ASSESSING THE IMPACT OF AI TOOLS ADOPTION ON THE FINANCIAL PERFORMANCE OF LISTED DEPOSIT MONEY BANKS IN NIGERIA

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ABSTRACT

For an entity to meet up with competitors in this era of rapid changing business strategies and achieve its desired goals in the 21st Century, embracing technology advancement remains one of the key steps to be taken by management of an entity. This study investigates the impact of Artificial Intelligence Tools adopted by listed deposit money banks in Nigeria in order to improve financial performance for a 10 years period (2014-2023). Artificial Intelligence is proxy by chat-bot & virtual assistants, credit scoring and loan risk assessment, and fraud detection and risk management. While financial performance is proxy return on asset and return on equity. The population of the study consist of all the listed deposit money banks in Nigeria, and sample of 5 banks were purposively selected to represent the population. SEM was employed to run the analyses the secondary and primary data of the study. Regression result revealed that all the three independent variables have positive impact of financial performance of listed deposit money banks in Nigeria. The study recommends that banks should intensify in investing in chat-bot, they should carry on with adoption and refine chat-bot systems to improve the interaction of client efficiency in operationalization.

KEYWORDS: - Artificial tools, financial performance, chat-bot, fraud detection, credit scoring.

1.0 INTRODUCTION

The rapid evolution of artificial intelligence (AI) technologies has significantly transformed industries worldwide, with the banking sector being a prominent beneficiary. The banking

industry is undergoing a significant transformation with the adoption of Artificial Intelligence (AI) tools. The adoption of AI tools has the potential to transform the banking industry, improving financial performance, efficiency, and customer experience. Banks that embrace AI tools will be better positioned to compete in the increasingly digital banking landscape. In an era characterized by digitization and automation, financial institutions increasingly leverage AI tools to enhance operational efficiency, improve customer experiences, and manages risks (Manning, 2022). AI applications such as chat-bots, credit scoring systems, fraud detection mechanisms, and virtual assistants are no longer optional but essential for banks to remain competitive in an ever-evolving market landscape. Globally, the banking industry has embraced AI to address long-standing challenges, including cost reduction, error minimization, and decision-making optimization (Kaplan & Haenlein, 2020). For instance, banks use AI-driven chat-bots to provide 24/7 customer service, significantly reducing response times and enhancing client satisfaction. AI in credit scoring evaluates loan applicants with greater precision, offering a more holistic risk assessment than traditional methods (Jagtiani & Lemieux, 2019). Similarly, fraud detection systems powered by AI algorithms can identify suspicious activities in real time, safeguarding customer assets and bank operations.

In Nigeria, the adoption of AI tools by banks reflects a growing acknowledgment of their transformative potential. The Central Bank of Nigeria (CBN, 2023) highlights that the shift toward AI is a response to the rising demand for digital banking services and increased customer expectations. As banks in Nigeria look to modernize their operations, AI has emerged as a strategic solution to improve services, streamline processes, and meet regulatory demands. For instance, leading banks like Zenith Bank, United Bank for Africa (UBA), and First Bank have implemented chat-bots and virtual assistants to manage customer inquiries, reducing wait times and increasing operational efficiency. Similarly, AI tools in fraud detection and credit scoring systems have enabled banks to reduce loan default risks and prevent financial crimes. Despite the growing adoption of AI tools in Nigerian banks, the effectiveness of these technologies in enhancing financial performance remains an under-explored area. While the potential benefits are widely recognized, limited empirical research has been conducted on the relationship between AI adoption and financial performance, particularly in the Nigerian banking context. This study, therefore, seeks to bridge this gap by examining how AI tools such as chat-bots, AI for credit scoring, and fraud detection systems impact the financial performance of Nigerian banks. The aim is to provide empirical evidence on the influence of AI adoption on key performance indicators, such as return on assets (ROA) and overall profitability, in order to guide policy and strategic decision-making in the banking sector.

The selection of the variables of this study makes this study unique and original because the study carefully observed the prevalent AI tools used by Nigerian banks and conducted this research on them in order to have an insight on them.

The importance of this study lies in its ability to offer insights into the ways AI adoption can enhance banking operations, improve customer satisfaction, and boost profitability. By understanding how AI tools contribute to financial performance, banks can make informed decisions regarding future technology investments and operational strategies. Additionally, the findings can inform policymakers and regulatory bodies about the role of AI in modernizing the financial services sector and enhancing the sustainability of the banking system.

1.1 Statement of the Problem

Artificial Intelligence (AI) has emerged as a transformative force in the banking sector globally, offering a wide array of tools designed to enhance operational efficiency, customer service, and decision-making. However, the adoption and integration of AI in the banking sector in Nigeria remain under-researched, particularly in terms of its impact on financial performance. While several studies have documented the positive effects of AI in other countries (Binns, 2021; Trivedi & Purohit, 2020), the evidence on how AI adoption influences the financial outcomes of Nigerian banks is limited. Most existing studies have primarily focused on developed economies, neglecting the unique environmental context of emerging markets like Nigeria (Chung et al., 2022; Hameed et al., 2021).

