

Artificial Intelligence-Based Credit Scoring and Financial Inclusion Among SMES in Akwa Ibom State, Nigeria

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Abstract— This study examines the effect of Artificial Intelligence (AI)-based credit scoring on financial inclusion among Small and Medium Enterprises (SMEs) in Akwa Ibom State, Nigeria. Financial inclusion remains a critical challenge for SMEs in developing economies, where traditional collateral-dependent lending models often exclude unbanked and underbanked business operators. The study adopts a cross-sectional survey research design, collecting primary data from a representative sample of SME operators at a single point in time to assess the relationship between AI-based credit scoring (independent variable) and financial inclusion (dependent variable). The survey approach is consistent with empirical research on financial inclusion in Nigeria and is suitable for capturing respondents' experiences, perceptions, and access to credit, enabling robust quantitative analysis. Findings reveal that AI-based credit scoring significantly enhances financial inclusion among SMEs in the state by leveraging alternative data streams such as transaction histories, digital wallets, and mobile money usage to build reliable credit profiles. Based on this evidence, the study concludes that AI-driven models play a pivotal role in expanding credit access to previously excluded business owners. To harness this potential, the paper recommends that local financial institutions transition from collateral-based lending to AI data-driven models; that the Akwa Ibom State Government partner with fintech firms to establish a unified digital identity system and transactional data repository; that digital literacy campaigns be launched to promote data-generating payment systems; that regulatory frameworks monitor algorithmic bias; and that micro-credit products with automated disbursement be introduced to streamline working capital access. These recommendations collectively offer a pathway to sustainable, inclusive SME financing in Akwa Ibom State..

Keywords— Artificial Intelligence, Financial Inclusion, SMEs, Credit Scoring, Akwa Ibom State.

I. INTRODUCTION

Small and Medium Enterprises (SMEs) constitute the backbone of Nigeria's economy, accounting for approximately 90% of businesses and contributing nearly 48% to the nation's Gross Domestic Product (GDP). These enterprises are pivotal to employment generation and economic development, particularly in subnational economies such as Akwa Ibom State, where SMEs are recognized as veritable tools for solving unemployment challenges. Despite their economic significance, a substantial financing gap persists, with an estimated 80% of Nigerian MSMEs lacking access to formal credit due to collateral constraints, high-risk perceptions from lenders, and prohibitive borrowing costs. This credit exclusion perpetuates a vicious cycle wherein viable businesses cannot scale operations, invest in productive capacity, or contribute optimally to employment generation. The challenge of SME financing is particularly acute in contexts where traditional credit assessment models fail to capture the economic realities of borrowers. Conventional lending systems rely heavily on formal documentation—salary records, bank statements, collateral, and credit histories—that exclude the majority of Nigerian entrepreneurs operating in the informal sector. This information asymmetry creates a "missing middle" wherein creditworthy borrowers are systematically excluded not because they lack repayment capacity, but because traditional systems lack sufficient visibility into their financial behaviour. Emerging evidence from across sub-Saharan Africa suggests that this exclusion

reflects limitations in assessment infrastructure rather than inherent borrower risk.

Artificial Intelligence (AI) and machine learning (ML) have emerged as transformative tools capable of addressing these credit assessment gaps. Systematic reviews of AI applications in African economics demonstrate that AI-driven credit scoring systems achieve F1 scores above 0.80, indicating robust predictive performance for creditworthiness assessment. These systems leverage alternative data sources—including mobile money transactions, utility payments, smartphone usage patterns, and social network indicators—to construct comprehensive borrower profiles that extend beyond traditional financial histories. Fintech innovations across the continent, from Zambia's Lupiya and eShandi to Kenya's PEMiG, have demonstrated the viability of AI-powered lending models that serve previously excluded populations while maintaining portfolio quality. In the Nigerian context, the adoption of AI for credit assessment has gained momentum through both fintech innovation and institutional recognition. Moniepoint's recent \$50 million funding round explicitly targets AI-powered credit scoring expansion for SMEs across Africa. Sofri's deployment of machine learning algorithms incorporating non-traditional data points demonstrates the practical application of AI in Nigerian lending. Concurrently, policy initiatives such as the establishment of the National Credit Guarantee Company reflect governmental recognition of the need for data-driven approaches to de-risk lending and expand financial inclusion. Despite these advances, significant gaps remain in

understanding how AI-based credit scoring specifically affects SME financial inclusion at the subnational level, particularly in states like Akwa Ibom where SME concentration is substantial but formal credit penetration remains limited.

Akwa Ibom State presents a compelling context for examining this nexus. The state has emerged as a laboratory for entrepreneurial development, with initiatives such as the Ibom Leadership and Entrepreneurial Development Centre (Ibom-LED) representing structured attempts to build entrepreneurial capacity and link skills development with access to finance. The state's SME sector, comprising nearly 12,000 registered enterprises, plays a crucial role in employment generation yet faces persistent financing constraints that hinder growth potential. As Akwa Ibom pursues an economic strategy centered on entrepreneurship and local content development, understanding the determinants of SME access to credit becomes increasingly urgent for policy formulation and economic planning. However, research specifically examining how AI-based credit scoring mediates financial inclusion among SMEs in Akwa Ibom State remains sparse. This study addresses this gap by investigating the relationship between AI-enabled credit assessment systems and SME access to formal finance in the state.

