Artificial Intelligence-Driven Credit Management and Financial Performance of Deposit Money Banks (DMBs) In Abuja, Nigeria

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ABSTRACT

This study examined Artificial Intelligence–Driven and Credit Management (AICM) on the financial performance of selected Deposit Money Banks (DMBs) in Abuja, Nigeria. Specifically, the research focused on two key AICM indicators Automated Credit Scoring Systems and Predictive Risk Analytics and their influence on profitability, asset quality, and overall financial stability. The study was motivated by the increasing integration of intelligent technologies in banking operations and the need to evaluate their measurable performance outcomes within Nigeria's financial sector. The population comprised 652 management staff and employees of selected DMBs in Abuja, from which a sample size of 248 respondents was determined using an appropriate sampling technique. Primary data were collected through structured questionnaires designed to capture perceptions and operational realities of AI-driven credit tools. Data analysis was conducted using the Statistical Package for Social Sciences (SPSS Version 27.0). Multiple linear regression, correlation analysis, and Analysis of Variance (ANOVA) were employed to test the study hypotheses and determine the strength, direction, and significance of relationships among variables. The findings revealed that Automated Credit Scoring Systems significantly enhance financial performance by improving credit appraisal efficiency, reducing default rates, and strengthening loan portfolio quality among the selected DMBs in Abuja, Nigeria. Similarly, Predictive Risk Analytics demonstrated a strong positive effect on financial performance through early risk detection, improved decision accuracy, and proactive credit monitoring. The regression results indicated that both variables jointly explain a substantial proportion of variations in financial performance among the selected banks in Abuja. The study concludes that AI-driven credit management serves as a strategic enabler of operational efficiency and financial sustainability of DMBs in Abuja, Nigeria. It recommends increased investment in intelligent credit technologies, continuous staff training, and the development of robust data governance frameworks to maximize the benefits of AI integration in Nigeria's banking sector.

Key words: Artificial Intelligence–Driven Credit Management, Automated Credit Scoring Systems, Predictive Risk Analytics, Financial Performance

INTRODUCTION

The accelerated advancement of Artificial Intelligence (AI) is transforming operational frameworks across global financial systems. In Nigeria, Deposit Money Banks (DMBs) are increasingly adopting AI-driven credit management systems as strategic tools to enhance operational efficiency, strengthen risk management, and improve overall financial performance (Husaeni, 2026). Historically, Nigeria's banking sector has faced persistent challenges, including high levels of non-performing loans, information asymmetry between lenders and borrowers, and inefficient credit appraisal mechanisms. These issues have often resulted in suboptimal lending decisions and weakened asset quality.

AI introduces a paradigm shift, moving banking practices away from traditional, judgment-based lending toward objective, predictive, and data-driven decision-making processes (Wahyuni, 2026). By leveraging machine learning algorithms, predictive analytics, and automated credit scoring models, Nigerian DMBs can now process and analyse large volumes of structured and unstructured customer data in real time (Akinwunmi, 2025). This capability enables banks to generate more accurate borrower risk profiles, design responsive loan pricing mechanisms, and accelerate credit approval timelines.

Beyond faster credit delivery, AI enhances portfolio surveillance through intelligent early-warning systems that detect emerging default patterns before they become critical. This proactive monitoring allows financial institutions to implement timely interventions, including loan restructuring, revised repayment arrangements, or targeted recovery measures, thereby safeguarding asset quality and minimizing credit losses. In Nigeria’s highly competitive banking environment, characterized by strict regulatory oversight and recurring macroeconomic volatility, the adoption of AI-based credit management systems is not merely innovative but a strategic necessity. Consequently, AI integration has become a vital pathway for banks to maintain resilience, strengthen risk governance, and sustain long-term growth (Nwachukwu, et al., 2026).

The implications of AI-driven credit management for the financial performance of Nigerian DMBs are extensive and multidimensional (Onoja, et al., 2026; Husaeni, 2026). One immediate benefit is the improved evaluation of credit risk, which reduces the probability of loan defaults and enhances portfolio quality. Lower default rates directly translate into reduced impairment provisions and stronger net interest margins, thereby contributing positively to bank profitability. Furthermore, automating credit assessment and monitoring significantly reduces operational costs associated with manual loan underwriting, documentation errors, and lengthy approval processes. These efficiencies improve key financial performance indicators, including return on assets (ROA) and return on equity (ROE).

AI technologies also enable advanced customer segmentation and the development of personalized credit products tailored to diverse borrower needs. This approach supports financial inclusion, allowing banks to extend credit to previously underserved individuals and small enterprises through the analysis of alternative data sources. By broadening access to credit while maintaining rigorous risk assessment standards, banks can diversify their portfolios and reduce exposure to sector-specific concentration risks. Moreover, AI systems strengthen regulatory compliance by generating accurate documentation, maintaining transparent audit trails, and ensuring adherence to prudential guidelines established by monetary authorities (Alsobai, & Aassouli, 2026). Despite these advantages, effective deployment of AI-driven credit systems requires robust data governance frameworks, advanced cybersecurity measures, and continuous human oversight. Without these safeguards, risks such as algorithmic bias, data misuse, and systemic vulnerabilities may compromise AI reliability. Overall, integrating AI into credit management is a critical determinant of financial resilience, operational efficiency, and competitive positioning for Nigerian DMBs within the rapidly evolving financial ecosystem (Leonelli, et al., 2026).

