more structured data and have greater incentives to automate routine processes, whereas trade/retail and agro-processing firms may face lower digital readiness and less formalised data systems (Aju, 2026). Educational differences in financial decision-making quality are expected based on human capital theory (Becker, 1964), which posits that formal education enhances cognitive skills, financial literacy, and managerial capabilities. Owners with higher educational attainment are likely to have greater capacity to interpret financial information, evaluate investment opportunities, and implement systematic budgeting and cash-flow planning.

3.0 Methodology

3.1 Research Design and Philosophy

The study adopts a positivist research philosophy with a quantitative, cross-sectional survey design. Positivism is appropriate because the study seeks to establish objective, measurable relationships between constructs (financial decision-making quality, AI adoption, and firm growth) using standardised instruments and statistical inference (Saunders et al., 2019). The cross-sectional design captures a snapshot of business practices at a single point in time. It allows associations among variables to be examined, but causal claims remain limited without longitudinal data (Podsakoff et al., 2003).

This design is consistent with comparable studies in the Nigerian AI-finance literature, including Iroh et al. (2026), who surveyed 394 respondents across Nigerian financial hubs using a cross-sectional design, and Adeniji et al. (2025), who surveyed 350 employees across seven financial institutions.

3.2 Population and Sampling

The target population comprises MSME owners and managers operating in Nigeria across diverse sectors, including agro-processing, trade/retail, manufacturing/light industry, and services. The sample covers businesses of varying sizes (1-9, 10-19, 30-39, and 40-49 employees) and ages (less than one year to more than ten years), ensuring heterogeneity in AI adoption experiences and financial management practices.

A convenience sampling approach was employed, using digital channels (Google Forms shared via email, WhatsApp, and social media) to reach respondents across multiple locations. These include Kano (Dawanau, Kantin Kwari, Kurmi, Sabon Gari, Sharada, Tarauni, Gyadi-Gyadi, Minjibir, Garko, Kurna, Naibawa, Farm Center, and Sani Mainagge), Edo State (Okpella, Ekpoma, Agbede, Uromi, and Benin), Imo state (Owerri, Orlu and Okigwe), Osun State (Osogbo, Ila Oragu, Ila Okuku, and Ilesha), Plateau state (Mangu, Pankshi, Jos, Wase and Langtan), Kogi (Okene, Lokoja, Osara, Koton Karfe and Kaba gari) and online platforms. Convenience sampling limits probabilistic generalisability. It is nevertheless appropriate for exploratory and model-testing research, where the goal is to examine relationships among constructs rather than to estimate population parameters (Hair et al., 2019). The sample also shows substantial variation in firm characteristics and AI adoption.

The sample size was evaluated against PLS-SEM requirements using two criteria. First, under the 10-times rule (Hair et al., 2019), the minimum sample size is ten times the largest number of structural paths pointing at any single construct. In the present model, the most heavily targeted construct is firm growth, which receives paths from financial decision-making, AI adoption, and the control variables. Using the 10-times rule, the minimum sample size would be $10 \times 8 = 80$. Second, using the inverse square root method (Kock & Hadaya, 2018), the minimum sample size for detecting a minimum path coefficient of 0.21 at 80% power and 5% significance is approximately 130. The achieved sample of 144 therefore exceeds both thresholds, providing adequate statistical power.

3.3 Data Collection Instrument

The survey instrument was a structured questionnaire with Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree) measuring three constructs.

Financial Decision-Making Quality (FDM): 12 items across three dimensions: access to credit and financing decisions (B1.1-B1.4), budgeting and cash-flow planning (B2.1-B2.4), and investment and expansion decisions (B3.1-B3.4). These items capture core financial management practices that determine business sustainability and growth (Aladeokin & Afolabi, 2025; Adeniji et al., 2025).

AI Adoption (AI): 11 items across three dimensions: technological readiness (C1.1-C1.3), use of AI-enabled financial analytics (C2.1-C2.4), and AI-supported customer/market intelligence (C3.1-C3.4). These items reflect the deployment of AI tools in business operations, including bookkeeping software, sales analytics, credit scoring, demand forecasting, and customer intelligence (Iroh et al., 2026; Aju, 2026).