1.1 Objective of the Study

To examine the effect of Artificial Intelligence-based credit scoring on financial inclusion among Small and Medium Enterprises in Akwa Ibom State, Nigeria.

1.2 Research Question

What is the effect of Artificial Intelligence-based credit scoring on financial inclusion among SMEs in Akwa Ibom State?

1.3 Research Hypothesis

Artificial Intelligence-based credit scoring has no significant effect on financial inclusion among SMEs in Akwa Ibom State.

II. REVIEW OF RELATED LITERATURE

A. Artificial Intelligence-Based Credit Scoring

Artificial Intelligence-based credit scoring refers to the application of machine learning algorithms and advanced data analytics to assess the creditworthiness of borrowers (Razavi & Elbahnasawy, 2024). Unlike traditional credit scoring systems that rely heavily on formal financial histories, collateral documentation, and credit bureau reports, AI-powered systems leverage a broader spectrum of data sources to construct comprehensive borrower profiles (Osei-Dwomoh & Forkuo, 2026). These systems incorporate alternative data points such as mobile money transaction histories, utility payment records, smartphone usage patterns, social media engagement, and web browsing habits (Kembabazi et al., 2024). Research demonstrates that combining call detail records (CDR) with non-CDR mobile attributes—including social media engagement and browsing patterns—can achieve classification accuracy of up to 89% in predicting credit risk (Razavi & Elbahnasawy, 2024). In the Nigerian context,

financial institutions like Sofri now employ machine learning algorithms that consider phone usage patterns, location data, education level, and even social media influence when assessing borrowers, with social capital serving as an indicator of trustworthiness (Punch Newspapers, 2025). Similarly, FairMoney deploys alternative credit scoring systems that evaluate transaction velocity, app engagement patterns, and broader digital footprints to assess creditworthiness for SMEs that would otherwise be excluded from formal financial systems (Businessday NG, 2026).

a. Financial Inclusion

Financial inclusion is conceptualised as the process of ensuring that individuals and businesses have access to useful and affordable financial products and services that meet their needs—transactions, payments, savings, credit, and insurance—delivered in a responsible and sustainable manner (Ndem et al., 2022). In the context of SMEs, financial inclusion encompasses access to formal credit facilities, banking services, and digital financial tools that enable business growth and economic participation (Ndem et al., 2022). Ndem et al. (2022) operationalised financial inclusion among SMEs in Akwa Ibom State through indicators including bank loans, access to Automated Teller Machines (ATMs), and internet banking services. The study revealed that while bank loans to SME operators did not demonstrate a statistically significant correlation with poverty alleviation, access to ATM and internet banking services showed statistically significant correlations, highlighting the differentiated impact of various financial inclusion dimensions (Ndem et al., 2022). More recent conceptualisations recognise credit-based financial inclusion (CFIN) as more complex than deposit-based financial inclusion (DFIN), as the former requires sophisticated creditworthiness assessments that traditional systems often fail to provide for underserved populations (Razavi & Elbahnasawy, 2024).

b. Small and Medium Enterprises (SMEs) in Nigeria

Small and Medium Enterprises in Nigeria are defined along parameters of employee numbers and fixed assets. Small enterprises typically employ between 6 and 29 employees with fixed assets of \$100,000, while medium enterprises employ between 30 and 99 employees with fixed assets of up to \$1 million (Wangmo, 2021). According to the Small and Medium Enterprises Development Agency of Nigeria (SMEDAN), SMEs account for approximately 96% of all businesses in Nigeria, contribute over 48% to the nation's Gross Domestic Product, and provide between 84% of total employment (Businessday NG, 2026). In Akwa Ibom State, SMEs constitute a critical component of the economic landscape, though studies indicate persistent challenges in accessing formal credit, with bank loans to SME operators showing no statistically significant correlation with poverty alleviation outcomes (Ndem et al., 2022). The SME financing gap in Nigeria reflects broader systemic issues, with traditional financial institutions often viewing SME lending as high-risk due to information opacity and inadequate financial documentation (Wangmo, 2021).