Deposit Money Banks in Nigeria operate in a complex and volatile credit environment, marked by high default risks, limited transparency in borrower information, and macroeconomic instability. While AI-driven credit management systems offer solutions such as improved risk prediction, automated loan monitoring, and sophisticated fraud detection, their actual impact on Nigerian banks’ financial performance remains underexplored. Much of the existing literature broadly examines financial technology adoption or digital transformation without specifically isolating AI-driven credit management tools as strategic resources influencing financial outcomes (Sarkar, 2026; Khan, et al., 2026). Empirical evidence linking AI-enabled credit scoring, loan recovery optimization, and fraud detection to measurable financial performance indicators such as ROA, ROE, and cost-to-income ratios within Nigerian DMBs remains limited and fragmented (Stefanelli, & Cotugno, 2026; Dubey, et al., 2026; Rizinski, & Trajanov, 2026). Many studies also overlook contextual factors unique to Nigeria’s banking sector, including regulatory complexities, inconsistent data quality, technological infrastructure limitations, and digital skill gaps, all of which can affect the effectiveness of AI adoption (Eberi-Kalu, 2026; Akutson, & Sani, 2026). Additionally, comprehensive longitudinal research examining whether AI integration yields sustained financial performance improvements, rather than short-term operational gains, is largely absent. This study significant research gap persists regarding the mechanisms through which AI-driven credit management translates into measurable financial outcomes in Nigeria’s banking sector. Addressing this gap is essential for advancing academic understanding and providing evidence-based insights to guide strategic decision-making and policy development within the country’s evolving financial landscape.

Statement of Hypotheses

The following hypotheses were set up to guide the study:

HO_1: Automated Credit Scoring Systems has no significant effect on financial performance of DMB in Abuja, Nigeria.

HO_2: Predictive risk analytics has no effect on financial performance of DMB in Abuja, Nigeria.

LITERATURE REVIEW

AI-Driven Credit Management

AI-driven credit management leverages artificial intelligence to automate and enhance how lenders assess, monitor, and recover credit. By analysing real-time financial and behavioural data, AI predicts borrower risk, personalizes credit decisions, detects fraud, optimizes collections, and improves portfolio performance, while simultaneously reducing human bias, operational costs, and decision-making time across lending systems. The literature on AI-driven credit management reflects a significant shift from rule-based assessment to data-intensive, predictive, and adaptive systems.

Earlier credit risk models relied primarily on statistical techniques such as logistic regression and linear discriminant analysis, focusing on limited financial indicators and structured borrower data. In contrast, contemporary research emphasizes the superiority of machine learning algorithms such as decision trees, random forests, gradient boosting, and neural networks—in capturing nonlinear relationships and complex borrower behaviour (Japinye, 2026). Scholars argue that AI systems enhance credit scoring accuracy by integrating alternative data sources, including transactional histories, social signals, mobile usage, and behavioural patterns (Sarkar, 2026; Ali et al., 2026). This broader data ecosystem reduces information asymmetry and promotes financial inclusion, particularly for underbanked populations. Studies also highlight operational efficiency gains through automation, enabling real-time risk evaluation, continuous portfolio monitoring, and dynamic limit adjustments (Baghel, & Mamodiya, 2026; Vyas, 2025).

Recent discourse extends beyond predictive performance to governance, transparency, and ethical considerations. Researchers caution that algorithmic opacity can create accountability challenges, especially when automated decisions significantly affect individuals' financial access (Ayeni, et al., 2026; Sungkarungsri, & Kiattisin, 2026). As a result, explainable AI has become a central focus, promoting model interpretability without compromising accuracy. The literature further explores bias mitigation strategies, fairness metrics, and regulatory compliance frameworks to ensure responsible deployment (Rana, & Bhambri, 2026). Empirical studies also demonstrate that AI-driven credit management improves delinquency forecasting, early warning detection, and recovery optimization through adaptive learning mechanisms (Sarkar, 2026; Sabbineni, 2026). Integration with big data analytics and cloud infrastructure enhances scalability and resilience. Overall, research portrays AI-enabled credit management as a strategic asset that balances risk reduction with customer engagement while emphasizing the need for transparent design, regulatory alignment, and continuous human oversight to maintain trust and financial stability (Uzoamaka, & Ade, 2026; Dubey, et al., 2026).

