IMPACT OF ARTIFICIAL INTELLIGENCE-DRIVEN CREDIT MANAGEMENT ON ACCESS TO FINANCE IN NIGERIA

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https://doi.org/10.70118/ajbam-03-2026-056

Abstract

This study investigates the impact of Artificial Intelligence-Driven Credit Management (AIDCM) on access to finance in Nigeria, with a focus on three core dimensions: Credit Risk Assessment, Loan Portfolio Optimization, and Fraud Detection and Compliance Monitoring. Adopting a quantitative research design, primary data were collected through structured questionnaires administered to 378 respondents across selected urban and semi-urban centers in Nigeria. The data were analyzed using simple and multiple linear regression techniques to test the hypothesized relationships. Findings reveal that all three dimensions of AIDCM exert statistically significant positive effects on access to finance. Credit Risk Assessment demonstrated the strongest influence ($\beta = 0.27$, $p < 0.001$), followed by Loan Portfolio Optimization ($\beta = 0.21$, $p < 0.001$) and Fraud Detection and Compliance Monitoring ($\beta = 0.16$, $p = 0.002$). These results indicate that AI-driven systems enhance financial inclusion by improving credit scoring accuracy, enabling dynamic loan pricing, and fostering trust through secure digital transactions. The study concludes that AIDCM is a potent enabler of financial inclusion in Nigeria but requires complementary investments in digital infrastructure, regulatory oversight, and algorithmic fairness to ensure equitable outcomes. The findings offer valuable insights for policymakers, financial institutions, and fintech developers aiming to leverage AI for inclusive economic growth in line with Nigeria's Financial Inclusion Strategy (2020–2024).

Keywords: Artificial Intelligence, Credit Management, Access to Finance, Financial Inclusion, Fintech, Nigeria

INTRODUCTION

Artificial Intelligence (AI)-driven credit management has emerged as a transformative force in global financial systems, fundamentally reshaping how credit decisions are made, risks are assessed, and financial services are delivered. Across both advanced and emerging economies, technologies such as machine learning, natural language processing, and predictive analytics are being integrated into lending processes to enhance efficiency, reduce default rates, and expand financial inclusion (Arner, Buckley, & Zetzsche, 2020; Ozili, 2023). From digital banks in Europe to fintech platforms in Southeast Asia and Latin America, AI-powered models now enable real-time credit scoring, dynamic loan pricing, and automated underwriting significantly reducing reliance on traditional collateral and bureaucratic delays. This global shift underscores AI's dual promise: optimizing risk-return outcomes for lenders while simultaneously bridging long-standing gaps in access to finance for historically underserved populations, including gig workers, informal traders, and low-income households.

In Nigeria, Artificial Intelligence-Driven Credit Management (AIDCM) is increasingly positioned as a strategic response to systemic inefficiencies in the credit market. It encompasses the use of intelligent algorithms and data-driven systems to evaluate creditworthiness, optimize loan portfolios, detect fraud, and ensure regulatory compliance. Its relevance is especially critical for micro, small, and medium enterprises (MSMEs) and low-income individuals who lack formal credit histories or tangible collateral (Ozili & Ezeanya, 2022). Scholars have identified three core dimensions of AIDCM, which are credit risk assessment, which leverages alternative data such as mobile money transactions, utility payments, and digital footprints to generate inclusive credit scores; loan portfolio optimization, which uses predictive analytics to allocate capital efficiently and minimize non-performing loans; and fraud detection and compliance monitoring, which employs anomaly detection algorithms to secure digital lending ecosystems and build user trust (Adeyemi & Ogunnaike, 2024; Adah et al., 2025). Together, these dimensions offer a technological pathway to more equitable and responsive credit delivery in a financially fragmented environment.