B. Theoretical Review

a. Information Asymmetry Theory

Information asymmetry theory, as articulated by Stiglitz and Weiss (1981), provides a foundational framework for understanding the credit constraints faced by SMEs and the potential of AI-based credit scoring to address these constraints. The theory posits that in lending relationships, borrowers possess more knowledge and relevant information about their financial position and repayment capacity than lenders, creating an imbalance that hinders informed lending decisions (Stiglitz & Weiss, 1981). This information asymmetry manifests in two primary problems: adverse selection, where lenders cannot distinguish between high-risk and low-risk borrowers, leading to credit rationing or the rejection of creditworthy applicants; and moral hazard, where borrowers may engage in risky behaviour not specified in credit contracts (Stiglitz & Weiss, 1981). In the context of SME financing, information asymmetry is particularly acute because many SMEs lack formal financial records, audited statements, and established credit histories that banks traditionally rely upon for risk assessment (Wangmo, 2021). As Wangmo (2021) documents, SMEs' high information opacity and credit risk induce adverse selection and credit rationing on the part of finance providers, creating a persistent SME financing gap, particularly in developing economies where access to bank loans is subject to collateral availability. Traditional banks respond to this information gap by imposing collateral requirements, increasing interest rates, and demanding extensive documentation—measures that effectively exclude the majority of SMEs from formal credit markets (The Sun Nigeria, 2026).

AI-based credit scoring represents a technological intervention that directly addresses the information asymmetry problem. By leveraging alternative data sources—including mobile money transactions, digital footprints, and behavioural patterns—AI systems generate visibility into borrowers' financial behaviour that traditional assessment models cannot capture (Razavi & Elbahnasawy, 2024). As Mathesis Analytics founder Winston Osuchukwu argues, many Nigerian borrowers labelled as "high-risk" are assessed based on data limitations rather than actual repayment behaviour, with informal traders and gig workers often maintaining consistent cash flows that remain invisible to conventional credit assessment systems (The Sun Nigeria, 2026). AI-powered credit decisioning analyses alternative datasets to provide lenders with a more comprehensive understanding of borrowers' repayment capacity, thereby reducing information asymmetry and enabling credit extension to previously underserved segments (Razavi & Elbahnasawy, 2024). The theory also illuminates the role of "special agents" in extending financial services to underserved populations. Razavi and Elbahnasawy (2024) employ the "special agent theory of financial inclusion" to argue that mobile operators, fintech companies, and other specialised agents are instrumental in extending financial services to populations excluded from formal banking. Leveraging widespread smartphone adoption and mobile data availability, these agents create innovative credit scoring models that transcend traditional credit histories, moving beyond the limitations identified by information asymmetry theory (Razavi & Elbahnasawy, 2024). This theoretical perspective suggests that

AI-based credit scoring does not merely supplement existing assessment mechanisms but fundamentally transforms the information environment, reducing the opacity that has historically constrained SME access to finance (Osei-Dwomoh & Forkuo, 2026).

C. Empirical Review

a. Empirical Evidence on AI-Based Credit Scoring and Financial Inclusion

Empirical studies increasingly demonstrate the efficacy of AI and machine learning in expanding credit access to underserved populations. Razavi and Elbahnasawy (2024) conducted a study using actual mobile usage data from over 1,500 demographically diverse individuals over a two-week period, employing a range of machine learning algorithms to assess the predictive power of mobile data in credit risk assessment. The study found that while mobile usage attributes alone could not fully replace traditional FICO scores in regression models ($R^2=0.30$), they significantly enhanced classification accuracy when combined with CDR data, achieving accuracy of 89% (Razavi & Elbahnasawy, 2024). Crucially, the research demonstrated that non-CDR mobile attributes—including social media engagement and web browsing habits—surpassed CDR data in predicting credit risk, suggesting that broader mobile behavioural data offers superior insights for creditworthiness assessment (Razavi & Elbahnasawy, 2024). Kembabazi et al. (2024) developed a Mobile Money Micro-Credit Scoring System employing machine learning algorithms and artificial neural networks to analyse transaction histories and assess creditworthiness for loan eligibility in Uganda. The study addressed the challenge that borrowers targeted by micro-credit often lack traditional credit histories, necessitating reliance on alternative data sources such as mobile phone usage and utility payment histories (Kembabazi et al., 2024). The system was designed to provide timely and accurate credit assessments, balancing risk management with enhanced accessibility to financial services for individuals traditionally excluded from formal financial systems (Kembabazi et al., 2024).

Osei-Dwomoh and Forkuo (2026) conducted a systematic review of artificial intelligence applications in African economics, examining performance metrics and ethical risks across the continent. The review found that AI-driven credit scoring systems achieve F1 scores above 0.80, indicating robust predictive performance for creditworthiness assessment (Osei-Dwomoh & Forkuo, 2026). The study documented how fintech innovations across the continent, from Zambia's Lupiya and eShandi to Kenya's PEMiG, have demonstrated the viability of AI-powered lending models that serve previously excluded populations while maintaining portfolio quality (Osei-Dwomoh & Forkuo, 2026). In the Nigerian context, empirical evidence reveals substantial adoption of AI-powered lending models. FirstBank's digital lending ecosystem, deployed with Artificial Intelligence and Machine Learning, has achieved cumulative disbursements of over N1 trillion in digital loans, reaching over 1.5 million unique borrowers across Nigeria (Leadership Newspapers, 2025). The bank's model eliminated collateral requirements and reduced approval times from weeks to under five minutes,