Automated Credit Scoring Systems*:* Automated credit scoring systems are data-driven tools that enable lenders to quickly assess a borrower's creditworthiness. They analyse large volumes of financial and behavioral data, apply statistical or machine learning models, and generate risk scores to guide lending decisions. These systems reduce human bias, improve consistency, accelerate approvals, and support responsible credit management across financial institutions.

The literature traces the evolution of automated credit scoring systems from traditional statistical models to advanced machine learning frameworks (Jammalamadaka, & Itapu, 2023). Early studies emphasized logistic regression and discriminant analysis for predicting borrower default, prioritizing transparency and interpretability (Abbas, et al., 2025; 2026; Deng, et al., 2026). Over time, researchers noted limitations in handling nonlinear relationships and large, complex datasets, prompting the adoption of decision trees, neural networks, and ensemble techniques, which offered stronger predictive accuracy. Scholars also highlighted the importance of data quality, variable selection, and model validation in ensuring system reliability and robustness (Jafari, & Mousavi, 2026; Sarkar, 2026). Recent research emphasizes fairness, explainability, and ethical deployment (Rama, & Prinsloo, 2025). Concerns about algorithmic bias, data privacy, and regulatory compliance have led to interdisciplinary investigations. Contemporary literature stresses balancing predictive power with accountability, ensuring that automated systems support responsible lending while maintaining financial inclusion and consumer trust (Arowona, & Yinusa, 2025).

Predictive Risk Analytics*:* Predictive risk analytics is a data-driven approach that uses statistical modeling, machine learning, and historical information to identify patterns indicating potential risks before they occur. By forecasting the likelihood and impact of adverse events, organizations can prioritize mitigation strategies, allocate resources efficiently, and support proactive, evidence-based decision-making across financial, operational, security, and strategic domains.

This field has evolved from traditional statistical risk assessment into a data-driven discipline integrating machine learning, big data infrastructures, and domain-specific expertise. Scholars highlight its ability to transform historical records into forward-looking insights that anticipate financial losses, operational disruptions, health complications, and security threats (Kera, & Dewanti, 2026; Renshaw, 2026). Early research focused on regression models and probability theory, whereas recent studies emphasize ensemble learning, neural networks, and real-time streaming analytics (Verma, et al., 2025; Alhumaidi, et al., 2025). Researchers consistently note that model transparency, interpretability, and ethical governance remain critical alongside predictive accuracy (Shafik, et al., 2026; Randeniya, et al., 2026).

The literature also explores sector-specific applications, including banking fraud detection, supply chain resilience, insurance underwriting, and health surveillance (Islam, & Islam, 2025). Comparative analyses indicate that hybrid frameworks combining statistical reasoning with machine learning often outperform single-method approaches (Alawi, Al-Sodani, 2026; Kmen, et al., 2026). However, scholars caution that data quality, bias mitigation, regulatory compliance, and organizational readiness significantly influence implementation outcomes (Ansari, et al., 2026; Boyina, & Chettier, 2026).

Financial Performance

Financial performance is how effectively an organization utilizes its resources to generate revenue, manage costs, and create sustainable value over time. It is commonly assessed through indicators such as profitability, liquidity, efficiency, and growth, which collectively reflect a firm’s overall economic health. By analysing financial statements, cash flows, and returns on investment, stakeholders can evaluate operational success, strategic decisions, and an organization’s capacity to remain competitive, meet its obligations, and achieve long-term financial stability in a changing economic environment.

Financial performance analysis often begins with examining how scholars conceptualize and measure organizational success. Key measures include profitability, liquidity, solvency, and efficiency indicators, such as return on assets, return on equity, net profit margin, and current ratios (Yahaya, 2026; Giyatiningrum, 2026). Researchers argue that these metrics provide a structured framework for assessing how efficiently a firm uses its resources to generate earnings and sustain operations (Amanda, 2026; Fransisca, et al., 2026). Beyond traditional accounting measures, contemporary studies also incorporate market-based indicators, including share price performance and earnings per share, to reflect investor perceptions and market confidence. The literature underscores that financial performance is shaped by internal factors such as management efficiency, capital structure decisions, and operational strategies (Ahmed, et al., 2024).

Extensive research further links financial performance to external determinants, including economic conditions, regulatory frameworks, technological advancements, and competitive pressures (Yahaya, 2026; Duong, & Nguyen, 2026). Scholars have emphasized the importance of corporate governance, innovation, and sustainability practices in influencing long-term financial outcomes (Ciurel, & Dobrescu, 2025; Limna, 2026; Babic, et al., 2026). Overall, the literature suggests that financial performance is multidimensional, dynamic, and context-dependent, necessitating integrated evaluation approaches to enable meaningful interpretation and informed strategic decision-making (Imam-Binuyo, et al., 2026).

