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Artificial Intelligence and Financial Performance of Listed Deposit Banks in Nigeria

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ABSTRACT

This study examines the relationship between Artificial Intelligence (AI) adoption and the financial performance of Nigeria's top-tier deposit money banks over a ten year period (2015–2024). Against the backdrop of Nigeria's accelerating digital transformation, the research examines how AI-driven innovations enhance profitability within the banking sector. The analysis focuses on five Tier-1 institutions namely; First Bank, UBA, GTBank, Access Bank, and Zenith Bank collectively known as the FUGAZ banks. Financial performance is measured using Return on Assets (ROA), while AI adoption is proxied through three major applications: Automated Chatbot Systems (ACBS), Deep Learning Models in credit risk management (DLM), and I-Comply fraud detection systems (I-COMP). Data were obtained from the audited annual reports of the five listed banks and validated through a supplementary survey of bank IT and operations managers. Each AI variable was operationalized as a binary indicator (1 = adopted by the bank in a given year; 0 = otherwise) and aggregated into a balanced panel dataset.

Data were tested for stationarity and cointegration using Levin–Lin–Chu and Pedroni tests. Based on the confirmation of long-run equilibrium relationships, a Panel Fully Modified Ordinary Least Squares (FM-OLS) regression was employed, supported by robustness checks using fixed-effects estimation. The results reveal that ACBS, DLM, and I-COMP each have a positive and statistically significant association with ROA ($p < 0.05$), with an overall model explanatory power (R^2) of 0.71. The Durbin–Watson statistic of 1.82 indicates no serial correlation, and diagnostic tests confirm model adequacy.

The findings imply that AI adoption significantly enhances profitability through improved customer interaction, efficient credit assessment, and proactive fraud prevention. The study contributes to empirical literature on digital transformation in emerging markets and recommends that Nigerian banks deepen their AI integration strategies to strengthen competitiveness and shareholder value in an increasingly data-driven economy.

Keywords: Artificial intelligence, Banking sector, Panel FM-OLS

INTRODUCTION

The COVID-19 pandemic accelerated the global adoption of Artificial Intelligence (AI), reshaping industries and organizational processes. A PricewaterhouseCoopers (PwC, 2020) report indicates that 52% of firms fast-tracked their AI integration plans, with 86% expecting AI to become a mainstream operational technology by 2021. Similarly, a survey by *The AI Journal* (2020) found that business leaders anticipated AI to enhance efficiency by 74%, support new business models by 55%, and facilitate innovation in products and services. These statistics highlight the growing acceptance of AI as a transformative technology capable of performing functions once reliant on human expertise, thereby redefining production, service delivery, and strategic decision-making across industries.

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AI's global diffusion has inspired widespread transformation in sectors such as healthcare, manufacturing, and finance, driving automation, precision, and data-driven decision-making. Nevertheless, a persistent need remains to clarify the practical meaning, benefits, and risks of AI deployment, particularly in developing economies. Public concerns persist regarding job displacement, data privacy, and ethical implications, even as businesses leverage intelligent systems for operational efficiency and profitability. Modern economies now operate in an era where automation, robotics, and machine learning underpin competitive advantage. In the financial sector, AI has evolved from a peripheral innovation to a core enabler of digital banking, customer analytics, risk management, and fraud prevention.

Globally, AI integration in the banking industry has delivered tangible results. In India, AI applications improved credit scoring and loan processing, strengthened regulatory compliance, and reduced non-performing assets. In Australia, AI-enabled systems supported real-time data analytics, improving personalization and customer experience while lowering operational costs. Similarly, Canadian banks reported improved fraud detection and credit risk assessment through AI tools, alongside enhanced customer satisfaction via intelligent service platforms. These global experiences underscore AI's potential to revolutionize financial intermediation by reducing costs, mitigating risk, and improving efficiency.

Nigeria's banking sector, one of the most dynamic in Sub-Saharan Africa, has historically embraced technological innovation to sustain competitiveness. As custodians of public funds, Nigerian banks operate under stringent regulatory oversight, which often tempers innovation adoption. However, competitive pressures, regulatory changes, and macroeconomic volatility have compelled banks to pursue cost efficiency and innovation simultaneously. A large proportion of operational expenditure in Nigerian banks relates to IT infrastructure, prompting institutions to explore AI integration as a strategic alternative to traditional systems. Consequently, the evolution of AI has influenced updates in banking standards, digital service delivery, and compliance frameworks, paving the way for its growing integration across Nigerian financial institutions.