demonstrating the practical viability of AI-driven lending (Leadership Newspapers, 2025). The bank's digital lending strategy aligns with broader financial inclusion goals, with the EFInA Survey Report on Access to Financial Services in Nigeria showing that 64% of the Nigerian population is now formally included in the financial system, largely attributed to increased adoption of mobile money and digital financial services (Leadership Newspapers, 2025). Sofri (powered by Links Microfinance Bank) has deployed machine learning algorithms that consider non-traditional data points—including phone usage patterns, location, education level, and social media influence—to assess borrowers, providing loans as small as N2,000 to underserved individuals without formal credit histories (Punch Newspapers, 2025). Similarly, FairMoney enables eligible SMEs to access loans of up to N5 million without requiring physical collateral, using alternative credit scoring systems that evaluate transaction patterns and digital activity (Businessday NG, 2026). Mathesis Analytics has processed more than 40 million credit scores and facilitated over \$272 million in credit disbursements across Nigeria, illustrating the scalability of AI-powered credit assessment solutions (The Sun Nigeria, 2026).

b. Empirical Evidence on SME Financial Inclusion in Akwa Ibom State

Ndem et al. (2022) conducted an empirical investigation into financial inclusion and poverty alleviation among SMEs in Akwa Ibom State, surveying 295 SME operators using purposive sampling and analysing relationships through Spearman rank correlation. The study yielded mixed findings: financial inclusion in terms of bank loans to SME operators did not demonstrate statistical significance in correlation with poverty alleviation, while financial inclusion in terms of access to ATM and internet banking showed statistically significant correlations (Ndem et al., 2022). The authors recommended that banks should reduce interest rates to induce SME operators to access bank loans for their businesses, acknowledging the persistent barriers to formal credit access (Ndem et al., 2022). This finding suggests that increasing the availability of financial services without addressing the structural barriers to access—including information asymmetry and collateral requirements—may not yield the desired developmental outcomes (Ndem et al., 2022).

c. Empirical Evidence on SME Financing Constraints in Nigeria

Research examining SME financing constraints in Nigeria reveals that information asymmetry and risk perception are fundamental barriers to credit access. A Nigerian study identified the key inhibiting factors to SME financing as lack of business collateral, high lending rates, and absence of verifiable business financial information, with high-interest rates and low verifiable business financial information emerging as the two most important variables (Thomas et. al 2024). The study found that bank size does not pose a significant obstacle to SME financing, though larger banks often perceive SME lending as an invitation to accumulation of bad debts. This finding aligns with the credit rationing theory that information asymmetry and perceived costs create access constraints for SMEs (Wangmo, 2021). Moreover, many SMEs in Nigeria fail to maintain adequate records that

can assist banks in processing loan requests, resulting in a significant percentage of SMEs facing disappointment in their quest for financial assistance from financial institutions (Abaikpa, et al 2025).

d. Empirical Evidence on Alternative Data for Credit Scoring

Emerging empirical evidence supports the use of alternative data sources to enhance credit scoring for underserved populations. Razavi and Elbahnasawy (2024) specifically investigated non-CDR mobile data, finding that social media engagement and web browsing habits significantly improve credit risk prediction. The study contributes to the financial inclusion literature by emphasising how innovative methods for assessing creditworthiness using alternative data sources can improve the chances of marginalised populations accessing credit (Razavi & Elbahnasawy, 2024). These findings carry significant implications for policymakers and consumers in developing regions characterised by large unbanked populations, suggesting that harnessing mobile data can enhance financial inclusion and foster broader economic participation (Razavi & Elbahnasawy, 2024). In the Zambian context, eShandi (formerly PremierCredit) utilises AI-powered credit scoring to offer loans to underbanked individuals and SMEs, leveraging alternative data sources including mobile money transaction history, smartphone usage, and platform transaction behaviour to build accurate risk profiles (FinTech Futures, 2025). The fintech company's mission explicitly targets underserved groups, especially women and SMEs historically excluded from traditional banking, demonstrating the cross-border applicability of AI-based credit assessment models in Africa (FinTech Futures, 2025).

III. METHODOLOGY

A. Research Design

The study adopts a cross-sectional survey research design. This design is appropriate as it allows for the collection of data from a representative sample of SME operators at a single point in time to examine the relationships between AI-based credit scoring (the independent variable) and financial inclusion (the dependent variable). This approach is consistent with empirical studies on financial inclusion in Nigeria, which have employed cross-sectional surveys to investigate similar constructs and relationships. The survey design is particularly suitable for gathering primary data on SME operators' experiences, perceptions, and access to credit, enabling quantitative analysis of the hypothesized relationships.

B. Study Area

The study is conducted in Akwa Ibom State, Nigeria. Akwa Ibom State presents a compelling context for examining the nexus between AI-based credit scoring and financial inclusion. The state has emerged as a laboratory for entrepreneurial development, with initiatives such as the Ibom Leadership and Entrepreneurial Development Centre (Ibom-LED) representing structured attempts to build entrepreneurial capacity and link skills development with access to finance. The state's SME sector plays a crucial role in employment generation yet faces persistent financing constraints that hinder growth potential. As Akwa Ibom pursues an economic

strategy centered on entrepreneurship and local content development, understanding the determinants of SME access to credit becomes increasingly urgent for policy formulation and economic planning.