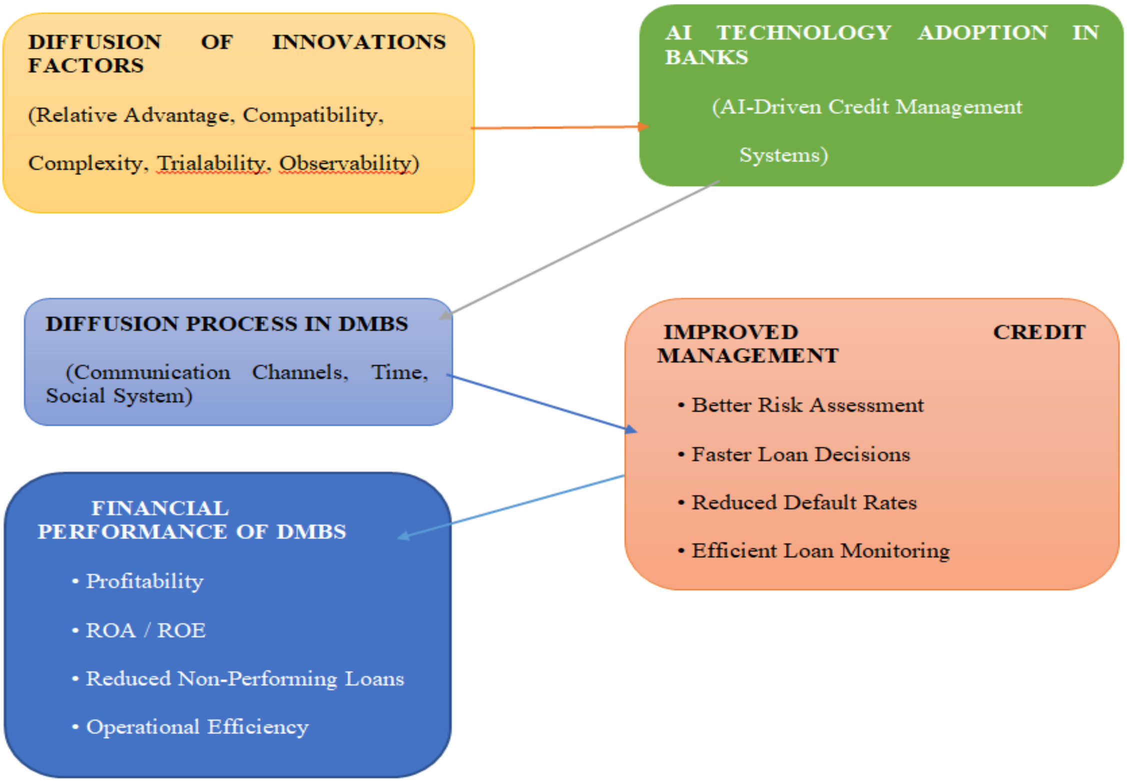
Theoretical Framework

The study adopted Diffusion of Innovations Theory to offer a robust analytical framework for examining the effects of artificial intelligence (AI)–driven credit management on the financial performance of Deposit Money

Banks (DMBs) in Nigeria. Originally developed by Everett Rogers, this theory explains how new technologies spread within social systems over time (Singh & Strzelecki, 2026; Tsogbe, et al., 2026). AI-powered credit management tools including automated risk assessment, predictive analytics, and real-time loan monitoring that constitute technological innovations whose adoption depends on factors such as perceived relative advantage, compatibility with existing banking processes, complexity, trialability, and observability (Singh, & Strzelecki, 2026; Reis, & Pinheiro, 2025). These characteristics significantly influence the decision of Nigerian DMBs to adopt such systems, especially in a competitive and rapidly evolving financial environment (Hamzah, et al., 2026; Kumar, et al., 2025).

Moreover, the theory supports evaluating how institutional readiness, communication channels, and leadership engagement affect both the speed and depth of adoption. As banks witness improvements in loan recovery rates, reductions in non-performing assets, and enhanced profitability among early adopters, the diffusion of AI-based credit management accelerates. Consequently, this framework effectively links the uptake of innovation with tangible financial performance outcomes.

THEORETICAL MODEL



The model assumes that banks adopt AI technologies only when they perceive them as beneficial and compatible with existing systems. According to the Diffusion of Innovations Theory, innovations spread gradually as organizations observe their usefulness and learn how to implement them effectively. When AI systems are integrated into credit management, banks enhance their analytical capacity to assess borrowers and monitor loan performance. This leads to a reduction in loan losses and operational inefficiencies. Over time, these improvements translate into stronger financial performance, particularly through increased profitability and improved asset quality.

The theoretical framework based on the Diffusion of Innovations Theory provides a robust lens for understanding how artificial intelligence technologies shape credit management practices and financial performance in deposit money banks. By framing AI-driven credit management as an innovation, the model explains how the adoption and diffusion of these technologies within banking institutions can enhance operational efficiency, strengthen credit risk management, and ultimately improve financial outcomes. Specifically, in the context of deposit money banks in Abuja, the model highlights the critical role of technological adoption, organizational readiness, and the diffusion of innovations in shaping the future of banking operations and ensuring financial sustainability.