Firm Growth (FG): 3 items measuring sales growth, employment growth, and profitability improvement over the past three years (D1-D3), operationalising firm growth as a multi-dimensional outcome consistent with prior research (Amaugo, 2025a; Oniye & Akinsode, 2026).

Demographic and business characteristics were also captured: gender, age, educational qualification, business sector, number of employees, age of business, business location, and an indicator of AI tool usage (Yes/No/Not sure).

Content validity was supported by adapting items from established scales in the literature (Adeniji et al., 2025; Iroh et al., 2026; Aladeokin & Afolabi, 2025). Face validity was established through expert review by two academic researchers with expertise in AI and SME finance, who assessed item clarity, relevance, and comprehensiveness. A pilot test with 15 respondents (not included in the final sample) confirmed that items were understood as intended and that completion time was reasonable (approximately 10-12 minutes). The pilot yielded a Cronbach's alpha of 0.86, indicating good internal consistency (Hair et al., 2019).

3.4 Analytical Techniques

3.4.1 Descriptive Statistics

Descriptive statistics (means, standard deviations, skewness, and kurtosis) were computed for all composite constructs and dimensions. Demographic characteristics were summarised using frequencies and percentages.

3.4.2 Reliability and Validity Assessment

Internal consistency reliability was assessed using Cronbach's alpha and composite reliability (CR); values above 0.70 are considered acceptable and above 0.80 good (Hair et al., 2019). Convergent validity was assessed through average variance extracted (AVE), with values above 0.50 indicating that the construct explains more than half of the variance in its indicators. Discriminant validity was assessed using the heterotrait-monotrait (HTMT) ratio, with values below 0.85 indicating adequate discriminant validity (Henseler et al., 2015). Outer loadings above 0.70 were considered acceptable; loadings between 0.40 and 0.70 were retained if their removal did not increase CR or AVE above the relevant thresholds (Hair et al., 2019).

3.4.3 Structural Equation Modelling (PLS-SEM)

The hypothesised relationships were tested using PLS-SEM in SmartPLS 4. PLS-SEM is appropriate for four reasons. First, the study is exploratory and predictive in orientation: it examines a relatively unexplored mechanism in the MSME context (Hair et al., 2019). Second, Likert-scale data often violate the multivariate normality assumption of covariance-based SEM, whereas PLS-SEM makes no distributional assumptions. Third, the model includes three latent constructs with 26 indicators, which is manageable in PLS-SEM but may strain covariance-based SEM with a sample of 144. Fourth, PLS-SEM provides bootstrapped indirect effects, enabling rigorous testing of mediation (Hair et al., 2019).

The analysis followed the two-step approach recommended by Hair et al. (2019): Step 1 assessed the measurement model (outer loadings, CR, AVE, HTMT), and Step 2 assessed the structural model (path coefficients, R^2, effect sizes f^2, and bootstrapped indirect effects). Bootstrapping with 5,000 subsamples was used to estimate standard errors, t-values, and p-values. Blindfolding was used to assess out-of-sample predictive power (Q^2), with values above zero indicating predictive relevance.

3.4.4 Mediation Analysis

Mediation (H2) was tested using the bootstrapped indirect effect approach (Hair et al., 2019). The following paths were estimated: the direct effect c' (FDM → FG, controlling for AI adoption); path a (FDM → AI); path b (AI → FG, controlling for FDM); the indirect effect (a × b); and the total effect (c = c' + a × b). Partial mediation is established if both the direct and indirect effects are significant, and full mediation if the indirect effect is significant but the direct effect is not (Baron & Kenny, 1986; Hair et al., 2019). The variance accounted for (VAF), the ratio of the indirect to the total effect, was computed, with values of 20-80% indicating partial mediation (Hair et al., 2019). While Baron and Kenny's (1986) causal-steps approach provides a conceptual foundation, the bootstrapped indirect effect is the primary inferential test, as recommended by Hair et al. (2019), because it does not assume normality of the indirect effect sampling distribution. The VAF should be interpreted as a descriptive index of the magnitude of mediation rather than as a definitive classificatory test (Hair et al., 2019).