C. Population of the Study

The population of this study consists of all registered Small and Medium Enterprises (SMEs) operating in Akwa Ibom State. According to the directorate of SMEs of Akwa Ibom State, there are approximately 11,990 registered SMEs in the state as recorded in 2021. This population includes SMEs across various sectors, including manufacturing, services, trade, and agriculture, operating within the state's three senatorial districts. These enterprises constitute the target population from which a representative sample will be drawn for the study.

D. Sampling Technique and Sample Size

The study employs purposive sampling technique combined with proportionate stratified sampling to select respondents. Purposive sampling is appropriate for selecting SME operators who are knowledgeable about their credit access experiences and financial inclusion status. This technique has been successfully employed in similar studies on financial inclusion among SMEs in Akwa Ibom State. The sample size is determined using the Taro Yamane formula:

$$n = \frac{N}{1 + N(e)^2}$$

Where: N = Population. 1 = constant. e = Level of significance. n = sample size.

$$n = \frac{11,990}{1 + 11,990(0.05)^2}$$

$$n = 387$$

E. Instrument for Data Collection

Data were collected using a structured questionnaire titled "Artificial Intelligence-based Credit Scoring on Financial Inclusion Among Small and Medium Enterprises in Akwa Ibom State, Nigeria Questionnaire" (AICSFISMEQ), developed by the researcher.

F. Method of Data Analysis

The statistical methods adopted for data analysis were simple percentages and simple regression. The data were analyzed with the help of a statistical tool using SPSS

IV. DATA PRESENTATION, ANALYSIS AND INTERPRETATION

The researcher presents data presentation, analysis and interpretation of results in this chapter. Research hypotheses are tested and findings from the analysis are also discussed in this chapter.

A. Data Presentation

The data presented contains responses to the items in the questionnaire and the computed data for variables of the study. The data on the items are based on the five-point Likert scale used in scoring the instrument. The questionnaires administered to the respondents were collected and presented as shown in Table 1 below:

TABLE 4.1: Questionnaire Administered

Questionnaires	Percentage (%)	Number of questionnaires
Number of questionnaires administered	100	387
Number of questionnaires correctly filled and returned	98.45	381
Number of questionnaires not returned	1.60	6

Source: Field Survey Data (2026)

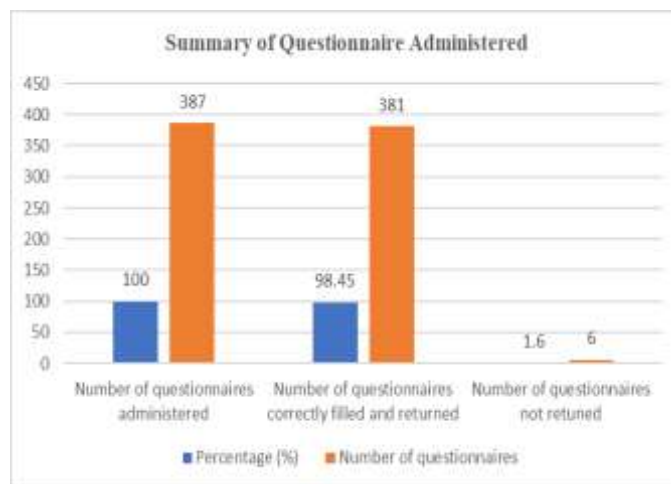


Fig. 1. Bar chart representation of Questionnaire Administered

Source: Researcher's Representation (2026)

Figure 1 shows that out of 387 questionnaires served, 381 questionnaires were correctly filled and returned which represent 98.45% while 6 questionnaires were not filled and returned which represent only 1.60%. Subsequently, the data collated from the 381 questionnaires were used for the analysis.

B. Data Analysis

Under this section, the demographics data were analyzed first followed by the analysis of data from the responses on the research construct based on the objectives of the study. Other subheadings were descriptive statistics and normality tests analysis, inferential tests analysis, and discussion of the findings.

a. Analysis of Demographics Data

The research adopted Pyramid statistical tool to analyze the demographics data of the respondents for easy representations and interpretations.

Figure 2 below reveals the gender distribution of the respondents. It was observed that, 195 were male representing 51.2%, while 186 respondents were female representing 48.8%. This implies that the majority of the respondents were male.

Figure 3 below shows that 18 respondents representing 4.7% were under the age bracket of 18-25 years, 95 respondents 24.9% were 26-33 years. 177 respondents representing 46.5% of the sampled respondents were within the age bracket of 34-41 years, 91 respondents representing 23.9% were within the age bracket of 42-49 years.