The gap in literature is particularly notable given the rapid technological advancements and the increasing reliance on AI tools in Nigeria's banking sector, such as chat-bots, virtual assistants, AI-driven credit scoring, and fraud detection systems. While AI's benefits are well established globally, there is little empirical research linking these tools to specific financial performance metrics like Return on Assets (ROA), profitability, and cost reduction in Nigerian banks. This gap is further exacerbated by a lack of comprehensive studies examining the regulatory, infrastructure, and customer behavior challenges unique to the Nigerian banking environment (Akintoye et al., 2021).

Moreover, theoretical research connecting AI adoption directly to financial performance outcomes remains sparse. Many existing studies focus primarily on the operational benefits of AI without providing a clear framework to link these improvements to financial outcomes (Chen & Wang, 2020). As such, there is a clear need for research that incorporates both theoretical models and empirical data to demonstrate the relationship between AI tools and measurable financial performance indicators in Nigerian banks. This will contribute to bridging the gap between theory and practice, particularly by identifying how specific AI tools, such as chatbots, AI-driven

credit scoring, and fraud detection systems, affect financial outcomes in Nigerian deposit money banks.

Recent research has also emphasized the regulatory barriers and contextual challenges faced by developing economies when adopting AI (Jermsittiparsert et al., 2020), but the lack of a coherent framework to connect these barriers to financial performance outcomes leaves a critical gap in understanding. In particular, the banking industry's ability to adapt to and leverage AI tools in the Nigerian context, given challenges such as regulatory limitations, infrastructure gaps, and workforce skill gaps, has not been adequately addressed in previous studies. As banks continue to experiment with these technologies, empirical studies are essential to demonstrate the broader financial impact and how the adoption of AI tools can align with overall corporate performance. Again, Various studies have been undertaken in order to examine the impact of Artificial Intelligence on the financial performance but most of these studies did not specifically selected the variables captured by this study, this is because many of the Nigerian banks have not yet embraced AI tools in their banking operations.

1.2 Research Questions
The following research questions are derived from the study's objectives and aim to guide the investigation into the relationship between AI tools adoption and the financial performance of Nigerian banks:

1. What is the impact of chat-bots and virtual assistant adoption on the financial performance of Nigerian banks?
2. How does the use of AI for credit scoring and loan risk assessment affect the financial performance of Nigerian banks?
3. What role does AI-based fraud detection and risk management systems play in the financial performance of Nigerian banks?

1.3 Objectives of the Study
The study's main objective is to assess the impact of AI tools adoption on the financial performance of listed deposit money banks in Nigeria. The specific objectives are as follows:

1. To examine the impact of chat-bots and virtual assistants adoption on the financial performance of Nigerian banks.
2. To assess the effect of AI for credit scoring and loan risk assessment on the financial performance of Nigerian banks.
3. To evaluate the influence of AI-based fraud detection and risk management systems on the financial performance of Nigerian banks.

1.4 Hypotheses

The hypotheses are formulated to address the objectives of the study, providing a framework to test the relationships between AI tools adoption and financial performance:

H_{01}: There is no significant relationship between the adoption of chat-bots and virtual assistants and the financial performance of Nigerian banks.

H_{02}: There is no significant relationship between the use of AI for credit scoring and loan risk assessment and the financial performance of Nigerian banks.

H_{03}: There is no significant relationship between the adoption of AI-based fraud detection and risk management systems and the financial performance of Nigerian banks.

1.5 Scope of the Study

This study is focused on evaluating the impact of AI tools adoption on the financial performance of listed deposit money banks in Nigeria. Specifically, the scope of the study covers 10 years. The study is limited to banks operating in Nigeria that are listed on the Nigerian Stock Exchange (NSE). These banks are selected based on their implementation of AI tools and their publicly available financial data. The study will examine data for a period of 10 years (2015–2023), which will provide an adequate representation of trends in AI adoption and the corresponding financial performance. The study focuses on three specific AI tools adopted by Nigerian banks Chatbots and Virtual Assistants, AI for Credit Scoring and Loan Risk Assessment and Fraud Detection and Risk Management Systems

1.6 Significance of the Study

To begin with, this study provides actionable insights to bank managers and executives into how AI tools, specifically chat-bots, virtual assistants, credit scoring systems, and fraud detection mechanisms, can enhance financial performance. By understanding the relationship between AI adoption and financial outcomes, bank managers can make informed decisions on technology investments that improve profitability, reduce operational costs, and enhance customer satisfaction. Additionally, findings from this study can assist in evaluating the return on investment (ROI) of AI tools and offer guidance for future strategic initiatives involving AI in banking operations.