3.4.5 Control Variables and Group Comparisons

The following control variables were included in the structural model to reduce omitted-variable bias: gender (1 = Male, 0 = Female), age (ordinal), educational qualification (ordinal), business sector (categorical, with Trade/Retail as the reference category), number of employees (ordinal), and age of business (ordinal) (Aju, 2026; Okoye, 2026). H4a and H4b were tested with an independent-samples t-test (AI users versus non-users) and one-way ANOVAs with Tukey HSD post-hoc comparisons. Given the exploratory nature of the group comparisons and the limited number of tests (three), no Bonferroni correction was applied; however, results should be interpreted with caution given the inflated familywise error rate.

3.5 Ethical Considerations

Informed consent was obtained at the beginning of the survey, with respondents informed of the study's purpose, the voluntary nature of participation, and anonymity. No personally identifiable information was collected, and responses are reported in aggregate form only. The study complies with the Nigeria Data Protection Act (2023).

4.0 Results

4.1 Descriptive Statistics

4.1.1 Demographic Profile of Respondents

Table 1 presents the demographic profile of the 144 valid responses.

Table 1

Demographic Profile of Respondents (n = 144)

Characteristic	Category	Frequency	Percentage
Gender	Male	94	65.3
	Female	50	34.7
Age	18-25	48	33.3
	26-35	72	50.0
	36-45	20	13.9
	46-55	4	2.8

Characteristic	Category	Frequency	Percentage
Education	Secondary	12	8.3
	Diploma/NCE	18	12.5
	Bachelor's	68	47.2
	Postgraduate	46	31.9
Sector	Agro-processing	18	12.5
	Trade/Retail	44	30.6
	Manufacturing/Light industry	58	40.3
	Services	24	16.7
Employees	1-9	112	77.8
	10-19	20	13.9
	30-39	4	2.8
	40-49	8	5.6
Business age	Less than 1 year	22	15.3
	1-3 years	28	19.4
	4-6 years	32	22.2
	7-10 years	28	19.4
	More than 10 years	34	23.6
AI usage	Yes	84	58.3
	No	48	33.3
	Not sure	12	8.3

The sample is predominantly male (65.3%), consistent with the gender composition of MSME ownership in Nigeria (Aju, 2026). Half of the respondents are aged 26-35 (50.0%), and 79.2% hold a bachelor's degree or higher, indicating a relatively educated sample. The sectorial distribution is diverse, with manufacturing/light industry (40.3%) and trade/retail (30.6%) the largest sectors. Most businesses are micro-enterprises with 1-9 employees (77.8%), and 23.6% have operated for more than 10 years. Notably, 58.3% of respondents reported using AI tools, 33.3% reported not using AI, and 8.3% were unsure. This adoption rate is higher than that reported in some Nigerian bank studies (e.g., Salemcity et al., 2025), possibly reflecting the broad definition of AI tools in this survey (including smartphones, social media analytics, and basic accounting software).

4.1.2 Descriptive Statistics for Constructs

Table 2 presents the descriptive statistics for the constructs and their dimensions.

Table 2

Descriptive Statistics for Constructs (n = 144)

Construct	Items	Mean	SD	Skewness	Kurtosis
Financial Decision-Making (FDM)	12	3.58	0.72	−0.41	0.28
B1: Access to Credit & Financing	4	3.42	0.88	−0.32	−0.14
B2: Budgeting & Cash-Flow Planning	4	3.72	0.76	−0.55	0.42
B3: Investment & Expansion	4	3.60	0.81	−0.38	0.18
AI Adoption (AI)	11	3.44	0.84	−0.29	−0.08
C1: Technological Readiness	3	3.68	0.82	−0.48	0.31
C2: AI-Enabled Financial Analytics	4	3.28	0.94	−0.18	−0.32
C3: AI-Supported Customer/Market Intelligence	4	3.42	0.89	−0.24	−0.19
Firm Growth (FG)	3	3.61	0.86	−0.42	0.22

Note. All items were measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). SD = standard deviation.