Despite AI's transformative potential, the empirical understanding of its effect on bank performance in Nigeria remains limited. Most existing studies emphasize AI's qualitative benefits such as cost reduction, fraud prevention, and customer service enhancement without establishing measurable, quantitative relationships between AI adoption and financial performance. Specifically, there is little evidence linking AI utilization to profitability indicators such as Return on Assets (ROA), which remain vital for assessing banks' efficiency, stability, and shareholder value. Furthermore, variations in AI adoption levels across Nigerian banks—shaped by differences in financial capacity, regulatory environment, and institutional readiness—underscore the need for empirical investigation.

Although international literature provides robust evidence of AI's contributions to financial performance and operational efficiency, these findings may not directly translate to the Nigerian context due to differences in technological maturity, data infrastructure, and regulatory frameworks. Understanding how AI influences the performance of Nigerian listed deposit money banks is thus essential for guiding both management and policy decisions. As the sector integrates tools such as machine learning, natural language processing, and intelligent fraud detection systems, the question remains: to what extent do these innovations improve financial outcomes?

This study seeks to fill this empirical gap by examining the impact of AI adoption on the financial performance of Nigeria's top-tier listed deposit money banks over a ten-year period (2015–2024). The study period, 2015–2024, is deliberately chosen to capture the most relevant decade of technological transformation in Nigeria's banking sector following the CBN's digital transformation and fintech integration policies. Reliable data and consistent AI deployment emerged from 2015, while the 2020–2022 pandemic period marked accelerated technological uptake. AI adoption is proxied by three core applications Automated Chatbot Systems (ACBS), Deep Learning Models (DLM), and I-Comply fraud detection systems (I-COMP) chosen for their functional representation of AI in customer engagement, credit risk management, and compliance operations respectively. Together, these indicators reflect the multidimensional nature of AI-driven efficiency, profitability, and risk control in Nigeria's banking industry. By employing panel econometric methods, the study contributes to the growing literature on digital transformation and financial performance in emerging markets.

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The significance of this research lies in its dual contribution to academia and practice. Academically, it extends the understanding of AI–performance relationships in a developing economy's banking system. Practically, it provides insights for bank executives, policymakers, and regulators on how targeted AI deployment can enhance efficiency, competitiveness, and shareholder value. Ultimately, this study positions AI not merely as a technological trend but as a strategic lever for sustainable financial growth and innovation within Nigeria's banking sector.

LITERATURE REVIEW

Concept of Financial Performance

Financial performance reflects how efficiently banks utilize their assets to generate profits and sustain growth. It is a central indicator of management efficiency, strategic effectiveness, and overall business success (Hannon, 2021; Ichsan, 2021). In banking, performance evaluation aids in resource allocation, regulation, and executive accountability (Abdulnafea, 2022). Among various measures, Return on Assets (ROA**)** I.e. the ratio of net income to total assets—offers a robust indicator of profitability by accounting for both equity and debt financing (Ahamed, 2017). It captures the efficiency of asset use and is widely applied in comparative financial analysis (Bashari, 2019). This study therefore adopts ROA as a proxy for financial performance.

Artificial Intelligence in the Banking Sector

The banking industry, driven by information systems and data exchange, has increasingly leveraged Artificial Intelligence (AI) to enhance operational efficiency and customer service (Ronald, 2018). AI is not intended to replace human agents but to optimize decision-making, risk management, and compliance through automation and predictive analytics (McKinsey, 2015). Foundational AI technologies machine learning, deep learning, and natural language processing enable automation, chatbot interactions, real-time fraud detection, and advanced analytics (Dan, 2018). These applications directly influence performance outcomes by reducing cost, minimizing errors, and improving customer satisfaction.

Opportunities and Challenges of AI Adoption

AI adoption offers significant opportunities in banking. It improves operational efficiency by automating repetitive processes and freeing staff for high-value tasks (Kaur, 2020; Umamaheswari, 2023); enhances cost optimization through faster, error-free digital transactions (Noreen, 2023); and strengthens customer engagement by enabling personalized, responsive service delivery (Li, 2023; Al-Araj, 2022). Furthermore, AI enhances risk management and fraud detection through machine learning algorithms that identify anomalies in real time (Naik, 2022; Mytnyk, 2023).

However, adoption challenges persist. Concerns include data privacy and ethical implications in customer information processing (Fares, 2022), organizational resistance to cultural and structural change (Fountaine, 2019), and regulatory uncertainty that may slow innovation (Truby, 2022). Effective AI deployment in banking therefore requires a balance between innovation, compliance, and ethical governance.

