Effect of AI-Powered Credit Assessment on Loan Performance and Small Business Growth Stability in Nigeria

Olayiwola, Khafilat Temitope*, Oyelakin, Oluwabusayo Tejumade

Department of Accounting and Finance, Faculty of Management Sciences, Ajayi Crowther University, Oyo, Oyo State.

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ABSTRACT

SMEs consist of 96% of Nigerian businesses, account for 48% of GDP, and provide 84% of employment, and concurrently, present a ₦24.2 trillion (≈USD 50 billion) credit gap. The credit models that rely on proper collateral placement, formal credit histories, and manual credit assessment and approval are ill-advised to the Nigerian economy and its environment. Within the Nigerian FinTech space, the AI-enabled credit assessment models that utilize alternative data sources, such as mobile money, utility bills, and digital footprints, are on the rise. While the enthusiasm for these range of technologies presents a positive outlook for the use of AI FinTech to both curb non-performing loans and improve credit possibilities for SMEs, the actual on the ground data that measures the impact on SME business growth, as well as the impact on the NPLs, are non-existent. This study seeks to address this gap.The study, grounded in Information Asymmetry Theory and the Technology Acceptance Model, used a survey of 150 OPay credit staff in Lagos. Simple linear regression tested four hypotheses. All were rejected ($p < 0.001$). AI-powered credit assessment explained 41.2% of loan performance variance, 34.5% of NPL reduction, 49.1% of access to finance, and 42.9% of SME growth stability. Access to finance showed the strongest association; NPL reduction the weakest. AI thus enables lending to viable SMEs that traditional systems exclude. The study recommends that the Central Bank of Nigeria establish a transparent, consumer-protective regulatory framework for AI lending, and that SMEs formalise digital records and use multiple AI platforms to build credit history.

Keywords: AI, credit assessment, loan performance, small and medium enterprises, Nigeria, Fintech.

INTRODUCTION

Small and Medium Enterprises (SMEs) serve as critical drivers of economic growth globally, particularly in emerging economies. In Nigeria, SMEs constitute approximately 96 percent of all businesses, contribute more than 48 percent of national GDP, and provide an estimated 84 percent of total employment (Central Bank of Nigeria, 2025). Despite this vital role, Nigerian SMEs face a substantial credit gap of ₦24.2 trillion (approximately USD 50 billion) annually, which severely constrains their growth potential and economic contribution.

The primary barrier to SME financing remains the inadequacy of conventional credit evaluation models. Traditional lending approaches, heavily reliant on collateral requirements, formal credit histories, and manual underwriting, prove largely ineffective in markets characterized by thin-file borrowers and extensive informal economic activity (Agu et al., 2024). These conventional models systematically exclude millions of potential entrepreneurs particularly women, micro-enterprises, and informal businesses due solely to the absence of formal documentation required by legacy banking infrastructure.

Artificial Intelligence (AI) and machine learning (ML) have created new opportunities for transforming credit assessment. AI-powered credit scoring systems can leverage alternative data including mobile money transactions, utility payments, digital footprints, and behavioral patternsto determine creditworthiness with greater speed and precision than traditional methods (Addy et al., 2024). These technologies potentially enable lenders to evaluate borrowers' actual financial capacity without conventional credit reports, thereby expanding access to finance for underserved populations.

The adoption of AI in Nigerian credit assessment has accelerated rapidly. According to the Central Bank of Nigeria's 2025 Fintech Report, 87.5 percent of Nigerian fintech companies now implement AI across multiple functions, with fraud detection, customer service, and credit scoring representing the most common applications. Nigerian fintech firms including FairMoney, OPay, and Andray Finance have deployed AI to offer uncollateralized loans to SMEs, using alternative data to construct dynamic financial identities for business owners previously excluded from formal banking channels.

Statement of the Problem

While digital lending in Nigeria continues to expand rapidly and AI-based credit evaluation offers transformative potential, significant gaps remain in understanding the precise impacts of these technologies on loan performance and SME development. The digital lending industry has broadened credit access but has also become associated with predatory lending practices, excessive interest rates, and debt traps for vulnerable borrowers. Furthermore, although AI adoption has demonstrated reduced default rates in certain contexts, rigorous empirical research on AI applications within the Nigerian SME sector remains limited.

The central problem this research addresses is the deficiency of causally-identified empirical evidence regarding AI-based credit assessment systems' effects on critical financial outcomes: loan performance, non-performing loan rates, SME access to finance, and business growth stability. Without such evidence, policymakers, financial institutions, and AI-focused fintech operators lack guidance for developing effective, responsible, and inclusive AI-driven lending frameworks.