The mean scores indicate moderate to high levels of financial decision-making quality (M = 3.58), AI adoption (M = 3.44), and firm growth (M = 3.61). Among the FDM dimensions, budgeting and cash-flow planning scored highest (M = 3.72) while access to credit and financing scored lowest (M = 3.42), reflecting the well-documented credit-access constraints facing Nigerian MSMEs (Okoye, 2026). Among the AI dimensions, technological readiness scored highest (M = 3.68) while AI-enabled financial analytics scored lowest (M = 3.28), suggesting that although businesses have basic digital tools, they are less likely to use advanced AI analytics for financial decisions. Skewness and kurtosis values are within the acceptable range of ±2.0 (Hair et al., 2019).

4.1.3 Correlation Analysis

Table 3

Correlation Matrix of Composite Constructs

Construct	FDM	AI	FG
FDM	1.000		
AI	0.612**	1.000	
FG	0.548**	0.634**	1.000

Note. **p < .01 (two-tailed). FDM = Financial Decision-Making; AI = AI Adoption; FG = Firm Growth.

All correlations are positive and significant at p < .01. The strongest is between AI adoption and firm growth (r = 0.634), followed by FDM and AI adoption (r = 0.612) and FDM and firm growth (r = 0.548). These are consistent with the hypothesised relationships and provide preliminary support for the mediation model. Their moderate magnitudes indicate that the constructs are related but distinct.

4.2 Measurement Model Assessment

4.2.1 Reliability and Convergent Validity

Table 4

Reliability and Convergent Validity

Construct	Items	Outer loadings range	Cronbach's α	CR	AVE
FDM	12	0.68-0.86	0.88	0.90	0.62
AI	11	0.71-0.89	0.91	0.92	0.68
FG	3	0.82-0.91	0.84	0.87	0.69

Note. CR = composite reliability; AVE = average variance extracted. All loadings significant at $p < .001$. Thresholds: $\alpha > 0.70$; CR > 0.70; AVE > 0.50 (Hair et al., 2019).

All outer loadings exceed 0.70, with the exception of two FDM items (B1.1 and B3.3), whose loadings are 0.68 and 0.69. These were retained because their removal did not increase CR or AVE above the thresholds and because they are theoretically important (Hair et al., 2019). Cronbach's alpha values range from 0.84 to 0.91 and CR values from 0.87 to 0.92, indicating good internal consistency. AVE values range from 0.62 to 0.69, exceeding 0.50 and confirming convergent validity.

4.2.2 Discriminant Validity

Table 5

Heterotrait-Monotrait (HTMT) Ratios

Construct pair	HTMT ratio
FDM → AI	0.68
FDM → FG	0.61
AI → FG	0.72

Note. HTMT threshold < 0.85 (Henseler et al., 2015).

All HTMT ratios are below 0.85, confirming discriminant validity. The highest ratio is between AI adoption and firm growth (0.72), which is expected given their close theoretical relationship, but remains below the threshold.

4.3 Structural Model Assessment

4.3.1 Hypothesis Testing

Table 6 and Figure 2 present the PLS-SEM structural model results.

Table 6

PLS-SEM Structural Model Results

Path	β	SE	t-value	p-value	Decision
H1: FDM → FG (direct)	0.218	0.072	3.028	0.003	Supported
H2: FDM → AI (path a)	0.612	0.058	10.552	< .001	Supported
H3: AI → FG (path b)	0.542	0.068	7.971	< .001	Supported
H2: FDM → AI → FG (indirect)	0.332	0.054	6.148	< .001	Supported
Total effect (FDM → FG)	0.550	0.062	8.871	< .001	-
R^2 (FG)	0.482				
R^2 (AI)	0.375				

Note. β = standardised path coefficient; SE = standard error; bootstrapping with 5,000 subsamples. Controls: gender, age, education, sector, number of employees, and business age. All paths significant at $p < .01$. Control variable coefficients are not reported for brevity but are available from the corresponding author.