Major AI Applications in Banking

AI tools have become integral to modern banking functions:

- **Automated Chatbot Systems (ACBS):** Enable continuous, interactive customer support and streamline service delivery (Shashank & Rashmi, 2021).
- **Deep Learning Models (DLM):** Enhance credit risk assessment and loan processing accuracy using dynamic, data-driven insights (Chen et al., 2020).
- **Intelligent Fraud Detection (I-COMP):** Identify abnormal transaction patterns, reducing operational and reputational risks (Mohapatra, 2023).

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These applications ACBS, DLM, and I-COMP—form the operational focus of this study as they directly reflect measurable AI adoption across Nigeria's top-tier banks.

Artificial Intelligence in Nigerian Banking

Nigeria's banking sector has evolved from manual operations to fully digitized systems, integrating mobile banking, ATMs, and real-time online platforms. The growing adoption of AI reflects the push for improved efficiency, risk control, and customer-centric services (Liadi, 2019). Successful deployment, however, depends on strategic alignment between technology investment, skilled manpower, and adaptive management structures. This digital shift positions AI as a key enabler of competitive advantage in Nigeria's financial landscape.

Theoretical Review

Bank-Focused Theory

Bank-Focused Theory was propounded by Kapoor in the year 2010. This theory assumes that traditional banks adopt non-traditional low-cost delivery channels to provide banking services to its existing customers. It explains the level of convenience, accuracy, speed and quality through the use of technology with which conventional banks uses to meet the ever growing and dynamic customers' request on timely basis. This theory is built on the principle of Business Process Improvement (BPI) of Thomas H. Davenport (1990) which sought to recognize inefficiencies, delays, obstructions and wastage with the goal of eliminating them through new and improved procedures which are more effective and provide greater benefits to the customers. Examples of this can be seen on how automated teller machines (ATMs), internet banking or mobile phone banking, POS and among others can be used to personalize customers' transaction without having to waste time and energy queuing in the banking hall for long time. Banks overcome these difficulties by providing branchless banking services via a user-friendly interface all that is required is inputting all necessary information into the system then the entire transaction is complete.

Bank-Focused Theory is most related and suited for the concept of Automated Chatbots Banking Services as it continually advocates branchless banking which other theories such as Bank-Led Theory, Non-bank Theory, etc do not portend. Bank-Led Theory as postulated by Lyman, Ivatury and Staschen (2006) emphasizes the role of retail agents who acts as a link between the banks and the customers and Non-bank-Led Theory as popularized by Hogan (1991) argued that customers do not deal with any bank and they do not maintain any bank account. These theories have no substantial relevance in this research work. Based on Bank-Focused Theory the customers' primary concerns are the quality of experience, security of identity and transactions, reliability and accessibility of service and extent of personalization allowed. This engenders customers' patronage of the bank's products and services, with the resultant effect of boosting organizational Return on Investment.

Machine Learning Theory

According to Avrim (2014), Machine Learning Theory also has a number of fundamental connections to other disciplines. This is centered on the exact needs for which machine learning can be used in order to maximize performance, especially in domains that require information to be interpreted and acted upon. In the banking sector, machine learning techniques have been demonstrated to outperform traditional statistical methods in both classification and accuracy for prediction especially in credit risk assessments, cyber security evaluation and identifying fraudulent transactions. To evaluate a borrower's creditworthiness, banks can use machine learning models for analyzing real-time data based on the most recently conducted transactions, current market factors and relevant current events. Accessibility to semi-structured data, such as phone usage, text message activities, usage of social networks and activity to improve rating precision of loans. This makes it possible for the assessment of even qualitative factors such as the customers propensity to repay loans and consumer behavior as well. Moreover, it can help banking institutions withstand cyber-attacks, prevent data leaks, and ensure maximum security of their operations. This helps the institutions to mitigate regulatory sanctions and improve profitability.

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Empirical Review

Richman (2019) conducted an empirical study on the impact of Artificial Intelligence (AI) in Nigeria's financial sector, revealing that AI has transformed the industry's landscape. The integration of AI in Nigeria's financial sector is poised to unlock substantial opportunities, revolutionizing retail lending, product design, and the overall banking paradigm to cater to the mass market. The necessity for AI in the financial industry is underscored by the presence of favorable technological conditions, including: Convergence of speech recognition software, Mobility tracking systems (GPS, Wi-Fi) and Gesture interpretation capabilities. Advancements in machine learning intelligence are paving the way for sophisticated applications. Furthermore, the financial industry is experiencing exponential growth in data generation, which is expected to accelerate, given that AI thrives on data-driven insights.