Empirical Review

Benedicta, et al. (2025) conducted an empirical study examining the adoption of artificial intelligence (AI)–driven credit scoring models and their impact on financial reporting transparency in Nigerian deposit money banks (DMBs). The research employed a qualitative approach, relying primarily on secondary sources, including annual reports, regulatory filings, and compliance documents from the Central Bank of Nigeria (CBN) and the Securities and Exchange Commission (SEC). The analysis focused on a thematic evaluation of disclosure practices, governance frameworks, and transparency in reporting AI-driven credit scoring outcomes. Findings indicated that Tier-1 and globally affiliated banks demonstrated higher levels of disclosure (59%) compared to Tier-2 and local banks (34%). Key factors supporting effective disclosure included the use of advanced analytics in credit risk management (68%), governance oversight of credit models (61%), impairment and loan loss provisioning practices (55%), and the explainability of AI outcomes (38%). Conversely, barriers such as model complexity (66%), inadequate regulatory guidance (58%), sensitivity of proprietary information (54%), and limited technical reporting capacity (49%) hindered comprehensive disclosure. The study further observed that robust disclosure positively influenced stakeholder confidence in reported credit risk (41%), the credibility of financial statements (38%), and overall transparency (39%). The authors concluded that comprehensive disclosure of AI-driven credit practices is crucial for enhancing the reliability of financial reports and fostering investor trust in Nigerian DMBs.

Sarkar, (2026) provided a systematic empirical review of AI-driven credit risk assessment models in commercial banking from 2018 to 2026. Following PRISMA guidelines, the review synthesized findings from 27 peer-reviewed studies, exploring machine learning and deep learning applications in default probability estimation, exposure modelling, early-warning systems, portfolio monitoring, and automated credit decision-making. The evidence consistently demonstrated that AI models outperform traditional statistical methods in predictive accuracy, sensitivity to borrower behaviour, and portfolio risk assessment, particularly when ensemble techniques and temporal or transactional features are incorporated. Despite these advantages, the review highlighted ongoing challenges, including data quality issues, limited model generalizability, low explainability, potential fairness biases, model drift, and regulatory compliance concerns. Sarkar emphasized a gap between research innovation and operational adoption, driven by practical requirements such as continuous monitoring, thorough documentation, and system interoperability. The review concluded that while AI-driven models hold substantial promise, there is an urgent need for interpretable architectures, standardized validation frameworks, privacy-preserving data ecosystems, and benchmarking mechanisms to ensure regulatory compliance and trustworthy deployment in commercial banking.

METHODOLOGY

Research Design

The researchers adopted explanatory and analytical research design to investigate artificial intelligence (AI)-driven credit management and the financial performance of deposit money banks (DMBs) in Abuja, Nigeria, is well justified. This design is particularly suitable because it allows for the systematic exploration of causal relationships. Specifically, it enables researchers to examine how AI applications in credit assessment, risk prediction, and loan monitoring influence key financial metrics such as profitability, asset quality, and operational efficiency. The analytical component of this design facilitates rigorous evaluation of both quantitative and qualitative data, uncovering patterns, correlations, and the underlying mechanisms that drive financial performance. By integrating explanation with analysis, this approach supports evidence-based conclusions, offering policymakers and bank managers insights not only into the magnitude of AI's impact but also into its strategic implications for sustainable growth and risk mitigation within the Nigerian banking sector.

Sampling Techniques

The study employed stratified random sampling as an appropriate technique, to ensures the representative inclusion of diverse bank categories, customer segments, and regional operations. By dividing the population into strata based on factors such as bank size, geographic location, and credit portfolio type, this method captures subtle variations in AI adoption, allowing for more precise measurement of its effects on financial indicators

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like profitability, liquidity, and non-performing loans. Additionally, stratified random sampling enhances the reliability and generalizability of findings across Nigeria's banking sector. It enables researchers to systematically analyse specific subgroups without overgeneralizing, ensuring that insights regarding AI-driven credit management accurately reflect operational realities. Consequently, this method supports robust, evidence-based recommendations for both policy formulation and managerial decision-making.

Population of the Study and Sample Size

Table 3.1 Population Frame of Selected DMBs in Abuja, Nigeria.

S/N	Selected DMBs	Management Staff	Employees	Total
1.	Zenith Bank Plc	27	102	129
2.	Access Banks Plc	31	109	140
3.	First Bank Plc	36	98	134
4.	Union Bank Plc	29	70	99
5.	GTCO Plc	38	112	150
	Total	**161**	**491**	**652**

Researcher's Computation (2026)

The sample size for this study was determined by Yamane's (1967) formula. This sample size helped the study ensure the appropriate and equal participation of each prospective respondent from the selected DMBs in Abuja, Nigeria. Based on the Yamane formula, the sample size determined by the above formula was 248 respondents from the selected DMBs in Abuja, Nigeria.