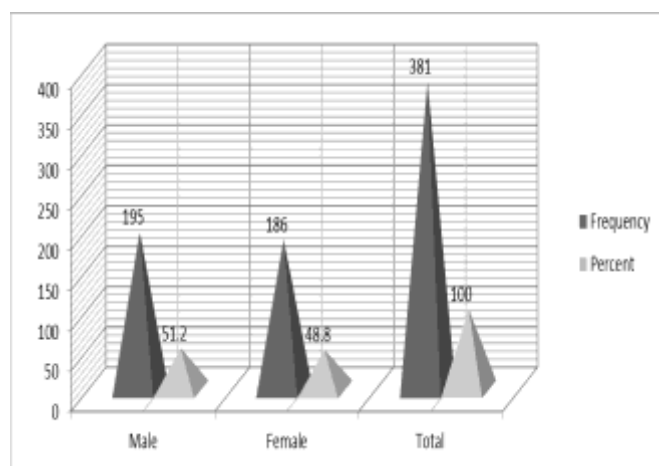


Fig. 2. Gender Distribution of Respondents

Source: Researcher's Representation (2026)

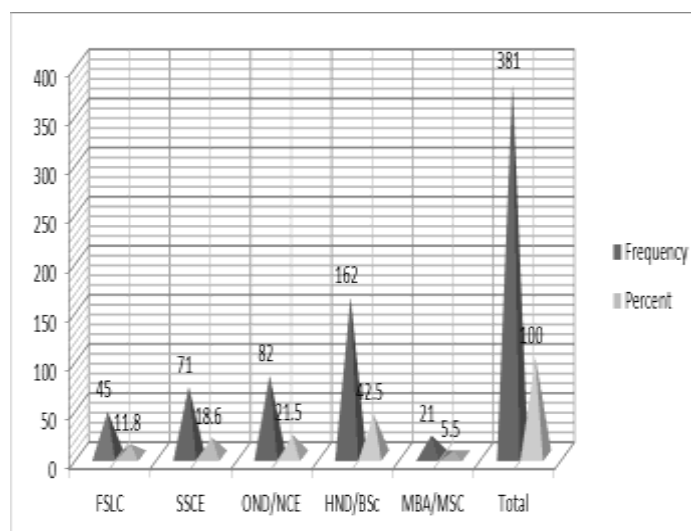


Fig. 5. Educational Qualification Distribution of Respondents

Source: Researcher's Representation (2026)

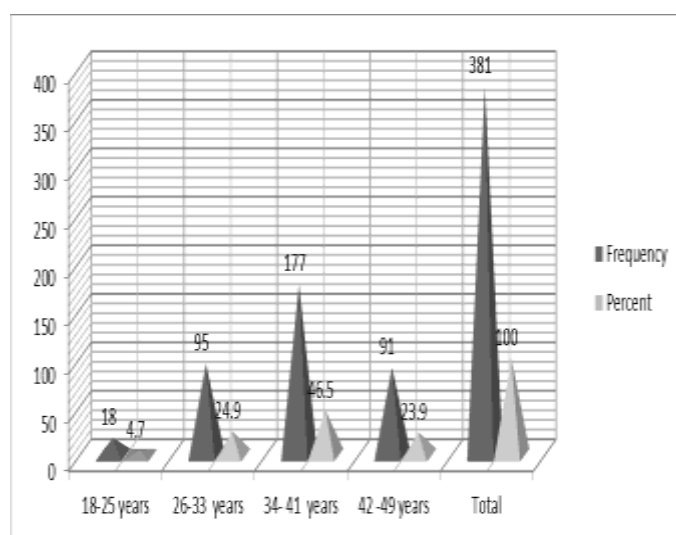


Fig. 3. Age Distribution of Respondents

Source: Researcher's Representation (2026)

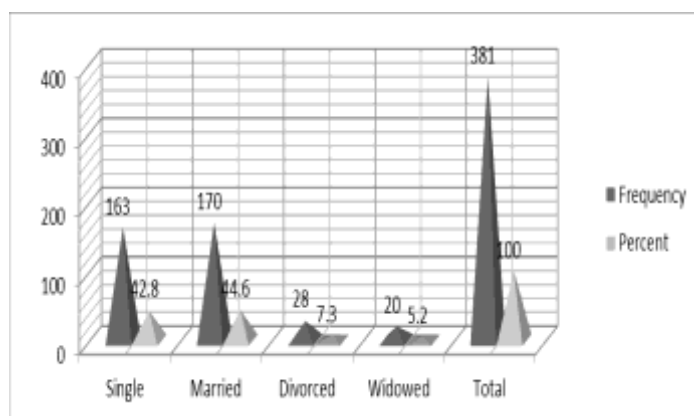


Fig. 4. Marital Status Distribution of Respondents

Source: Researcher's Representation (2026)

In the above figure, 163 respondents were single representing 42.8% while 170 respondents were married representing 44.6%. 28 respondents were divorced 7.3% while 20 respondents representing 5.2% were widowed.