Aim and Objectives

This research aims to explore associations between AI-based credit evaluation and loan performance and SME growth stability in Nigeria. The objectives are to:

i. assess the association between AI-powered credit assessment and loan performance in Nigerian SMEs
ii. determine the association between AI-powered credit assessment and non-performing loan (NPL) reduction
iii. examine the association between AI-powered credit assessment and SME access to finance
iv. evaluate the association between AI-powered credit assessment and SME growth stability

Hypotheses

The following null hypotheses were formulated for exploratory testing:

H_{01}: AI-powered credit assessment has no statistically significant association with loan performance in Nigerian SMEs.

H_{02}: AI-powered credit assessment has no statistically significant association with non-performing loan (NPL) reduction.

H_{03}: AI-powered credit assessment has no statistically significant association with SME access to finance.

H_{04}: AI-powered credit assessment has no statistically significant association with SME growth stability.

LITERATURE REVIEW

AI-Powered Credit Assessment

Contemporary credit risk evaluation has been transformed by the integration of artificial intelligence (AI) and machine learning (ML) methodologies, which fundamentally differ from traditional statistical approaches.

Whereas conventional frameworks such as logistic regression and linear discriminant analysis operate under linear assumptions and rely on a limited set of structured financial variables, AI-driven models can assimilate heterogeneous, high-dimensional data and detect complex, non-linear behavioral patterns that conventional methods cannot fully capture (Addy et al., 2024). Wang, Han Wen, Zhou and Zhang (2023) conducted a comparative analysis of four models applied to credit card default prediction, finding that random forest and XGBoost models performed best with AUC scores of 0.771 and 0.753, respectively, demonstrating that the use of predictive models can help financial institutions identify good and bad customers and make better decisions regarding issuing credit cards.

Loan Performance and Non-Performing Loans

Loan performance denotes borrowers' capacity to adhere to contracted repayment schedules, with non-performing loans (NPLs) those in default or approaching default serving as the primary metric of credit deterioration. Adegoke, Olaniyi and Adebayo (2024) explain that elevated NPL ratios systematically erode financial institution profitability, restrict lending capacity, and can precipitate systemic financial instability if left unaddressed. Defaults matter because they reduce earnings, deplete capital buffers, and erode investor confidence. In Nigeria, the digital lending sector has experienced rapid expansion while simultaneously confronting escalating credit risks.

The International Monetary Fund (IMF, 2025), in its Article IV consultation report on Nigeria, warned that high NPLs in several non-bank financial institutions, new mortgage and consumer lending schemes, and fast-growing fintech and crypto sectors pose potential risks to financial stability. Additionally, the IMF noted that loose underwriting standards, minimal regulatory oversight, and inadequate borrower verification have contributed to rising default rates. According to the Central Bank of Nigeria's (2025) Q2 2025 Credit Condition Survey, higher default rates were reported for both secured and unsecured lending, with small businesses emerging as the most vulnerable group. Notably, lenders also reported increased credit availability for secured, unsecured, and corporate lending, attributed to a changing economic outlook and heightened risk appetite.

Conventional risk management models, which rely heavily on formal credit histories and collateral requirements, prove largely ineffective in contexts characterized by thin-file borrowers and macroeconomic volatility. This structural gap reflects a fundamental problem: when large portions of the population cannot be assessed using traditional tools, credit access becomes constrained regardless of actual repayment capacity. Adegoke, Olaniyi and Adebayo (2024) note that the Central Bank of Nigeria has consistently reported concerns regarding NPLs within the banking sector. The authors cite data from the CBN showing that the industry NPL rose to 4.5 per cent in May 2024, which, while still within the regulatory threshold, prompted operators to express fears that the tough economy is already putting pressure on the real sector's ability to fulfill debt obligations. Industry experts have pointed to the contraction of the industrial sector by 7.1 index points occasioned by rising input costs and low-capacity utilisation as a sign that many companies will default on loan obligations due to high interest rates and foreign exchange losses.

The application of predictive analytics offers a potential pathway toward improved loan performance. When implemented effectively, predictive modelling can absorb thousands of behavioral and transactional signals from income variability to repayment patterns—and generate real-time probability scores that reduce NPLs, lower operational costs, and enable institutions to tailor credit offerings with precision. However, many Nigerian financial institutions continue to rely on outdated scoring methods, manual assessments, and opaque vendor tools, exposing lenders to rising default rates and creating systemic risks in an environment where regulatory clarity remains incomplete. The Nigeria Data Protection Act (2023) adds further compliance requirements, mandating that automated credit decisions be transparent and subject to human review obligations that opaque algorithms may inadvertently breach.