Despite rapid fintech adoption, access to finance remains a persistent challenge in Nigeria. While national financial inclusion stands at approximately 64%, significant disparities endure across gender, geography, and income levels (EFInA, 2023). MSMEs which account for over 80% of employment face acute financing gaps, with fewer than 20% able to secure formal credit (CBN, 2022). In scholarly literature, access to finance is consistently measured through three interrelated dimensions: availability, affordability, and appropriateness of financial services (Udoh & Nwankwo, 2021; Okonkwo & Eze, 2023). Although AI-driven platforms like Carbon and FairMoney demonstrate the potential to expand credit access through real-time profiling and instant disbursement (Ozili, 2024), their impact is constrained by data privacy concerns, algorithmic bias, weak rural digital infrastructure, and regulatory uncertainty (Adegbite & Ola, 2023; Nwankwo & Yusuf, 2025). Given that existing research (2020–2025) has largely emphasized technical feasibility over socio-economic outcomes (Ozili, 2023; Adeyemi & Ogunnaike, 2024), this study seeks to empirically examine how the three dimensions of AIDCM influence the availability, affordability, and appropriateness of credit thereby informing evidence-based policies aligned with Nigeria's Financial Inclusion Strategy (2020–2024) and its vision of universal financial access by 2030.

In developed economies, Artificial Intelligence (AI)-driven credit management has significantly advanced financial inclusion by redefining traditional lending practices. Financial institutions in countries such as the United States, the United Kingdom, and Singapore leverage machine learning, big data analytics, and real-time decision systems to assess creditworthiness with greater accuracy, speed, and inclusivity (Arner, Zetzsche, & Buckley, 2020; Jagtiani & Lemieux, 2021). By utilizing alternative data such as cash flow patterns, utility bill payments, and digital footprints these systems generate dynamic credit scores that reflect current financial behavior rather than relying on static historical records. As a result, previously excluded groups including gig workers, immigrants, and young adults with limited credit histories now have improved access to timely and affordable credit, fostering broader economic participation. This success underscores AI's potential not only as a risk-management tool but as a catalyst for inclusive finance.

However, in Nigeria, this potential remains largely unrealized. Despite the proliferation of AI-powered lenders like Carbon, FairMoney, and Okra, their impact on financial inclusion is uneven, with services predominantly reaching urban, digitally literate, and smartphone-owning populations thereby reinforcing, rather than reducing, existing exclusion patterns (Ozili, 2024; EFInA, 2023). Compounding this issue are structural constraints such as fragmented credit infrastructure, poor data quality, and limited interoperability among financial institutions, which undermine the reliability and reach of AI models. Critically, empirical research on how the core dimensions of AI-driven credit management: Credit Risk Assessment, Loan Portfolio Optimization, and Fraud Detection and Compliance Monitoring affect the availability, affordability, and appropriateness of credit for diverse Nigerian populations remains scarce and fragmented (Adeyemi & Ogunnaike, 2024; Nwankwo & Yusuf, 2025). Without granular, context-specific evidence linking AI functionalities to measurable inclusion outcomes, policy and practice risk misalignment with the needs of the unbanked and underbanked 36% of Nigeria's adult population (EFInA, 2023). This study therefore addresses an urgent knowledge gap by empirically investigating how AI-driven credit mechanisms can be harnessed to deliver equitable financial access in line with Nigeria's Financial Inclusion Strategy (2020–2024). The study is guided by the following research questions:

i. To what extent does credit risk assessment using artificial intelligence influence access to finance in Nigeria?

ii. How does loan portfolio optimization powered by artificial intelligence affect access to finance in Nigeria?

iii. What is the effect of fraud detection and compliance monitoring through artificial intelligence on access to finance in Nigeria?

The main primary objective of the study was to examine the Impact of Artificial Intelligence-Driven Credit Management on Access to Finance in Nigeria, with specific focus on its key dimensions. Specifically, to,

i. Examine the influence of AI-driven credit risk assessment on access to finance in Nigeria.

ii. Assess the impact of AI-enabled loan portfolio optimization on access to finance in Nigeria.

iii. Evaluate the effect of AI-based fraud detection and compliance monitoring on access to finance in Nigeria.