Figure 5 shows that 45 respondents representing 11.8% have FSLC, 71 respondents representing 18.6% have SSCE while 82 respondents representing 21.5% have OND/NCE. 162 respondents representing 42.5% were holders of HND/BSc while 21 respondents representing 5.5% were holders of MBA/MSc.

b. Analysis of Research Construct

The responses to the various questions on the items measuring each construct are presented and analyzed in this section. As presented in each table, the responses to the questions on the items measuring research construct or opinions and the analysis is done to know the position of the respondents on each Likert scale. The presentation and analysis is done based on the research objectives.

1 Artificial Intelligence-based credit scoring and financial inclusion among SMEs in Akwa Ibom State

The main objective was on the effect of Artificial Intelligence-based credit scoring on financial inclusion among SMEs in Akwa Ibom State.

Table 4.2 shows that 118 respondents representing 31.0% and 40 (10.5%) strongly agreed and agreed respectively that they are aware of Artificial Intelligence (AI)-based credit scoring platforms that assess SMEs for loans (e.g., FairMoney, Carbon, Moniepoint, Sofri). Also, 158 respondents representing 41.5% strongly agreed and 66 (17.3%) agreed that AI-based credit scoring systems use alternative data (such as mobile money transactions, utility payments, and digital footprints) to assess my business creditworthiness. 174 respondents representing 45.7% agreed and 32 (8.4%) strongly agreed that AI-based credit scoring provides faster and more efficient loan approval processes compared to traditional banking methods. Also, 187 (49.1%) of the respondents strongly agreed that AI-based credit scoring systems are fair and transparent in assessing my business for credit without requiring physical collateral. Additionally, 156 (40.9%) respondents agreed that they have personally applied for or accessed credit through an AI-powered lending platform for their business. It was further observed that 139 respondents representing 36.5% strongly agreed that their business has

access to formal credit facilities (bank loans, microfinance loans, or fintech loans) to support business operations. Moreover, 134 respondents representing 35.2% agreed that AI-based credit scoring has improved their business access to formal financial services that were previously unavailable through traditional banks while 113 respondents representing 29.7% agreed that their business uses banking services such as

ATM, internet banking, or mobile banking for financial transactions. Also, 146 (38.3%) of the respondents strongly agreed that the credit facilities accessible to their business are affordable and have reasonable interest rates. 172 (45.1%) of the respondents strongly agreed that in overall, the availability of AI-based credit scoring platforms has increased their business participation in the formal financial system.

TABLE 4.2. Analysis of research constructs on Artificial Intelligence-based credit scoring and financial inclusion among SMEs in Akwa Ibom State

S/N	Artificial Intelligence-Based Credit Scoring on Financial Inclusion Among Small And Medium Enterprises in Akwa Ibom State, Nigeria	SA	A	SD	D	N
A	Artificial Intelligence-based credit scoring Dimension					
1	I am aware of Artificial Intelligence (AI)-based credit scoring platforms that assess SMEs for loans (e.g., FairMoney, Carbon, Moniepoint, Sofri).	118 (31.0%)	40 (10.5%)	65 (17.1%)	100(26.2%)	58 (15.2%)
2	AI-based credit scoring systems use alternative data (such as mobile money transactions, utility payments, and digital footprints) to assess my business creditworthiness.	158(41.5%)	66 (17.3%)	88 (23.1%)	35 (9.2%)	34 (8.9%)
3	AI-based credit scoring provides faster and more efficient loan approval processes compared to traditional banking methods.	32 (8.4%)	174(45.7%)	109 (28.6%)	48 (12.6%)	15 (3.9%)
4	AI-based credit scoring systems are fair and transparent in assessing my business for credit without requiring physical collateral.	187 (49.1%)	69 (18.1%)	36 (9.4%)	71 (18.6%)	18 (4.7%)
5	I have personally applied for or accessed credit through an AI-powered lending platform for my business	68(17.8%)	156(40.9%)	114(29.9%)	27 (7.1%)	16 (4.2%)
B	Financial Inclusion Dimension					
6	My business has access to formal credit facilities (bank loans, microfinance loans, or fintech loans) to support business operations.	139 (36.5%)	90 (23.6%)	98 (25.7%)	30(7.9%)	33 (8.7%)
7	AI-based credit scoring has improved my business access to formal financial services that were previously unavailable through traditional banks.	58 (15.2%)	134(35.2%)	95(24.9%)	61(16.0%)	33 (8.7%)
8	My business uses banking services such as ATM, internet banking, or mobile banking for financial transactions.	96(25.2%)	113(29.7%)	110(28.9%)	43(11.3%)	19 (5.0%)
9	The credit facilities accessible to my business are affordable and have reasonable interest rates.	146(38.3%)	83(21.8%)	58 (15.2%)	79(20.7%)	15 (3.9%)
10	Overall, the availability of AI-based credit scoring platforms has increased my business participation in the formal financial system.	172(45.1%)	85 (22.3%)	95 (24.9%)	17 (4.5%)	

Source: Field Survey Data (2026)

C. Descriptive Statistics Analysis

TABLE 4.3: Descriptive Statistics Results

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
Financial inclusion	381	1.3	4.8	3.344	.5990	-.917	.125
Artificial Intelligence-based credit scoring	381	1.5	5.0	3.497	.7257	-.079	.125
Valid N (listwise)	381						

As depicted on a compilation of descriptive data for the characteristics shown in the above Table, the mean and standard deviation scores were minimal indicating that the dataset were clustered below the mean translating to a desired outcome that the dataset has low level of variability. This indicates that Artificial Intelligence-based credit scoring was at low level leading to the mean score of 3.344 of financial inclusion among SMEs in Akwa Ibom State.