[Insert Figure 2: estimated structural model showing path coefficients, R^2 values, and significance levels]

Figure 2. Estimated structural model.

The results support the mediation model:

H1 (direct effect): Financial decision-making is positively and significantly associated with firm growth (β = 0.218, t = 3.028, p = .003), controlling for AI adoption. Better financial management practices, such as budgeting, cash-flow monitoring, and investment evaluation, are therefore associated with firm growth even after accounting for AI adoption.

H2, path a: Financial decision-making is strongly associated with AI adoption (β = 0.612, t = 10.552, p < .001). Businesses with higher-quality financial decision-making are more likely to adopt AI tools, possibly because they have the resources, skills, and strategic orientation to integrate technology into their operations.

H3 (path b): AI adoption is strongly associated with firm growth (β = 0.542, t = 7.971, p < .001), controlling for financial decision-making.

H2 (indirect effect): The indirect effect of financial decision-making on firm growth through AI adoption is positive and significant (β = 0.332, t = 6.148, p < .001). The VAF is 0.332 / 0.550 = 60.4%, indicating partial mediation (VAF between 20% and 80%): about 60% of the total effect is transmitted through AI adoption, and about 40% is direct.

The model explains 48.2% of the variance in firm growth ($R^2 = 0.482$), which is substantial by Cohen's (1988) criteria ($R^2 \geq 0.26$), and 37.5% of the variance in AI adoption ($R^2 = 0.375$).

4.3.2 Effect Sizes and Predictive Relevance

Table 7

Effect Sizes (f^2)

Path	f^2	Interpretation
FDM → FG	0.062	Small
FDM → AI	0.598	Large

Path	f^2	Interpretation
AI → FG	0.412	Large

Note. f^2 thresholds: 0.02 = small, 0.15 = medium, 0.35 = large (Cohen, 1988).

The effect of FDM on AI adoption is large (f^2 = 0.598), as is the effect of AI adoption on firm growth (f^2 = 0.412). The direct effect of FDM on firm growth is small (f^2 = 0.062), consistent with partial mediation in which most of the association is transmitted through AI adoption. Blindfolding yielded a Q^2 of 0.312 for firm growth; because this exceeds zero, the model has predictive relevance (Hair et al., 2019).

4.4 Additional Analyses

4.4.1 Comparison of AI Users and Non-Users

An independent-samples t-test compared firm growth between AI users (n = 84) and non-users (n = 48); respondents who answered "Not sure" (n = 12) were excluded. AI users reported significantly higher firm growth (M = 3.82, SD = 0.78) than non-users (M = 3.28, SD = 0.91), t(130) = 3.61, p < .001. This provides additional evidence of a positive association between AI use and firm growth, although causal inference is limited by the cross-sectional design.

4.4.2 Sectoral Differences in AI Adoption (H4a)

A one-way ANOVA indicated significant differences in AI adoption across sectors, F(3, 140) = 4.28, p = .006. Tukey HSD post-hoc comparisons showed that the services sector (M = 3.72, SD = 0.81) and manufacturing/light industry (M = 3.58, SD = 0.79) reported higher AI adoption than trade/retail (M = 3.18, SD = 0.92) and agro-processing (M = 3.32, SD = 0.88). These differences may reflect varying levels of digital maturity and resource availability (Aju, 2026). H4a is supported.

4.4.3 Educational Differences in Financial Decision-Making (H4b)

A one-way ANOVA indicated significant differences in financial decision-making quality across education levels, F(3, 140) = 5.14, p = .002. Post-hoc comparisons showed that respondents with postgraduate degrees (M = 3.82, SD = 0.68) and bachelor's degrees (M = 3.64, SD = 0.71) reported higher financial decision-making quality than those with diplomas/NCE (M = 3.28, SD = 0.82) and secondary education (M = 3.12, SD = 0.88). This is consistent with human capital theory, which posits that education enhances managerial capabilities (Becker, 1964; Okoye, 2026). H4b is supported.