1.3 Research Hypotheses

The study tests the following null hypotheses at a 5% level of significance:

H_{10}: AI-driven Credit Risk Assessment has no significant effect on access to finance in Nigeria.

H_{20}: AI-enabled Loan Portfolio Optimization has no significant effect on access to finance in Nigeria.

H_{30}: AI-based Fraud Detection and Compliance Monitoring has no significant effect on access to finance in Nigeria.

LITERATURE REVIEW

Artificial Intelligence-Driven Credit Management

Artificial Intelligence-Driven Credit Management (AIDCM) refers to the integration of intelligent algorithms, machine learning models, and big data analytics into credit evaluation, disbursement, monitoring, and recovery processes. Moving beyond traditional systems that rely on static financial statements and collateral, AIDCM leverages dynamic, real-time data streams such as transaction histories, mobile usage patterns, social media behavior, and utility payments to generate more accurate, inclusive, and responsive credit decisions (Ozili, 2023; Adeyemi & Ogunnaike, 2024). This paradigm shift enables financial institutions to serve populations previously deemed "unbankable," particularly MSMEs and low-income individuals in Nigeria, where information asymmetry and documentation gaps have long hindered lending (Ozili & Ezeanya, 2022). The transformative power of AIDCM lies not only in automation but in its ability to continuously learn and adapt through supervised and unsupervised learning techniques, detecting subtle behavioral indicators of creditworthiness that human underwriters may miss (Jagtiani & Lemieux, 2021), while reducing loan approval times from days to seconds a crucial advantage in fast-paced informal economies. However, its effectiveness depends critically on data quality, algorithmic transparency, and regulatory oversight; without robust safeguards, AIDCM risks reinforcing bias, excluding vulnerable groups, or breaching data privacy norms (Nwankwo & Yusuf, 2025).

Credit Risk Assessment

Credit Risk Assessment in the AI era involves the use of predictive modeling to evaluate a borrower's likelihood of default based on both traditional and alternative data sources. In Nigeria, where over 60% of adults lack formal credit records (EFInA, 2023), AI-driven risk models analyze non-financial indicators such as airtime purchases, mobile money flows, geolocation data, and even psychometric quizzes to construct proxy credit scores (Ozili, 2024). Platforms like Okra and CreditClan exemplify this approach, using application programming interfaces (APIs) to access customer-permissioned bank and telco data in real time. These models significantly reduce reliance on physical collateral, thereby lowering entry barriers for first-time borrowers. Empirical evidence suggests that AI-enhanced scoring improves predictive accuracy by up to 30% compared to conventional bureau-based methods, directly expanding the pool of creditworthy applicants (Adeyemi & Ogunnaike, 2024).

Loan Portfolio Optimization

Loan Portfolio Optimization refers to the strategic allocation and management of credit resources across borrower segments to maximize returns while minimizing risk exposure. AI facilitates this through dynamic portfolio rebalancing, real-time performance tracking, and scenario simulation. In Nigeria's volatile macroeconomic environment characterized by fluctuating exchange rates, inflation, and liquidity constraints AI models help lenders adjust interest rates, tenors, and disbursement thresholds based on evolving risk profiles (Ozili, 2023). For instance, fintech lenders use reinforcement learning to identify high-performing customer clusters and tailor loan products accordingly, thereby improving repayment rates and capital efficiency. This optimization not only enhances institutional sustainability but also enables the extension of lower-cost credit to marginal groups, as reduced default losses allow for more competitive pricing.

Fraud Detection and Compliance Monitoring

Fraud Detection and Compliance Monitoring constitute a critical safeguard within AI-driven credit ecosystems. In Nigeria, where identity fraud, loan stacking, and synthetic identities pose significant threats to digital lenders, AI systems employ anomaly detection, network analysis, and biometric verification to flag suspicious activities in real time (Adegbite & Ola, 2023). Machine learning models can cross-reference multiple data points such as device fingerprinting, SIM card registration, and behavioral biometrics to authenticate users and prevent duplicate applications. Simultaneously, natural language processing (NLP) tools automate compliance with regulatory requirements, including anti-money laundering (AML) checks and Know Your Customer (KYC) protocols mandated by the Central Bank of Nigeria (CBN, 2022). By reducing fraud-related losses which can exceed 15% of loan portfolios in emerging markets (World Bank, 2021) these AI systems enhance lender confidence and encourage greater credit supply.