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

Where: N = Population Size 1= Constant

n= Sample size

e = Error of Margin $(0.05)^2$

$$n = \frac{652}{1+652\ (0.05)^2} \quad n = \frac{652}{1+652(0.0025)} = \frac{652}{1+1.63}$$

$$n = \frac{652}{2.63}$$

n = 247.91 = 248 respondents

Table 3.2 Sample Size

S/N	BUA Nigeria Plc	Population	Sample Size
1.	Management Staff	161	61
2.	Employees	491	187
	Total	**652**	**248**

Researcher's Computation (2026)

The study employed a 95% confidence level with a 5% margin of error, resulting in a sample size of 248 respondents. To address potential challenges such as non-responses, incomplete questionnaires, or loss of questionnaires during transportation, an additional 20% of the sample was added as a contingency (Naing et al., 2022; Anderson et al., 2017; Cochran, 1963). Calculating 20% of 248 gives 49.6, which was rounded to 50, bringing the total sample size to 298. To ensure comprehensive and representative data, the sample was distributed with 30% allocated to management and 70% to employees.

Sources of Data Collection

This study relied on primary data. Data were collected directly from employees and management using structured questionnaires, providing first-hand insights into how pension management policies affect employee performance in the selected DMBs in Abuja. This approach captures real-time, context-specific information, which is essential for understanding nuanced employee perceptions and experiences. The combination of these data sources enables a robust exploration of the research problem, integrating practical employee perspectives with theoretical and documented evidence. This methodological approach supports empirically grounded conclusions regarding the impact of artificial intelligence–driven credit management on the financial performance of DMBs in Abuja, Nigeria.

Methods of Data Analysis

Data analysis involved both descriptive and inferential statistical techniques. Descriptive statistics, including percentages, tables, and other related tools, were used to summarize the data. For inferential analysis, Multiple Linear Regression, Analysis of Variance (ANOVA), and correlation analysis were applied using the Statistical Package for Social Science (SPSS Version 27.0). The use of multiple linear regression was justified as it allows for the examination of the impact of artificial intelligence–driven credit management on the financial performance of DMBs. This technique enables the researcher to assess the strength, direction, and statistical significance of each independent variable while controlling for the effects of others. It also enhances predictive accuracy and supports robust hypothesis testing by explaining the proportion of variation in employee performance attributable to pension management policies. Regression analysis is particularly suitable for social science research with large samples, such as this study, and aligns with the objective of determining causal relationships rather than simple associations.

ANOVA was employed to complement regression analysis by comparing mean differences in financial performance across categories of artificial intelligence–driven credit management. This technique determines whether observed variations are statistically significant, thereby strengthening the inferential rigor of the study. Correlation analysis was used to examine the direction and strength of the relationships between pension management policies and employee performance. It provides preliminary evidence of associations, identifies potential multicollinearity issues, and supports the appropriateness of regression modelling. Together, these techniques enhance the methodological rigor of the study, ensure triangulation of findings, and increase the reliability and validity of conclusions drawn within the context of the Nigerian banking sector.

Model Specification

The study's variables have a structural model that addresses the two main variables in the study, which were the independent and dependent variables. The independent variable was Artificial Intelligence–Driven Credit Management= AICM that was proxies by (I) Automated Credit Scoring Systems = ACSS (II) Predictive Risk Analytics = PRA. Financial Performance = FP. As a result, FP is the dependent variable and the two dimensions of are the independent variables AICM corresponding to HO1, and HO2, the regression model is specified as follows:

Structural Regression Model

The general form of the regression model can be expressed as:

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$FP=\beta0+\beta1ACSS+\beta2PRA+\epsilon$

Where:

FP = Financial Performance (dependent variable)

ACSS = Automated Credit Scoring Systems (dimension of AICM)

PRA= Predictive Risk Analytics (dimension of AICM)

$\beta0$ = Intercept (baseline financial performance when ACSS and PRA are zero)

$\beta1,\beta2$= Regression coefficients representing the effect of each AICM dimension on FP

ϵ = Error term (captures unobserved factors affecting FP)

DATA ANALYSIS AND DISCUSSION OF FINDINGS

Test of hypothesis One

HO_1: Automated Credit Scoring Systems has no significant effect on financial performance of DMB in Abuja, Nigeria.

Model 1

HO1: $FP=\beta0+ \beta_1ACSS_1+\varepsilon$

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.713[a]	.508	.506	.36425
a. Predictors: (Constant), ACSS				

The table indicates a strong positive relationship between Automated Credit Scoring Systems (ACSS) and the financial performance (FP) of Deposit Money Banks (DMBs) in Abuja, Nigeria, with an R of 0.713 and R^2 of 0.508, suggesting ACSS explains over 50% of FP variations. The model's low standard error (0.36425) shows reliable predictive accuracy, implying ACSS significantly influences financial outcomes.