4.4.4 Summary of Hypotheses

Table 8

Summary of Hypothesis Tests

Hypothesis	Statement	Key statistic	Decision
H1	FDM → FG	β = 0.218, p = .003	Supported
H2	FDM → AI → FG (partial mediation)	β = 0.332, p < .001; VAF = 60.4%	Supported
H3	AI → FG	β = 0.542, p < .001	Supported
H4a	AI adoption differs by sector	F(3, 140) = 4.28, p = .006	Supported
H4b	FDM differs by education	F(3, 140) = 5.14, p = .002	Supported

4.5 Discussion

4.5.1 The Mediating Role of AI Adoption

The central finding is that AI adoption partially mediates the relationship between financial decision-making quality and firm growth: 60.4% of the total association between the two operates through AI adoption. Theoretically, this pattern is consistent with the Technology Acceptance Model (Davis, 1986) and the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), which hold that perceived usefulness and facilitating conditions drive technology adoption and, through adoption, performance. Businesses with higher-quality financial decision-making, characterised by systematic budgeting, cash-flow monitoring, and investment evaluation, are plausibly more likely to perceive AI tools as useful and to have the organisational readiness to adopt them. In turn, AI adoption may enhance firm growth through mechanisms such as improved forecasting accuracy, decision speed, and customer intelligence, although these mechanisms were not directly tested in this study and remain plausible explanations rather than demonstrated pathways (Adeniji et al., 2025; Iroh et al., 2026). Because the data are cross-sectional, these interpretations describe a pattern consistent with the theory rather than proof of the causal sequence.

Practically, the results suggest that financial management and AI adoption are complementary rather than substitutive. Businesses that invest in financial management without adopting AI may forgo growth opportunities, while businesses that adopt AI without sound financial management may fail to realise its full benefits. This is consistent with Iroh et al. (2026), who find that AI and FinTech are complementary technologies, and with Aladeokin and Afolabi (2025), who find that the effect of AI on credit assessment is contingent on occupational capacity. The present study extends these themes to the MSME context.

4.5.2 The Direct Association between Financial Decision-Making and Firm Growth

The significant direct effect of financial decision-making on firm growth ($\beta = 0.218$, $p = .003$) indicates that sound financial management practices are associated with growth independently of AI adoption. This is consistent with Financial Intermediation Theory (Leland & Pyle, 1977), which emphasises information production and monitoring in financial decisions. Businesses that compare financing options, keep proper loan records, separate business and personal money, and plan for seasonal changes are better positioned to allocate resources efficiently, avoid cash-flow crises, and invest in growth opportunities (Adeniji et al., 2025; Okoye, 2026). The finding also highlights the continued importance of human judgement: AI augments rather than replaces financial managers, consistent with the human-in-the-loop model discussed by Aladeokin and Afolabi (2025) and Okoye (2026).

4.5.3 The Association between AI Adoption and Firm Growth

The strong positive association between AI adoption and firm growth ($\beta = 0.542$, $p < .001$) is consistent with a growing body of evidence from Nigeria. Adeniji et al. (2025) find that AI-powered decision support systems enhance operational efficiency ($\beta = 0.694$, $p < .05$) and that AI-driven fraud detection improves investment decision quality ($\beta = 0.763$, $p < .05$). Amaugo (2025a) reports that AI enhances decision efficiency by 40% and reduces human error by 35% at Fidelity Bank. Oniye and Akinsode (2026) find that automated chatbot systems, deep learning credit models, and fraud detection systems are positively associated with return on assets in Nigerian banks. In the MSME context, AI adoption may be associated with growth through several mechanisms: improved financial analytics (AI-powered bookkeeping and accounting software enable more accurate and timely financial reporting; Iroh et al., 2026); enhanced customer intelligence (AI tools such as social media analytics and chatbots help businesses understand customer preferences, forecast demand, and identify new market opportunities; Aju, 2026); operational efficiency (AI automation reduces manual workloads, freeing time for strategic activities; Salemcity et al., 2025); and risk mitigation (AI-based credit scoring and fraud detection reduce losses and improve asset quality; Adedire-Ampitan et al., 2024). These mechanisms were not tested directly in this study and remain candidate explanations.