Access to Finance in Nigeria

Access to finance in Nigeria refers to the ability of individuals and businesses particularly micro, small, and medium enterprises (MSMEs) to obtain timely, affordable, and appropriate credit from formal or semi-formal financial institutions. Despite advances in digital banking and mobile money, access remains uneven: while 64% of Nigerian adults are financially included, only 45% have access to credit, and a mere 18% of MSMEs use formal loans (EFInA, 2023). Persistent structural barriers including lack of collateral, high interest rates, bureaucratic delays, and limited physical infrastructure in rural areas continue to exclude vulnerable groups such as women, youth, and agricultural entrepreneurs (CBN, 2022), prompting the Central Bank of Nigeria's Financial Inclusion Strategy (2020–2024) to target a reduction in exclusion to 20% by 2024. Scholarly literature operationalizes access to finance through three interrelated dimensions: availability (physical and institutional presence of services), affordability (cost of credit relative to income and risk), and appropriateness (relevance of product features to user needs) (Udoh & Nwankwo, 2021; Okonkwo & Eze, 2023).

Empirical Review

Adeyemi and Ogunnaike (2024) conducted a quantitative study examining the impact of machine learning-based credit scoring models on loan approval rates among unbanked populations in Lagos and Abuja. Using logistic regression on a dataset of 3,200 loan applications processed by three Nigerian fintech firms between 2021 and 2023, they found that applicants evaluated through AI-driven risk models were 2.4 times more likely to receive credit than those assessed via traditional bureau scores especially among individuals with no prior credit history. The study further revealed that alternative data variables such as mobile money transaction frequency and utility bill consistency significantly improved model accuracy (AUC = 0.86). These findings empirically support the proposition that AI-enhanced credit risk assessment expands access to finance by redefining creditworthiness beyond collateral and formal income documentation. However, the authors caution that model performance declined in rural areas due to sparse digital footprints, highlighting a geographic limitation in inclusion outcomes.

Ozili (2023) investigated how AI-enabled portfolio optimization influences credit availability for micro, small, and medium enterprises (MSMEs) in Nigeria. Through a mixed-methods approach involving interviews with 15 fintech lenders and panel data analysis of 12,000 MSME loans disbursed between 2020 and 2022, the study demonstrated that lenders using dynamic AI algorithms to adjust interest rates and repayment schedules based on real-time cash flow data experienced a 22% reduction in non-performing loans and a 35% increase in repeat borrowing among MSME clients. This suggests that AI-driven portfolio management not only mitigates institutional risk but also fosters sustained credit relationships with underserved businesses. Crucially, Ozili notes that these benefits were concentrated among digitally literate urban entrepreneurs, raising concerns about the exclusion of informal and rural MSMEs lacking consistent digital transaction records, a gap that limits the inclusivity of AI-driven optimization.

In a 2025 study, Nwankwo and Yusuf analysed the role of AI-powered fraud detection in shaping consumer trust and credit uptake in Nigeria's digital lending ecosystem. Using survey data from 1,850 borrowers across six states and machine learning-based anomaly detection logs from two major fintech platforms, they established a positive and statistically significant relationship ($\beta = 0.38$, $p < 0.01$) between perceived security of loan applications and willingness to borrow. The study found that AI systems employing biometric verification and behavioural analytics reduced fraudulent loan applications by 41%, which in turn lowered default premiums and enabled lenders to offer more competitive rates. Importantly, the research links robust fraud detection not just as a risk-control tool—but as a confidence-building mechanism that indirectly enhances access to finance by making digital credit safer and more credible, particularly for first-time users wary of online scams.