SME Growth Stability

Small and medium enterprise (SME) growth stability encompasses the capacity of small businesses to sustain expansion trajectories, manage cash flow fluctuations, withstand economic shocks, and maintain long-term operational viability. Agu, et. al., (2024) argue that access to timely and affordable credit represents a critical determinant of this stability, enabling SMEs to invest in inventory, equipment, marketing, and working capital. However, the authors caution that credit access alone proves insufficient; the terms under which credit is extended interest rates, repayment schedules, and contractual flexibility substantially determine whether financing catalyzes growth or becomes an unsustainable financial burden. In Nigeria, PwC's (2024) MSME Survey indicates that MSMEs face an overwhelming financing gap currently estimated at USD 32.2 billion (approximately 13 trillion Naira), a constraint exacerbated by inflation, power shortages, and increasing interest rates.

Traditional banking channels, while offering stability, often impose stringent collateral requirements and high interest rates that make it difficult for small businesses to secure loans. This exclusion forces many SMEs to rely on informal financing sources or digital lenders operating with higher interest rates and shorter repayment tenors, arrangements that can undermine rather than support growth stability. The National Institute of Credit Administration (NICA, 2024) has advocated for access to single-digit interest rate loans with flexible repayment options as the ideal solution to bolster a business-friendly climate and empower businesses to thrive and expand. Therefore, policy interventions aimed at enhancing SME growth stability must address not only the quantity of credit extended but also its quality interest rates, repayment flexibility, and alignment with business operational realities. The Government Enterprise and Empowerment Programme (GEEP, 2025) initiative, offering interest-free loans up to ₦300,000 with flexible repayment terms and a moratorium period of approximately three months, exemplifies how targeted credit programmes can provide breathing space for beneficiaries to put funds to productive use before repayment begins.

Theoretical Framework

Information Asymmetry Theory (Akerlof, 1970)

Information Asymentry Theory explains how information disparities between borrowers and lenders can generate adverse selection and moral hazard. Traditional lenders lacking reliable borrower quality information may reject viable SMEs (adverse selection) or extend high-risk loans to compensate for perceived risk. AI-based credit evaluation potentially reduces information asymmetry by capturing detailed, real-time borrower behavioral data, enabling lenders to price risk more accurately and extend credit to previously excluded segments (Croxson et al., 2023).

Technology Acceptance Model (TAM) (Davis, 1989)

TAM posits that perceived usefulness and perceived ease of use drive technology adoption. Applied to AI credit assessment, TAM suggests that both lenders and borrowers will adopt AI-driven systems to the extent they perceive performance improvements and user-friendly interfaces. This receives empirical support from Nigeria, where 62.5 percent of fintechs have expressed interest in participating in AI-oriented regulatory sandboxes, indicating perceived value in AI technologies (Central Bank of Nigeria, 2025).

Empirical Review

Table 1 showing empirical studies on AI-powered credit assessment

Author(s)	Title	Findings	Gaps
Efekodo, K. O. (2024)	Evaluation of machine learning-based algorithm to predicting loan default in Nigeria (Master's thesis)	Gradient Boosting Classifier achieved 78.8% accuracy, reducing false positives and false negatives compared to traditional models	Dataset may not fully represent Nigeria's regional heterogeneity; no alternative data (mobile money, utilities); real-time deployment not tested
Abdulsalam, S. O., Yusuf, I.,	Development of a bank customers' credit rating	BPNN achieved 82.5% accuracy, outperforming	Dataset size/source not specified; potential

Awotunde, S. O., &Edafeajiroke, M. F. (2025)	system using neural networks algorithms	FPNN (81.2%) and traditional credit rating methods	overfitting; lack of model interpretability; no external validation across multiple banks
Ibrahim, S. H., Ya'u, A. U., & Ahmed, A. U. (2025)	The role of artificial intelligence in enhancing financial inclusion in microfinance lending in Nigeria	AI significantly increases loan approvals (β=0.38, p<0.001) and reduces defaults (β=−0.21, p<0.001). Large regional disparities: South West > North East in AI adoption	Self-reported AI adoption (not objective metrics); no specification of which AI techniques; no long-term loan performance data; reasons for North-East lag not explored
Faluyi, S. G., Idowu, P. A., Ogunsanwo, G. O., &Alaba, O. B. (2024)	Comparative analysis of machine learning models for predicting online loan defaults in Nigeria	CatBoost outperformed all others; CatBoost and AdaBoost judged reliable for real-time online credit decisions	Data from 2017 may be outdated; no analysis across loan sizes, tenors, or borrower demographics; no cost-benefit of false positives vs. negatives
Nduka, A. J., Okolie, O., &Ngangah, O. O. (2025)	Evaluating the impact of bank consolidation on SMEs financing in Nigeria: The emerging roles of AI and fintech innovation	Bank consolidation reduced relationship-based lending to SMEs. AI-driven alternative scoring and digital platforms are emerging as critical moderators offsetting this negative effect	Descriptive/correlational; no specific AI model tested; sparse longitudinal data on actual AI adoption; causal mechanisms unclear

METHODOLOGY

A survey design was employed to collect primary data on perceived AI credit assessment adoption and performance in Lagos, Nigeria, the country's commercial capital and fintech ecosystem hub. The study population comprised staff members of OPay, a prominent Nigerian fintech platform. Purposive sampling was used to select 150 respondents directly engaged in credit appraisal and lending processes. A structured questionnaire was adopted as research instrument.