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	36.563	1	36.563	275.580	.000[b]
	Residual	35.425	267	.133		
	Total	71.988	268			
a. Dependent Variable: FP						
b. Predictors: (Constant), ACSS						

The ANOVA results revealed a highly significant relationship between Automated Credit Scoring Systems (ACSS) and the financial performance (FP) of Deposit Money Banks (DMBs) in Abuja, Nigeria. The regression

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model explains a substantial portion of the variance, with a Sum of Squares of 36.563 and an F-value of 275.580, accompanied by a p-value of .000, indicating strong statistical significance. This outcome rejects the null hypothesis (HO1), demonstrating that the implementation of ACSS positively and significantly impacts the financial performance of DMBs.

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.478	.155		9.533	.000
	ACSS	.651	.039	.713	16.601	.000
a. Dependent Variable: FP						

The analysis of the coefficients for HO1 reveals that Automated Credit Scoring Systems (ACSS) significantly influence the financial performance (FP) of deposit money banks in Abuja, Nigeria. The unstandardized coefficient (B = 0.651, p = 0.000) indicates a strong positive effect, meaning that improvements in ACSS are associated with substantial increases in FP. The standardized beta (β = 0.713) further confirms that ACSS is a dominant predictor of financial outcomes, while the t-value (16.601) underscores the reliability and statistical significance of this relationship, rejecting the null hypothesis.

Testing of hypothesis Two

HO_2: Predictive risk analytics has no effect on financial performance of DMB in Nigeria.

Model 2

HO2: $FP=\beta 0+ \beta_2 PRA_2+\varepsilon$

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.775[a]	.600	.599	.32504
a. Predictors: (Constant), PRA				

The analysis of Model 2 reveals that predictive risk analytics (PRA) substantially influences the financial performance (FP) of deposit money banks (DMBs) in Abuja, Nigeria. With a correlation coefficient (R) of 0.775, the model indicates a strong positive relationship between PRA and FP, while the R^2 value of 0.600 shows that approximately 60% of variations in financial performance are explained by predictive risk analytics. The adjusted R^2 of 0.599 confirms the model's robustness, and the low standard error of 0.32504 indicates precise estimations, suggesting PRA is a critical driver of financial outcomes.

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	42.383	1	42.383	401.159	.000[b]
	Residual	28.209	267	.106		

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	Total	70.592	268			
a. Dependent Variable: FP						
b. Predictors: (Constant), PRA						

The ANOVA results for HO2 indicate that Predictive Risk Analytics (PRA) significantly influences the financial performance of deposit money banks (DMBs) in Abuja, Nigeria. The regression model shows a substantial sum of squares (42.383) and a high F-value of 401.159, with a p-value of .000, well below the 0.05 significance threshold, confirming statistical significance. This suggests that PRA effectively predicts financial outcomes, explaining a meaningful portion of variance in financial performance, while the residual variance (28.209) reflects other unexplained factors.

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.404	.133		10.564	.000
	PRA	.657	.033	.775	20.029	.000
a. Dependent Variable: FP						

The analysis of the coefficients table for HO2 reveals that Predictive Risk Analytics (PRA) exerts a statistically significant positive effect on the financial performance (FP) of Deposit Money Banks (DMBs) in Abuja, Nigeria. The unstandardized coefficient ($B = 0.657$, $p < 0.001$) indicates that for every one-unit increase in PRA adoption, financial performance improves by 0.657 units, while the standardized coefficient (Beta = 0.775) highlights a strong predictive influence. The t-value of 20.029 confirms the relationship's robustness, leading to the rejection of the null hypothesis and affirming PRA as a critical driver of banking sector performance.

Discussion of Findings

The findings from the analysis of ACSS revealed a strong and statistically significant relationship with the financial performance of DMBs in Abuja, Nigeria. The model summary indicates a high correlation coefficient ($R = 0.713$) and an R^2 of 0.508, suggesting that over 50% of variations in financial performance can be attributed to ACSS. The ANOVA results reinforce this, showing a significant F-value of 275.580 ($p = 0.000$), confirming that the regression model is a reliable predictor of FP. Coefficient analysis further demonstrates the magnitude of this effect, with an unstandardized coefficient ($B = 0.651$) and a standardized beta ($\beta = 0.713$), alongside a t-value of 16.601, indicating that enhancements in ACSS are strongly associated with increased financial outcomes. Consequently, the null hypothesis (HO1) is rejected, establishing ACSS as a dominant factor in banking sector performance and underscoring its importance in driving efficiency, loan assessment accuracy, and profitability (Sarkar, 2026; Benedicta, et al., 2025; Baghel, & Mamodiya, 2026).