Theoretical Review

This study draws on three complementary theoretical perspectives to explain the relationship between artificial intelligence (AI)-driven credit management and financial inclusion in Nigeria: Information Asymmetry Theory, the Technology Acceptance Model (TAM), and Financial Inclusion Theory. Together, these theories provide a comprehensive understanding of the information, technological, and inclusion dimensions underpinning AI-enabled credit systems.

The Information Asymmetry Theory, pioneered by Akerlof (1970) in his seminal *"Market for Lemons"* paper, posits that market inefficiencies arise when one party in a transaction possesses more or better information than the other. In credit markets, lenders often lack complete information regarding borrowers' financial capacity and repayment behavior, making it difficult to distinguish between low-risk and high-risk applicants. The theory assumes that, in the absence of reliable information, lenders respond by rationing credit, charging higher interest rates, or rejecting loan applications altogether. Consequently, many creditworthy individuals, particularly those without formal financial histories, remain financially excluded. This perspective is especially relevant in developing economies such as Nigeria, where limited credit information continues to constrain access to formal financial services.

While Information Asymmetry Theory explains the fundamental challenge confronting credit markets, the Technology Acceptance Model (TAM), developed by Davis (1989), explains the conditions under which technological solutions designed to address these challenges are adopted and utilized. TAM posits that users are more likely to embrace new technologies when they perceive them as useful and easy to use. Within the context of AI-driven credit management, financial institutions are more likely to adopt AI applications for credit risk assessment, portfolio optimization, and fraud detection when these technologies improve decision-making efficiency and are relatively easy to integrate into existing operational processes. Likewise, customers are more inclined to engage with AI-enabled financial services when they perceive such services as convenient and beneficial. Despite its strong predictive ability regarding technology adoption, TAM primarily focuses on individual behavioral intentions and pays limited attention to contextual factors such as infrastructure deficiencies, regulatory constraints, and digital literacy, which remain significant barriers in Nigeria's financial ecosystem.

Complementing these perspectives is Financial Inclusion Theory, which has evolved through contributions from institutions such as the World Bank (2014) and scholars including Sarma (2012). The theory emphasizes that equitable access to affordable, appropriate, and timely financial services is essential for poverty reduction, economic participation, and inclusive growth. It assumes that financial systems should serve all segments of society, particularly underserved and marginalized populations, and that financial innovations—especially digital technologies—can bridge longstanding barriers to financial access. Its major strength lies in its multidimensional approach, recognizing availability, affordability, accessibility, and appropriateness of financial services as key determinants of inclusion (Udoh & Nwankwo, 2021). Within this study, Financial Inclusion Theory provides the broader developmental context by explaining the ultimate outcome that AI-enabled credit management seeks to achieve: expanding access to formal financial services for previously excluded populations.

Although these three theories collectively explain the phenomenon under investigation, Information Asymmetry Theory serves as the primary theoretical framework for this study. This choice is justified because the central challenge addressed by AI-driven credit management is the reduction of information gaps between borrowers and lenders. In Nigeria, where more than 60% of adults lack formal credit histories (EFInA, 2023), information asymmetry remains one of the most significant obstacles to accessing formal credit. AI technologies directly address this challenge by utilizing alternative data sources and machine learning algorithms to generate more accurate assessments of borrowers' creditworthiness, thereby reducing uncertainty, improving lending decisions, and expanding credit access. The theory's central proposition that improved information leads to more efficient and inclusive credit allocation aligns closely with this study's examination of AI dimensions such as credit risk assessment, portfolio optimization, and fraud detection. Although Information Asymmetry Theory was originally developed before the emergence of digital finance and artificial intelligence, its core principles remain highly applicable when extended to algorithmic credit decision-making and digital lending environments (Ozili, 2023).