RESULTS AND DISCUSSION OF FINDINGS

H_{01}: AI-powered credit assessment has no statistically significant association with loan performance in Nigerian SMEs.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.642	0.412	0.408	0.584

Predictors: (Constant), AI-Powered Credit Assessment

Anova

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	18.234	1	18.234	104.19	.000
Residual	25.966	148	0.175		
Total	44.200	149			

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The regression model shows an R of 0.642, indicating a moderate-to-strong positive correlation between AI-powered credit assessment and loan performance. The R Square value of 0.412 means that AI-powered credit assessment explains 41.2% of the variance in loan performance among Nigerian SMEs. The anova result ($F = 104.19$, $p = .000$) confirms that the model is statistically significant at $p < 0.001$. Therefore, there is sufficient evidence to reject the null hypothesis. AI-powered credit assessment has a statistically significant positive association with loan performance in Nigerian SMEs.

H_{02}: AI-powered credit assessment has no statistically significant association with non-performing loan (NPL) reduction.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.587	0.345	0.340	0.612

Predictors: (Constant), AI-Powered Credit Assessment

Anova

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	16.728	1	16.728	78.17	.000
Residual	31.772	148	0.214		
Total	48.500	149			

The model yields an R of 0.587, representing a moderate positive correlation. The R Square value of 0.345 indicates that AI-powered credit assessment explains 34.5% of the variance in NPL reduction. The anova ($F = 78.17$, $p = .000$) demonstrates statistical significance. The null hypothesis is rejected. AI-powered credit assessment has a statistically significant positive association with NPL reduction in Nigerian SMEs.

H_{03}: AI-powered credit assessment has no statistically significant association with SME access to finance.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.701	0.491	0.488	0.556

Predictors: (Constant), AI-Powered Credit Assessment

Anova

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	22.456	1	22.456	143.03	.000
Residual	23.244	148	0.157		
Total	45.700	149			

The model shows the strongest relationship among all hypotheses, with an R of 0.701 (strong correlation). The R Square value of 0.491 means that AI-powered credit assessment explains 49.1% of the variance in SME access to finance—the highest explanatory power across all four models. The anova ($F = 143.03$, $p = .000$) confirms strong statistical significance. The null hypothesis is rejected. AI-powered credit assessment has a statistically significant and robust positive association with SME access to finance in Nigeria.

H_{04}: AI-powered credit assessment has no statistically significant association with SME growth stability.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.655	0.429	0.425	0.571

Predictors: (Constant), AI-Powered Credit Assessment

Anova

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	19.456	1	19.456	111.18	.000
Residual	25.944	148	0.175		
Total	45.400	149			

The model shows an R of 0.655 (moderate-to-strong correlation) and an R Square of 0.429, meaning AI-powered credit assessment explains 42.9% of the variance in SME growth stability. The anova (F = 111.18, p = .000) confirms statistical significance. The null hypothesis is rejected. AI-powered credit assessment has a statistically significant positive association with SME growth stability in Nigerian SMEs. The explanatory power ranks second highest among the four outcomes, behind only access to finance.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study provides evidence that AI-powered credit assessment has a statistically significant and practically meaningful positive association with key lending outcomes for Nigerian SMEs. All four null hypotheses were rejected at $p < 0.001$, with the strongest association observed for access to finance and the weakest for NPL reduction. This implies that AI-powered credit assessment does not merely predict risk; but appears to enable lending to viable SMEs that traditional systems systematically exclude. For a developing economy like Nigeria, where SMEs constitute approximately 96% of all businesses and contribute nearly 50% of GDP, this has transformative implications for financial inclusion and economic development.

Recommendations

The Central Bank of Nigeria should establish a regulatory framework for AI lending models to balance innovation with consumer protection, particularly regarding data privacy and algorithmic bias. Regulations must mandate transparency and explainability, requiring AI systems to provide human-interpretable reasons for adverse credit decisions to prevent discrimination against legitimate SMEs. SMEs should formalise their financial and operational data by maintaining digital records of transactions, inventory, and utility payments to maximize scoreability by AI systems, with business associations offering data literacy training. To build a diversified credit history, SMEs should initially test their creditworthiness across multiple AI-powered platforms to identify the most favourable assessment criteria for their specific business profile.

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