Similarly, PRA showed a pronounced positive influence on the financial performance of DMBs in Abuja, Nigeria. Model 2 indicates a higher correlation ($R = 0.775$) and an R^2 of 0.600, revealing that PRA explains 60% of FP variations, with low estimation error (0.32504) reflecting precision. The ANOVA output, with an F-value of 401.159 ($p = 0.000$), confirms strong statistical significance, while the coefficients table shows that each unit increase in PRA contributes 0.657 units to FP, supported by a robust Beta of 0.775 and a t-value of 20.029. These results reject HO2, affirming that PRA is a critical driver of financial performance, enhancing risk assessment, decision-making, and profitability. Collectively, the findings highlight that integrating ACSS and PRA into banking operations significantly strengthens financial outcomes, demonstrating the transformative impact of AI-driven credit management on Nigerian banks (Baghel, & Mamodiya, 2026; Ansari, et al., 2026; Ayeni, et al., 2026; Babic, et al., 2026).

CONCLUSION AND RECOMMENDATIONS

Conclusion

The findings from the analysis provide compelling evidence that Artificial Intelligence–Driven Credit Management (AICM) tools, specifically Automated Credit Scoring Systems (ACSS) and Predictive Risk Analytics (PRA), significantly enhance the financial performance of Deposit Money Banks (DMBs) in Nigeria. For HO1, the strong positive correlation ($R = 0.713$) and R^2 value of 0.508 indicate that ACSS accounts for over 50% of the variation in financial performance, demonstrating a substantial explanatory power. The ANOVA results, with an F-value of 275.580 and a p-value of 0.000, confirm the statistical significance of this relationship. Coefficient analysis further underscores that those improvements in ACSS directly translate to higher financial outcomes, with the unstandardized coefficient ($B = 0.651$) and standardized beta ($\beta = 0.713$) illustrating ACSS as a dominant predictor. These results conclusively reject the null hypothesis, establishing that the deployment of ACSS is critical for operational efficiency and profitability in Nigerian banking institutions.

Similarly, HO2 analysis revealed that Predictive Risk Analytics (PRA) exerts an even more pronounced influence on financial performance, with a correlation coefficient of 0.775 and R^2 of 0.600, indicating that PRA explains 60% of the variation in financial outcomes. The ANOVA results show a high F-value of 401.159 ($p = 0.000$), reinforcing the robustness and significance of the model. The coefficients ($B = 0.657$, Beta = 0.775, $t = 20.029$) confirm that PRA is a powerful predictor of financial performance, whereby incremental improvements in PRA adoption significantly boost banking profitability. Overall, the study establishes that AI-driven credit management tools are not only statistically significant but also practically indispensable for enhancing financial efficiency, risk mitigation, and competitive advantage among DMBs in Nigeria, highlighting their strategic role in modern banking operations.

Recommendations

Based on the analyses of HO1 and HO2, it is recommended that DMBs in Nigeria fully integrate and enhance Automated Credit Scoring Systems (ACSS) within their credit management processes. The strong positive relationship between ACSS and financial performance, evidenced by an R^2 of 0.508 and a significant beta coefficient, suggests that leveraging ACSS can improve loan assessment accuracy, reduce default risks, and ultimately boost profitability, making it a strategic tool for financial optimization.

Additionally, banks should prioritize the implementation of Predictive Risk Analytics (PRA) to further strengthen financial outcomes. With PRA explaining 60% of the variance in financial performance and exhibiting high statistical significance, its adoption enables proactive risk identification, informed decision-making, and improved capital allocation. Collectively, ACSS and PRA should be integrated into the banks' digital credit frameworks, supported by training, robust data infrastructure, and continuous monitoring, to sustain competitive advantage and enhance long-term financial stability in Nigeria's banking sector.

Contributions to Knowledge

This study advances knowledge by examining the intersection of Artificial Intelligence (AI) and credit management within Nigerian Deposit Money Banks (DMBs), particularly in Abuja, addressing gaps in theory, empirical evidence, methodology, and context. While previous research on Nigerian banking has largely concentrated on conventional credit risk practices such as collateral evaluation, loan monitoring, and financial ratios limited attention has been given to AI-driven tools like machine learning algorithms, predictive analytics, automated credit scoring, and intelligent risk assessment. By exploring how these AI applications influence financial performance, this research extends understanding beyond traditional frameworks, demonstrating that AI can enhance credit decision accuracy, improve predictive risk modelling, facilitate early detection of loan defaults, and automate borrower monitoring, ultimately strengthening loan portfolio quality and profitability.

The study contributes context-specific insights to the underrepresented Nigerian financial environment, recognizing that findings from developed economies may not generalize due to differing financial infrastructures, regulatory frameworks, and technological adoption levels. Theoretically, it integrates AI adoption and digital transformation frameworks with financial performance theories, bridging classical banking models with contemporary technological perspectives. Methodologically, it advances prior approaches by combining financial metrics with managerial and operational insights, providing a holistic view of AI deployment and its measurable outcomes. By introducing AI-specific operational indicators, the study fills empirical and methodological gaps, offering practical guidance for banking management and regulators seeking to leverage technology for improved credit management. It thereby strengthens understanding of technology-driven financial performance in emerging economies.

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