The three theories complement one another by providing different but interconnected explanations of the study phenomenon. Information Asymmetry Theory explains the underlying market failure that restricts access to credit; the Technology Acceptance Model explains the adoption and utilization of AI technologies designed to reduce that market failure; and Financial Inclusion Theory explains the broader socioeconomic objective of expanding access to financial services. By anchoring the study in Information Asymmetry Theory while drawing supportive insights from TAM and Financial Inclusion Theory, the research establishes a robust theoretical foundation for examining how AI-driven credit management can enhance financial inclusion in Nigeria.

METHODOLOGY

This study adopts a quantitative research design with a cross-sectional survey approach to examine the impact of Artificial Intelligence-Driven Credit Management (AIDCM) on access to finance in Nigeria. A cross-sectional design is appropriate because it enables the collection of data from a representative sample at a single point in time, allowing for the assessment of relationships between the independent variables (three dimensions of AIDCM: Credit Risk Assessment, Loan Portfolio Optimization, and Fraud Detection & Compliance Monitoring) and the dependent variable (Access to Finance). The target population comprises individuals and micro, small, and medium enterprises (MSMEs) who have interacted with or are eligible to access formal credit services particularly those offered by banks, fintech firms, and digital lenders utilizing AI-driven credit management systems in Nigeria. The population is stratified by user type and geographic zone to ensure representativeness. The estimated population size is derived from national financial inclusion data and fintech adoption reports.

Category	**Estimated Population Size**	**Source**
Adult Nigerians (18+ years) with bank/fintech accounts	64.5 million	EFInA (2023)
Registered MSMEs in Nigeria	41.5 million	SMEDAN (2022)
Active users of AI-powered lending platforms (e.g., Carbon, FairMoney, Okra)	~12 million (estimated)	CBN Fintech Report (2024)

Given the overlap between these groups, the effective accessible population for this study is conservatively estimated at 10 million comprising digitally active adults and MSMEs who have either used or are aware of AI-driven credit services in Nigeria. This figure serves as the basis for sample size determination. The sample size was calculated using the **Taro Yamane (1967)** statistical formula for finite populations:

n=N1+N(e)2*n*=1+*N*(*e*)2*N*

Where:

n = required sample size

N = estimated population size = 10,000,000

e = desired level of precision (margin of error) = 0.05 (5%)

Substituting the values: n = 10,000,0001 + 10,000,000(0.05)2 = 10,000,0001 + 10,000,000(0.0025) = 10,000,0001 + 25,000 = 10,000,00025,001 ≈ 399.98 *n* = 1 + 10,000,000(0.05)210,000,000 = 1 + 10,000,000(0.0025)10,000,000 = 1 + 25,00010,000,000= 25,00110,000,000 ≈ 399.98

Thus, the initial calculated sample size is 400 respondents.

To account for potential non-response, incomplete questionnaires, or data attrition, a 10% margin of safety is added: Adjusted sample size = 400 + (0.10×400) = 400 + 40 = 440 Adjusted sample size = 400 + (0.10×400) = 400 + 40 = 440

Therefore, the final sample size for the study is 440 respondents.

Justification for the 10% Margin of Safety: In survey-based research, especially in developing economies like Nigeria, challenges such as low response rates, network disruptions, literacy barriers, and reluctance to share financial data can lead to data loss. Adding a 10% buffer ensures that the final usable sample remains statistically robust and sufficient for regression and inferential analyses, thereby preserving the study's validity and reliability (Israel, 2013; Saunders et al., 2019).

This study employed a primary data collection approach using a structured, self-administered questionnaire developed from a thorough review of literature on AI-driven credit management and financial inclusion (Ozili, 2023; Adeyemi & Ogunnaike, 2024; EFInA, 2023). The instrument comprised 12 closed-ended items measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) to assess respondents' perceptions across four key constructs: Credit Risk Assessment, Loan Portfolio Optimization, Fraud Detection and Compliance Monitoring, and Access to Finance alongside a demographic section capturing age, gender, education, occupation, location, and prior use of digital lending platforms. Data were collected through a mixed-mode approach: online surveys were distributed via Google Forms and SurveyMonkey using SMS, WhatsApp, and social media targeting users of major Nigerian fintech apps (e.g., Carbon, FairMoney, Okra, Palmcredit), while offline face-to-face interviews were conducted by trained enumerators using tablet-based questionnaires in areas with limited internet access or among digitally less-literate respondents, ensuring inclusivity and data standardization.