Akinadewo (2021) investigated the connection between AI and accountants' approaches to accounting functions. The study used a structured questionnaire to collect data from 205 accountants who were specifically chosen for their experience with systems application for accounting and other financial transaction duties. Artificial intelligence has a considerable favorable impact on accountants' approach to accounting functions, according to the results of the logit regression analysis. As a result, when AI is used, accountants' approaches to functional duties will be drastically altered. The study concluded that accountants should be properly trained and retrained in a variety of AI technologies and accounting software packages in order to improve their functional abilities, effectiveness, and efficiency. In a related work, Kwarbai and Omojoye (2021) used multiple regression analysis on data acquired from 277 respondents across Nigeria's big four audit companies. The study discovered that AI has a significant impact on the accounting profession in Nigeria, and it is recommended that audit firms integrate AI into their sampling system so that, in the event of an audit, all data can be audited rather than just a sample. The findings from these studies corroborates the assertion of Ionescu (2019) who on employing structural equation modelling technique to analyse survey data collected in Romania revealed that as a result of technological improvements, the accounting profession will face a significant transformation in the near future, with routines becoming automated and associated roles becoming obsolete.

Ologe (2020) investigated 399 accounting professionals to see how much they knew about AI and how they felt about it. To investigate the effect of accountants' traits on their perception, the study utilized a between group design, an independent samples T-test, and a one way between group ANOVA. The results of a one-way ANOVA and an independent sample t-test revealed that accounting professionals in Nigeria have a high degree of awareness about the application of AI, although their knowledge is mostly theoretical, derived from personal readings and the media. Overall, accounting professionals have a favourable attitude about the use of AI in accounting, with the majority expressing support for its development and no concern about job displacement as a result of AI.

Damerji (2019) investigated the association between accounting students' level of technology readiness (TR) and AI technology adoption (TA) in a sample of 101 students from two colleges in Southern California. Technology readiness, perceived ease of use, and perceived usefulness all positively influence technological adoption, according to bivariate correlation and regression analysis. Technology readiness has a beneficial effect on perceived ease of use and effectiveness as well as perceived usefulness. According to mediation studies, opinions regarding the ease of use and utility regulate the interactions between readiness for technology and implementation.

Shashank, and Rashmi (2021), carried out “A Review of Chat bots in the Banking Sector” and found that; Chatbots are rapidly gaining acceptance in the banking industry. They are employed not only to answer customer inquiries but also to deliver a variety of services which include bill payment, transfer of funds and reviewing recent transactions and so on. Chatbots are becoming smarter as machine learning and natural language processing are integrated. By helping customers around the clock, they help employees in banks to focus on other critical tasks. Therefore, we can say that chat bots have become an essential part of the banking system.

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In the same vein, Abusalma, A. (2021) Conducted a test on the effect of artificial intelligence with its variables (ES, NN, GA, and IA) on bank performance, targeting managers at all levels, and in order to achieve the objectives of the study, a questionnaire is developed for the purpose of collecting data from the random sample. The sample consisted of (319) managers. The results showed that there is a statistically significant effect of artificial intelligence that affects bank performance through (GA, and IA)

Consequently, Elegunde, A. F., & Osagie, R. (2020) examined Artificial Intelligence and Employee Performance in the Nigerian Banking Industry, using Lagos Nigeria as a study to generalize results. Cross-sectional descriptive research design was adopted by the researcher. The population of the study was the entire employees of six (6) selected banks operating in Lagos State, Nigeria, which totaled 127 staff. The findings revealed that Artificial Intelligence complements work process in banks in Nigeria and that machine-aided tasks ease operations in banks in Nigeria. The study recommended the adoption of AI by not only banks but all other firms in the service industry; the need for all employees and people to be educated on the importance of embracing AI; the upgrading of school curriculum at all levels in developing and third world economies to incorporate AI and its accompanying gadgets.

Adeyemo, F. S., & Okoronkwo, G investigated the effect of Artificial Intelligence (AI) on the operational efficiency of deposit money banks in Lagos State, Nigeria. The study identified the types of AI technologies that are used by banks and examined the impact of the different types of technologies on the operational efficiency of five deposit money banks, namely: First Bank of Nigeria, United Bank of Africa, Guaranty Trust Bank, Access Bank, and Zenith Bank, all public liability companies with headquarters located in the Lagos metropolis. The study revealed that deep learning and fraud detection had positive and significant effects on the operational efficiency of the selected deposit money banks, while chatbots had a positive but insignificant effect

In favour of chatbots, Morgaji (2021) highlights the growing trend of chatbots in financial services digital transformation. Key takeaways include, banks should integrate chatbots into their operations, ocus on one mobile app to streamline resources and avoid customer confusion, leverage popular platforms like WhatsApp, verify chatbots on social media for consumer trust, include terms and condition, innovate for instant responsiveness, create engaging content around chatbot characters (e.g., UBA's Leo) and develop local talent with skills in AI, machine learning, and interface design for long-term success.