4.5.4 Heterogeneity by Sector and Education

AI adoption varies significantly by sector, with services and manufacturing reporting higher adoption than trade/retail and agro-processing, possibly reflecting differences in digital maturity, resource availability, and the nature of operations (Aju, 2026). Financial decision-making quality varies significantly by education level, consistent with human

capital theory (Becker, 1964; Okoye, 2026). Because financial decision-making quality is a strong correlate of AI adoption in this study, education may be indirectly related to adoption, although this link was not tested directly. These findings suggest that support for AI adoption should be targeted at less digitally mature sectors, and that financial-management training should be targeted at owners with lower levels of formal education. Such interventions could include digital literacy training, subsidised access to AI tools, and awareness campaigns (Okoye, 2026).

4.5.5 Regulatory and Infrastructural Constraints

The findings must be interpreted against Nigeria's regulatory and infrastructural backdrop. The CBN's open banking framework (CBN, 2021), operational guidelines (2023), and ongoing infrastructure development (2025) provide a foundational regulatory architecture, and the Nigeria Data Protection Act (2023) regulates certain forms of automated decision-making involving personal data. However, algorithmic bias, explainability, automated decision-making, and third-party AI accountability remain inadequately addressed (Okoye, 2026). There are currently no binding rules that clearly define how AI systems used in lending, fraud detection, or risk assessment should be audited, how developers should test for algorithmic bias, or whether customers have a right to an explanation when automated systems reject loan applications (Okoye, 2026). This governance gap could undermine trust in AI-driven financial decisions, particularly in credit assessment, where adverse selection and fair lending concerns are salient. The CBN has announced plans for a regulatory sandbox focused on AI and RegTech use cases, a positive step toward proportionate, innovation-sensitive regulation (Okoye, 2026). Infrastructure deficits (uneven broadband, power instability, and fragmented data systems) further constrain the scalability of AI solutions beyond Tier-1 banks and urban financial hubs (Aju, 2026). Because the sample was recruited online and may over-represent digitally active owners, the associations observed here may overstate the average contribution of AI among Nigerian MSMEs; broader diffusion will require coordinated investment in digital infrastructure and regulatory capacity (Aju, 2026; Okoye, 2026).

4.5.6 Limitations

Several limitations should be acknowledged:

• **Cross-sectional design:** The data limit causal inference. Although the mediation model is theoretically grounded, future research should use longitudinal designs or natural experiments (Podsakoff et al., 2003). The word "effect" in this paper refers to statistical paths in the model and should not be read as proof of causation.

• **Convenience sampling:** Recruitment through digital channels may introduce selection bias toward more digitally active owners. Future research should use probability sampling (Hair et al., 2019).

• **Self-report measures:** All constructs were measured using self-report Likert scales, which may be subject to common method bias. Harman's single-factor test indicated that the first unrotated factor accounted for 38.2% of the variance, below the 50% threshold, suggesting common method bias is not a major concern, and HTMT ratios supported discriminant validity (Podsakoff et al., 2003). Future research should incorporate objective measures such as financial statements and AI investment data.

• **Perception-based measure of AI adoption:** AI adoption was measured with Likert-scale items rather than objective indicators of AI intensity, and the broad definition of AI tools may have inflated reported adoption. Future research should develop more granular measures (Salemcity et al., 2025).

• **Statistical power:** A post-hoc power analysis using G-Power (Faul et al., 2007) indicated that the sample of 144 provides 80% power to detect path coefficients of approximately 0.21 or larger at $\alpha = .05$ (two-tailed); smaller effects, including some control-variable effects, may not have been detected.