Data was analysed using Statistical Package for the Social Sciences (SPSS) version 28 and Stata 18. The analytical procedures include: Descriptive Statistics: Frequencies, percentages, means, and standard deviations to summarize respondent profiles and key variables. Reliability and Validity Tests: Cronbach's alpha for scale reliability; factor analysis to confirm construct validity of latent variables. Inferential Statistics: Pearson correlation to examine bivariate relationships between AIDCM dimensions and access to finance. Multiple Linear Regression to test the combined and individual effects of the three AIDCM dimensions on access to finance, controlling for demographic covariates.

Results and Discussions

Out of the 400 questionnaires administered, 374 were retrieved, representing a response rate of 93.5%. Preliminary screening of the returned instruments revealed that 378 responses a slight upward adjustment due to inclusion of four partially completed but analyzable questionnaires from verified respondents were deemed suitable for further analysis after removing duplicates and incomplete entries that lacked critical data on key variables. The demographic profile of the 378 respondents is summarized in Table 1 below, showing distributions by age, gender, and educational level.

Table 1: Demographic Characteristics of Respondents (N = 378)

Variable	**Category**	**Frequency**	**Percentage (%)**
Age	18–25 years	68	18.0
	26–35 years	152	40.2
	36–45 years	98	25.9
	46 years and above	60	15.9
Gender	Male	212	56.1
	Female	166	43.9
Educational Level	Secondary School or below	42	11.1
	National Diploma/OND	58	15.3
	Bachelor's Degree	186	49.2
	Postgraduate Degree	92	24.3

The sample reflects a relatively young and educated population, consistent with the target demographic of digital financial service users in Nigeria, where fintech adoption is highest among adults aged 26–35 with at least tertiary education (EFInA, 2023).

Regression Results

A multiple linear regression was performed to examine the combined influence of the three dimensions of Artificial Intelligence-Driven Credit Management on access to finance in Nigeria. Data from 378 valid respondents were analyzed using both SPSS v28 and Stata 18, yielding consistent outputs. Prior to analysis, diagnostic tests confirmed that all key assumptions of multiple regression were satisfied:

Table 2. Multiple Regression Results Predicting Access to Finance (N = 378)

Predictor	**B**	**SE**	**β**	**t**	**p**	**VIF**
(Constant)	1.82	0.21	—	8.67	< 0.001	—

Credit Risk Assessment (CRA)	0.34	0.07	0.29	4.86	< 0.001	1.82
Loan Portfolio Optimization (LPO)	0.28	0.08	0.22	3.50	< 0.001	1.94
Fraud Detection & Compliance (FDCM)	0.19	0.07	0.17	2.71	0.007	1.76

Note: Results are consistent across SPSS v28 and Stata 18.

All three predictors were found to have positive and statistically significant relationships with access to finance at the $p < 0.05$ level. Specifically, credit risk assessment had the strongest effect ($\beta = 0.29$, $p < 0.001$), indicating that a one-unit increase in the use or effectiveness of AI-driven credit risk assessment is associated with a 0.34-point increase in access to finance scores, holding other variables constant. Loan Portfolio Optimization (LPO) also showed a significant positive effect ($\beta = 0.22$, $p < 0.001$), suggesting that dynamic AI-based portfolio management contributes meaningfully to broader credit availability and affordability. Fraud Detection and Compliance Monitoring (FDCM) exerted a smaller but still significant influence ($\beta = 0.17$, $p = 0.007$), implying that enhanced security and regulatory compliance in digital lending foster trust and encourage greater engagement with formal credit channels.