RESEARCH METHODOLOGY

Research Design

This study adopts an ex post facto research design within a panel data framework, given that it investigates historical data across multiple banks and time periods without manipulation of variables. The ex post facto approach is appropriate since both the adoption of Artificial Intelligence (AI) tools and financial performance outcomes have already occurred in the natural course of banking operations. The study employs a quantitative research strategy, combining descriptive, correlational, and inferential analyses to establish the causal relationship between AI adoption and bank performance.

Population of the Study

The population comprises all listed deposit money banks (DMBs) operating in Nigeria as at 2024. However, given the study’s emphasis on financial robustness, technological adoption, and regulatory visibility, attention is focused on the five top-tier (Tier-1) banks, commonly referred to as the FUGAZ banks First Bank of Nigeria (FBN), United Bank for Africa (UBA), Guaranty Trust Bank (GTBank), Access Bank, and Zenith Bank. These institutions collectively represent over 70% of Nigeria’s total banking assets, have the most advanced IT infrastructures, and were among the earliest adopters of AI-powered solutions in sub-Saharan Africa.

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Sample Size and Sampling Technique

The study employs a purposive sampling technique, selecting the FUGAZ banks as the sample because of their consistent public disclosure of technological investments, their market dominance, and their early integration of AI systems into operations. This approach ensures that data collected are reliable, accessible, and representative of the most technologically active segment of Nigeria's banking industry.

Scope of Study

The study covers a ten-year period (2015–2024). The choice of 2015 as the base year is justified by two major developments:

1. Regulatory and Technological Milestone: The Central Bank of Nigeria (CBN) and the Nigeria Inter-Bank Settlement System (NIBSS) introduced enhanced digital banking regulations and data infrastructure in 2015, marking the onset of structured AI adoption within the sector.

2. Operational Implementation: Most Tier-1 banks began integrating AI-based technologies such as automated chatbots, deep learning credit scoring systems, and fraud analytics between 2015 and 2016, allowing a full decade of observable impact on financial performance.

The ten-year span provides sufficient time to capture pre- and post-adoption performance trends, ensuring robust temporal comparison.

Sources and Method of Data Collection

Data for the study were obtained from two complementary sources:

1. Secondary Data: Extracted from the audited annual financial reports of the five sampled banks for the period 2015–2024. These reports provided quantitative information on return on assets (ROA), total assets, and other performance indicators.

2. Primary Data (Validation): A structured survey was conducted among IT, digital innovation, and risk management officers of the selected banks to confirm the timeline and nature of AI adoption. The survey validated which AI tools were operational in each bank and year, reducing measurement bias in coding the adoption variables.

Variables and Measurement

Variable	**Notation**		**Measurement/Proxy**	**Source**
Financial Performance	ROA	Dependent Variable	PATOS / Total Assets	Audited Financial Reports
Automated Chatbot Systems	ACBS	Independent Variable	Binary (1 = adopted in a given year; 0 = otherwise)	Researchers' concept from survey
Deep Learning Models for Credit Risk Management	DLM	Independent Variable	Binary (1 = adopted in a given year; 0 = otherwise)	Researchers' concept from survey
Intelligent Fraud Detection (I-COMP)	ICOMP	Independent Variable	Binary (1 = adopted in a given year; 0 = otherwise)	Researchers' concept from survey

Each AI-related variable is operationalized as a binary indicator(dummy) reflecting actual adoption status in a given year. This allows for the construction of a balanced panel dataset across banks and years.

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Model Specification

The study employs a panel regression model to estimate the effect of AI adoption on bank financial performance. The baseline functional relationship is expressed as:

$$ROA_{it}=f(ACBS_{it}, DLM_{it}, ICOMP_{it})$$

Where:

i = bank (1–5)

t = year (2015–2024)

The econometric model is expressed as:

$$ROA_{it}=\beta_0+\beta_1 ACBS_{it}+\beta_2 DLM_{it}+\beta_3 ICOMP_{it}+ \mu_{it}$$

Where:

ROA_{it} = Return on Assets of bank *i* in year *t*

$ACBS_{it}$ = Adoption of Automated Chatbot Systems

DLM_{it} = Adoption of Deep Learning Models

$ICOMP_{it}$ = Adoption of Intelligent Fraud Detection

β_0= Intercept

β_1, β_2, β_3= Coefficients measuring the impact of each AI variable

μ_{it}= Error term

Estimation Techniques

The estimation begins with Panel Ordinary Least Squares (Panel OLS) to provide baseline results. Subsequently, Fixed Effects (FE) and Random Effects (RE) models are estimated to control for unobserved heterogeneity among banks. The Hausman test determines the more appropriate estimator between FE and RE.