D. Test of Research Hypothesis

The simple regression technique was performed to test the hypothesis that Artificial Intelligence-based credit scoring has no significant effect on financial inclusion among SMEs in Akwa Ibom State.

TABLE 4.4. Regression Analysis Results

Model Summary ^b						
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson	
1	.554 ^a	.307	.299	.6827	2.070	
a. Predictors: (Constant), Artificial Intelligence-based credit scoring						
b. Dependent Variable: Financial inclusion						
ANOVA ^a						
Model	Sum of Squares	Df	Mean Square	F	Sig.	
1	Regression	77.580	4	19.395	41.607	.000 ^b
	Residual	175.271	376	.466		
	Total	252.852	380			
a. Dependent Variable: Financial inclusion						
b. Predictors: (Constant), Artificial Intelligence-based credit scoring						
Coefficients ^a						
Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.		
	B	Std. Error	Beta			
1	(Constant)	.630	.285		2.210	.028
	Artificial Intelligence-based credit scoring	.013	.004	.209	3.250	.002
a. Dependent Variable: Financial inclusion						

Decision Rule: 5% level of significance

This hypothesis was tested using regression statistics and the results are presented in Table 4.4. The test of the null hypothesis (H_0) against the alternate hypothesis (H_1) is that H_0 is rejected if the calculated p-value is less than the p-value of 0.05. From Table 4.4, since the calculated p-value of 0.002 is less than the p-value of 0.05, the researchers rejected the null hypothesis and accept the alternative hypothesis, which states

that Artificial Intelligence-based credit scoring has a significant effect on financial inclusion among SMEs in Akwa Ibom State. A coefficient of 0.013 implies that Artificial Intelligence-based credit scoring has a positive effect on financial inclusion among SMEs in Akwa Ibom State. By implication, 1% increase in Artificial Intelligence-based credit scoring causes 0.1% changes in the financial inclusion among SMEs in Akwa Ibom State.

E. Discussion of the Findings

The regression results obtained from the test of the hypothesis revealed that Artificial Intelligence-based credit scoring has a significant effect on financial inclusion among SMEs in Akwa Ibom State. This finding is consistent with the findings of that harnessing mobile data can enhance financial inclusion and foster broader economic participation (Razavi & Elbahnasawy, 2024). By implications, Artificial Intelligence-based credit scoring significantly improves financial inclusion for small and medium enterprises in Akwa Ibom State by replacing rigid collateral requirements with alternative behavioral and transactional data. This shift allows commercial banks and fintechs to accurately assess creditworthiness, lowering loan approval barriers and accelerating funding access for previously underserved local entrepreneurs.

Practically, this finding implies that regional economic growth can accelerate as micro and small businesses overcome chronic capital deficits to expand operations and create jobs. However, it also requires policymakers and financial regulators to establish clear ethical guidelines and infrastructure safeguards to prevent algorithmic bias and protect local consumer data.

V. CONCLUSION AND RECOMMENDATIONS

This paper has examined the effect of Artificial Intelligence-based credit scoring on financial inclusion among SMEs in Akwa Ibom State. It was found that Artificial Intelligence-based credit scoring has a significant effect on financial inclusion among SMEs in Akwa Ibom State. Based on the finding, we conclude that Artificial Intelligence-based credit scoring play significant role in the financial inclusion among SMEs in Akwa Ibom State. To leverage the finding that AI-based credit scoring significantly boosts financial inclusion for small and medium enterprises (SMEs) in Akwa Ibom State, local financial institutions should first transition from traditional collateral-dependent lending to alternative data-driven AI models. These models should capture localized transaction histories, digital wallets, and mobile money usage to build reliable credit profiles for previously unbanked business owners. Additionally, the Akwa Ibom State Government, through the Ministry of Science and Technology, should partner with fintech firms to establish a unified digital identity system and state-wide transactional data repository. This collaborative infrastructure will provide AI algorithms with the high-quality, localized data streams necessary to accurately assess SME creditworthiness and reduce lending risks. Furthermore, financial institutions and state agencies must actively launch targeted digital literacy campaigns to help traditional SME operators adopt digital payment systems,

which naturally generate the data footprints required for AI scoring. To ensure long-term stability and trust, regulatory frameworks must be established locally to monitor these AI algorithms for algorithmic bias, ensuring fair credit distribution across both urban and rural commerce hubs like Uyo, Ikot Ekpene, and Eket. Finally, local banks should introduce specialized micro-credit products that automatically trigger disbursement based on positive AI credit scores, streamlining access to immediate working capital for fast-growing small businesses.

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