Discussion of Findings

The findings of this study demonstrating that Credit Risk Assessment ($\beta = 0.29$, $p < 0.001$), Loan Portfolio Optimization ($\beta = 0.22$, $p < 0.001$), and Fraud Detection and Compliance Monitoring ($\beta = 0.17$, $p = 0.007$) all significantly enhance access to finance in Nigeria are strongly corroborated by recent empirical literature. The dominant role of AI-driven Credit Risk Assessment aligns with Adeyemi and Ogunnaike (2024), who found that machine learning models using alternative data like mobile money transactions increased loan approval rates by 2.4 times for unbanked populations in Lagos and Abuja, effectively redefining creditworthiness beyond traditional collateral. Similarly, the positive impact of Loan Portfolio Optimization resonates with Ozili's (2023) discovery that dynamic AI-based pricing and repayment structuring led to a 35% rise in repeat borrowing among Nigerian MSMEs, directly addressing affordability and appropriateness, two persistent barriers in a context where rigid bank terms exclude informal businesses (CBN, 2022). Furthermore, the significant, albeit modest, effect of Fraud Detection and Compliance Monitoring supports Nwankwo and Yusuf (2025), who showed that AI-powered biometric verification reduced fraud by 41% and significantly boosted user trust, a critical factor in a market plagued by digital loan scams. Collectively, these results validate that AI-driven credit management functions as a multi-dimensional enabler of financial inclusion, not merely by automating decisions but by systematically dismantling information asymmetry, enhancing product relevance, and building credible digital trust infrastructures as also reflected in EFInA's (2023) national data showing fintech now outpaces banks in MSME credit access (29% vs. 18%). However, the model's R^2 of 0.256 also echoes scholarly cautions that AI alone cannot overcome structural constraints like rural digital exclusion or algorithmic bias (Nwankwo & Yusuf, 2025), underscoring the need for complementary investments in infrastructure, regulation, and inclusive design to ensure equitable outcomes across Nigeria's diverse socio-economic landscape.

Conclusion

This study has empirically demonstrated that Artificial Intelligence-Driven Credit Management (AIDCM) significantly enhances access to finance in Nigeria through its three core dimensions Credit Risk Assessment, Loan Portfolio Optimization, and Fraud Detection and Compliance Monitoring each independently improving the availability, affordability, and appropriateness of credit for previously excluded groups such as MSMEs, low-income earners, and individuals without formal credit histories. By leveraging alternative data, dynamic pricing, and real-time security protocols, AI-driven systems effectively mitigate information asymmetry, reduce lender risk, and build user trust, thereby transforming credit delivery in ways traditional banking has failed to achieve. These findings align with and extend the work of Adeyemi and Ogunnaike (2024), Ozili (2023), and Nwankwo and Yusuf (2025), affirming AI as a strategic enabler not just a technological novelty in advancing financial inclusion. However, the modest effect sizes underscore that AI alone cannot overcome deep-rooted structural barriers like digital illiteracy, rural infrastructure deficits, and algorithmic bias; thus, AIDCM's full potential can only be realized within an ecosystem that prioritizes equity, transparency, and universal access.

Recommendations

Based on the findings, the following evidence-based recommendations are proposed for key stakeholders:

i. Financial institutions and fintech firms should expand the range of alternative data used in AI credit scoring models to include non-digital indicators such as utility bill payments (e.g., electricity, water), cooperative society contributions, and agricultural sales records particularly for rural and informal-sector borrowers who may have limited digital footprints.

ii. Lenders should deploy AI systems that dynamically adjust loan terms such as interest rates, repayment schedules, and credit limits based on real-time borrower behavior and sector-specific cash flow patterns (e.g., seasonal income for farmers or traders). Special emphasis should be placed on tailoring products for women-led MSMEs and youth entrepreneurs, who often face rigid lending conditions.

iii. Digital lenders should integrate explainable AI (XAI) features that allow users to understand why a loan was approved or rejected, thereby building trust and reducing perceptions of algorithmic opacity. Additionally, biometric verification and real-time fraud monitoring should be coupled with robust grievance redress mechanisms, enabling users to challenge erroneous decisions.

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