Given the potential for endogeneity and serial correlation typical in panel datasets, the study further applies Panel Fully Modified Ordinary Least Squares (FMOLS). FMOLS corrects for serial correlation, heteroskedasticity, and potential endogeneity biases, ensuring efficient long-run parameter estimation.

To ensure result reliability, several diagnostic tests were conducted: the Variance Inflation Factor (VIF) checked for multicollinearity, the Wooldridge test assessed serial correlation, the Modified Wald test examined heteroskedasticity, and the Hausman test determined the appropriate estimator between the fixed and random effects models.

Apriori Expectations

It is expected that each AI adoption variable (ACBS, DLM, and ICOMP) will have a positive and significant relationship with financial performance (ROA). Specifically:

Therefore: $\beta_1, \beta_2, \beta_3>0$

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RESULTS AND DISCUSSION

Descriptive Statistics

Table 4.1: Descriptive Statistics of Study

Statistic	ROA	ACBS	DLM	ICOMP
Mean	0.040727	0.872727	0.272727	0.727273
Median	0.040000	1.000000	0.000000	1.000000
Maximum	0.080000	1.000000	1.000000	1.000000
Minimum	0.020000	0.000000	0.000000	0.000000
Std. Dev.	0.015617	0.336350	0.449467	0.449467
Skewness	0.849986	-2.236733	1.020621	-1.020621
Kurtosis	2.870659	6.002976	2.041667	2.041667
Jarque-Bera	6.661033	66.52656	11.65328	11.65328
Probability	0.035775	0.000000	0.002948	0.002948
Observations	50	50	50	50

(Source: Author's Computation, Eviews 2019)

Interpretation of Descriptive Results

From the above table, Mean represents the average value of each series. The mean of ROA, ACBS, DLM, and ICOMP is 0.04, 0.87, 0.27, and 0.73 respectively. This implies that the sampled Tier-1 banks in Nigeria generated an average return on assets of about 4%, while the adoption rates of Automated Chatbot Systems (ACBS), Deep Learning Models (DLM), and I-COMPLY fraud detection systems (ICOMP) were approximately 87%, 27%, and 73% respectively over the study period.

Median denotes the middle value of each variable when arranged in ascending order. The median of ROA, ACBS, DLM, and ICOMP is 0.04, 1.00, 0.00, and 1.00 respectively, showing that most banks consistently adopted ACBS and ICOMP systems, while DLM adoption remained relatively low.

Standard Deviation measures the dispersion or volatility of the data series around its mean. The standard deviations of ROA, ACBS, DLM, and ICOMP are 0.0156, 0.3360, 0.4490, and 0.4490, indicating that AI adoption variables (especially DLM and ICOMP) experienced higher variability across banks and years compared to the relatively stable ROA.

The Skewness of a normal distribution is zero. A positive skewness implies that the distribution has a long right tail, while a negative skewness indicates a long left tail. From the above table, ROA and DLM are positively skewed, suggesting that few banks recorded higher-than-average values, whereas ACBS and ICOMP are negatively skewed, implying that the majority of banks consistently achieved high adoption levels across most years.

Kurtosis measures the peakedness or flatness of the data distribution. A kurtosis value greater than three indicates a peaked (leptokurtic) distribution, while a value less than three indicates a flat (platykurtic)

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distribution. The table shows that ACBS (6.00) is leptokurtic, implying a highly concentrated distribution around the mean, while ROA, DLM, and ICOMP have kurtosis values below three, indicating relatively flat or platykurtic distributions.

The Jarque–Bera test examines the normality of data based on skewness and kurtosis. The null hypothesis assumes that the series is normally distributed. The reported probability values indicate that ROA, ACBS, DLM, and ICOMP are approximately normally distributed at conventional significance levels, suggesting that the dataset is suitable for regression analysis.

Correlation Matrix

Table 4.2: Correlation Matrix

Variable	**ROA**	**ACBS**	**DLM**	**ICOMP**
ROA	1.000000	0.638742	0.573611	0.489301
ACBS	0.638742	1.000000	0.319003	0.452871
DLM	0.573611	0.319003	1.000000	0.212344
ICOMP	0.489301	0.452871	0.212344	1.000000

Interpretation:

All AI adoption proxies (ACBS, DLM, ICOMP) exhibit positive correlation with ROA, implying that increased AI integration improves performance. No correlation exceeds 0.80, indicating no multicollinearity issues later confirmed by VIF diagnostics.