• **Single-country context:** The study is set in Nigeria, and comparative work across African emerging markets (e.g., Kenya, South Africa, and Ghana) would help establish generalisability (Aju, 2026).

5.0 Conclusion and Recommendations

5.1 Conclusion

This study examined the mediating role of AI adoption in the relationship between financial decision-making quality and firm growth among Nigerian MSMEs. Using PLS-SEM on a cross-sectional survey of 144 owners and managers, the study finds that financial decision-making quality is positively associated with firm growth directly ($\beta = 0.218$, $p = .003$) and indirectly through AI adoption (indirect effect = 0.332, $p < .001$; VAF = 60.4%), and that AI adoption is strongly associated with firm growth ($\beta = 0.542$, $p < .001$). AI adoption differs significantly by sector, with services and manufacturing firms reporting higher adoption, and financial decision-making quality differs significantly by education level. The study concludes that AI adoption is a plausible enabler of firm growth, but one whose benefits are neither automatic nor uniform: they appear to depend on the quality of financial decision-making, the sectoral and educational context, and the availability of digital infrastructure and skills.

5.2 Theoretical Contributions

The study makes three theoretical contributions. First, it extends technology-acceptance perspectives (Davis, 1986; Venkatesh et al., 2003) by positioning an organisational capability, financial decision-making quality, as an antecedent of AI adoption and by linking adoption to firm growth within a single model. Second, it extends an AI-finance literature dominated by banks (Aju, 2026; Iroh et al., 2026) to MSMEs, the segment that constitutes most Nigerian businesses. Third, the finding of partial rather than full mediation indicates that financial decision-making and AI adoption are complementary, in line with the view that technology and human capability jointly shape performance (Aladeokin & Afolabi, 2025).

5.3 Practical Recommendations

For business owners and managers:

• **Strengthen financial management first.** Establish systematic budgeting, cash-flow monitoring, separation of business and personal funds, and evaluation of investment opportunities, which appear to underpin AI's growth benefits (Iroh et al., 2026).

• **Adopt AI strategically.** Prioritise AI applications that address the most pressing needs rather than adopting AI for its own sake. AI-enabled financial analytics was the least-used AI application in this sample (M = 3.28), suggesting room for growth (Adeniji et al., 2025).

• **Invest in staff training** to raise occupational capacity, particularly in explainable AI, model risk management, and algorithmic fairness (Aladeokin & Afolabi, 2025; Okoye, 2026).

For policymakers:

• **Promote digital literacy and AI awareness,** targeting less digitally mature sectors and owners with lower formal education (Aju, 2026).

• **Invest in digital public infrastructure:** broadband, power, digital identity, and interoperable data rails are essential for AI diffusion beyond urban centres and Tier-1 firms (Aju, 2026; Okoye, 2026).

• **Develop a risk-based AI governance framework** that addresses algorithmic bias, explainability, data protection, and third-party accountability (CBN, 2021; Nigeria Data Protection Act, 2023; Okoye, 2026).

For financial institutions:

• **Develop AI-enabled products for MSMEs**, such as automated bookkeeping, credit scoring, and cash-flow forecasting (Iroh et al., 2026).

• **Provide training and advisory support** to build MSMEs' financial management capacity and AI readiness (Salemcity et al., 2025).

These recommendations should be interpreted in light of the study's cross-sectional design and convenience sample; causal claims await longitudinal and experimental evidence.

5.4 Directions for Future Research

Future research should (i) employ longitudinal or experimental designs to examine the temporal ordering of financial decision-making, AI adoption, and growth; (ii) use probability sampling to enhance generalisability; (iii) incorporate objective measures of AI adoption and firm performance; (iv) test sector and education as formal moderators; (v) examine other mediators and moderators, such as data quality, organisational agility, and regulatory readiness (Iroh et al., 2026; Aladeokin & Afolabi, 2025); and (vi) conduct comparative studies across African emerging markets (Aju, 2026).

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