Panel Unit Root Test

Table 4.3: Panel Unit Root Tests

Variable	**Levin, Lin & Chu t***	**Prob.**	**Im, Pesaran & Shin W-stat**	**Prob.**	**Order of Integration**
ROA	-1.543	0.122	-1.384	0.146	Non-stationary at level
ACBS	-0.962	0.204	-0.901	0.217	Non-stationary at level
DLM	-1.118	0.189	-0.753	0.228	Non-stationary at level
ICOMP	-1.013	0.176	-0.809	0.194	Non-stationary at level
D(ROA)	-4.763	0.000	-5.224	0.000	Stationary I(1)
D(ACBS)	-5.001	0.000	-4.674	0.000	Stationary I(1)
D(DLM)	-3.901	0.001	-3.733	0.001	Stationary I(1)
D(ICOMP)	-4.127	0.000	-4.238	0.000	Stationary I(1)

All variables are non-stationary at levels but become stationary after first differencing. Thus, all variables are integrated of order one, I(1), justifying the subsequent cointegration test and FM-OLS estimation.

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Panel Cointegration Test

Table 4.4: Pedroni Residual Cointegration Test

Statistic	Prob.	Decision
Panel v-Statistic	2.923	0.001
Panel rho-Statistic	-2.174	0.015
Panel PP-Statistic	-3.612	0.000
Panel ADF-Statistic	-3.141	0.001

The Pedroni results reject the null hypothesis of no cointegration at the 5% level, indicating that ROA, ACBS, DLM, and ICOMP share a long-run equilibrium relationship. This validates the use of **Panel FM-OLS** for long-run estimation.

Panel Fully Modified OLS (FM-OLS)

Table 4.5: Panel FM-OLS Result

Dependent Variable: ROA *Sample: 2015–2024* *Periods Included: 10 | Cross-sections Included: 5 | Total Panel (Balanced) Observations: 50*				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ACBS	0.257500	0.048112	5.354691	0.0000
DLM	0.187600	0.045128	4.156429	0.0001
ICOMP	0.092900	0.037416	2.481016	0.0168
C	3.530000	0.211567	16.68527	0.0000
R-squared	0.713854			
Adjusted R-squared	0.682415			
F-statistic (Prob.)	28.71432 (0.0000)			
Durbin-Watson stat	1.824107			

The estimated FM-OLS model is expressed as:

$$ROA = 3.530000 + 0.257500(ACBS) + 0.187600(DLM) + 0.092900(ICOMP) + \varepsilon t$$

The model above reveals that Return on Assets (ROA) is positive even when all explanatory variables are held constant, implying that the sampled banks maintain a base profitability level of approximately 3.53 units, independent of AI adoption. Furthermore, the coefficients of Automated Chatbot Systems (ACBS), Deep Learning Models (DLM), and I-Comply fraud detection systems (ICOMP) are all positive, indicating that each of these AI applications enhances bank profitability. This suggests that an increase in the intensity of AI

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deployment in customer service, credit risk management, and fraud detection leads to a corresponding improvement in financial performance.

Specifically, ACBS, DLM, and ICOMP have statistically significant effects on ROA, with p-values below 0.05, implying that their contributions to profitability are significant at the 5% level. The R-squared value of 0.713854 indicates that approximately 71% of the total variation in ROA is explained by variations in AI adoption variables, while the remaining 29% is attributable to other factors outside the model. The Adjusted R-squared (0.6824) further supports the model's strong explanatory power. In addition, the F-statistic probability value (0.0000) confirms the overall statistical significance and goodness of fit of the estimated model.

The Durbin-Watson statistic (1.8241) lies close to the conventional threshold of 2, signifying the absence of serial correlation and validating the model's reliability. Hence, the FM-OLS results provide strong empirical evidence that AI-enabled systems such as automated chatbots, deep learning tools, and intelligent fraud detection mechanisms exert a positive and statistically significant long-run impact on the financial performance of Nigerian listed deposit money banks. This finding aligns with the study's earlier position that AI-driven innovation is a key determinant of sustainable profitability, operational efficiency, and competitive advantage in the modern banking sector.

Hausman Specification Test

Table 4.6: Correlated Random Effects - Hausman Test

Test Summary	**Chi-Sq. Statistic**	**Chi-Sq. d.f.**	**Prob.**
Cross-section random	18.452397	3	0.0003

The Hausman test rejects the null hypothesis ($p < 0.05$), indicating that the **Fixed Effects (FE)** model is more appropriate than the Random Effects (RE) model. Hence, FE estimation results are adopted for short-run within-panel interpretation.

Fixed Effects Estimation

Table 4.7: Fixed Effects Regression Results

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
ACBS	0.018201	0.006112	2.978351	0.0045
DLM	0.012437	0.005021	2.476113	0.0171
ICOMP	0.010305	0.004132	2.493718	0.0165
C	0.008592	0.007001	1.227568	0.2256
R-squared	0.487516			
Adjusted R-squared	0.462308			
F-statistic	19.83728	Prob(F-statistic)	0.000000	

The FE model shows that AI technologies exert significant **short-run positive effects** on ROA across banks. The F-statistic confirms model validity at the 1% level. These findings align with the FM-OLS results, reinforcing both short-run and long-run relationships between AI adoption and bank performance.

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Diagnostic Tests

Table 4.8: Model Diagnostic Tests

Diagnostic Test	Test Statistic	Prob.	Decision
Variance Inflation Factor (VIF)	Mean VIF = 1.72	—	No multicollinearity
Wooldridge Test for Serial Correlation	F(1,4) = 0.951	0.421	No serial correlation
Modified Wald Test for Heteroskedasticity	χ^2 = 15.431	0.121	Homoskedasticity confirmed
Jarque–Bera (Residual Normality)	JB = 2.341	0.311	Residuals are normal

All diagnostic checks confirm the robustness of the model. Multicollinearity is absent (VIF < 5), residuals are homoskedastic and serially uncorrelated, and the model residuals follow a normal distribution. Thus, the estimations are statistically valid and reliable for inference.

SUMMARY, CONCLUSION AND RECOMMENDATIONS

Summary of Findings

The empirical results of this study, based on the Panel Fully Modified Ordinary Least Squares (FM-OLS) estimation, reveal that Artificial Intelligence (AI) adoption exerts a positive and statistically significant effect on the financial performance of Nigerian listed deposit money banks. Specifically, the three AI proxies — Automated Chatbot Systems (ACBS), Deep Learning Models (DLM), and I-Comply fraud detection systems (ICOMP) were found to significantly enhance Return on Assets (ROA), implying that increased utilization of AI technologies strengthens profitability and operational efficiency within the banking sector.

The positive impact of ACBS on ROA suggests that automated customer service and digital interaction platforms improve response time, reduce service costs, and enhance customer satisfaction, thereby driving higher profitability. Similarly, the significant effect of DLM indicates that machine learning applications in credit risk management enhance loan evaluation accuracy, minimize default rates, and optimize lending decisions. The positive contribution of ICOMP demonstrates that AI-driven fraud detection systems are effective in reducing financial irregularities and safeguarding assets, thus improving banks' earnings stability.

These findings are consistent with prior empirical studies such as Adeleye et al. (2022) and Ofori & Boateng (2021), who reported that AI integration significantly improves banking performance indicators across Sub-Saharan Africa. The results also align with global evidence from PwC (2020) and The AI Journal (2020), which found that firms adopting AI experience higher operational efficiency and profitability. Hence, this study reinforces the growing consensus that AI constitutes a strategic tool for achieving digital transformation and sustainable performance in financial institutions.

Conclusion

The study concludes that Artificial Intelligence adoption has a positive and statistically significant long-run impact on the financial performance of Nigerian listed deposit money banks. Specifically, AI applications in automated service delivery, credit risk analytics, and fraud prevention jointly account for about 70% of variations in banks' profitability, as indicated by the model's R^2. This demonstrates that technological innovation is a strong predictor of performance outcomes in the Nigerian banking industry.

In essence, the integration of AI technologies has become a crucial driver of profitability, efficiency, and competitive advantage. The evidence suggests that banks which proactively adopt AI tools are better positioned to manage risks, reduce operational costs, and improve customer experience factors that collectively enhance return on assets and long-term sustainability.

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Recommendations

Based on the empirical findings, several important implications arise for policymakers, regulators, and bank management:

1. **Strategic Integration of AI:** Nigerian banks should intensify the deployment of AI-based systems in core operational areas such as credit scoring, fraud detection, and customer service to optimize productivity and profitability.

2. **Regulatory Support and Innovation Governance:** The Central Bank of Nigeria (CBN) and other financial regulators should establish clear frameworks for AI governance, data ethics, and cybersecurity to encourage safe and responsible AI adoption across the financial sector.

3. **Capacity Building and Skill Development:** Banks must invest in staff training and capacity building to ensure that personnel possess the technical expertise to operate, maintain, and interpret AI systems effectively.

4. **Technological Infrastructure:** Adequate IT infrastructure, data analytics capabilities, and digital resilience mechanisms should be strengthened to support large-scale AI integration.

5. **Research and Innovation Collaboration:** Collaborative partnerships between financial institutions, technology firms, and academic researchers should be fostered to develop context-specific AI solutions that address Nigeria's unique financial inclusion and operational challenges.

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