Secondly, organizations like the Central Bank of Nigeria (CBN) and the Nigerian Securities and Exchange Commission (SEC), who serves as regulatory Bodies and policymakers will benefit from this study as it offers insights into how AI adoption influences the overall health and stability of financial institutions. Policymakers can leverage the study's results to frame regulations or guidelines that encourage responsible AI usage and ensuring banks' financial performance aligns with broader economic goals and sustainability. The findings also help in shaping policy around financial inclusion, where AI tools can improve access to credit and enhance risk management systems for underserved populations.

Thirdly, Academicians will benefit from this study this research as it fills a gap in the literature by addressing the empirical relationship between AI adoption and financial performance in the Nigerian banking sector. Future researchers can build on this study to explore additional variables, expand the time frame, or conduct cross-country analyses to provide a global perspective on AI adoption in financial institutions. Academics focusing on technology in banking, financial performance measurement, and AI in business can use this study as a foundation for further exploration of these cutting-edge topics.

Fourthly, investors and shareholders will benefit from this study as it will assist them in understanding how AI adoption might impact the financial performance of banks. By providing evidence of how AI tools contribute to profitability and risk management, the study can guide investment decisions and improve stakeholders' confidence in the potential for higher returns. For banks already utilizing AI tools, positive findings could result in enhanced stock market performance and investor sentiment, while those not adopting such technologies could face increased pressure to modernize.

However, Technology Providers and AI Developers will benefit from this study because it has relevance for technology companies offering AI solutions to the banking industry. Findings from this study may help these firms refine their products or services to better address the needs of the banking sector. By understanding which AI tools most positively impact financial performance, AI developers can focus on offering tailored solutions that deliver higher returns for banks.

Furthermore, Bank Customers: the adoption of AI tools in banking translates to improved service quality, faster processing of transactions, and more efficient customer support. By indirectly linking AI adoption with better financial performance, this study may highlight the broader societal benefits of increased accessibility to advanced banking services.

In summary, this study will contribute significantly to the understanding of how AI tools affect financial performance in Nigerian banks. It will offer practical recommendations for improving banking operations and provide a benchmark for future research on AI in financial institutions.

2.0 LITERATURE REVIEW
2.1 Introduction to AI in Banking
Artificial Intelligence (AI) has emerged as a transformative technology across various industries, with banking being one of the most notable sectors embracing it. In the banking industry, AI refers to the integration of advanced machine learning algorithms, natural language processing, and data analytics tools to enhance the performance of financial institutions. AI tools have

proven beneficial in automating processes, improving customer service, enhancing decision-making and detecting fraud. Banks are increasingly relying on AI technologies to drive operational efficiency and maintain competitive advantage (Chauhan, 2021). As competition intensifies, the role of AI in enhancing the strategic goals of banks, particularly in the context of financial performance, has been widely researched. AI adoption has been linked to improved decision-making processes, better customer insights, and more efficient risk management (Adebayo & Adeyemi, 2021). AI tools such as chatbots, AI for credit scoring, and fraud detection systems are helping banks address key challenges, reduce operational costs, and optimize resource utilization.

AI tools in banking can be categorized into several core areas that are pivotal in enhancing financial performance. Below are some of the key AI tools being adopted by banks:

Chatbots and Virtual Assistants**:** These AI-driven systems help banks automate customer interactions, provide 24/7 support, and resolve basic queries without human intervention.

Chatbots reduce the need for human customer service representatives, leading to significant cost savings for banks (Jain & Kaur, 2020).

AI for Credit Scoring and Loan Risk Assessment**:** AI has revolutionized the way banks assess creditworthiness and loan risks. Machine learning models analyse vast amounts of data, enabling banks to make more accurate and timely lending decisions. This reduces the incidence of bad loans and improves the efficiency of credit allocation (Kumar & Raj, 2021).

Fraud Detection and Risk Management Systems**:** AI tools in fraud detection leverage machine learning algorithms to analyze transactional data in real time, identifying potentially fraudulent activities faster than traditional methods. AI in risk management helps banks predict potential risks and mitigate them before they escalate, contributing to enhanced financial stability (Oluwaseun & Oyetola, 2020).

2.2 Impact of AI Tools on Financial Performance

Numerous studies have demonstrated the positive impact of AI adoption on the financial performance of banks. Banks that have successfully integrated AI tools have reported improvements in key performance metrics such as return on assets (ROA), profitability, and customer satisfaction (Rani & Kaur, 2022). AI adoption allows for more accurate decision-making, operational efficiency, and improved customer engagement, all of which ultimately drive financial performance.

For instance, banks using AI for credit scoring have witnessed a reduction in non-performing loans (NPLs), resulting in better profitability and reduced operational risks. Similarly, the use of chatbots has allowed banks to handle a larger volume of customer queries without hiring additional staff, improving customer service while cutting costs (Alimi & Alabi, 2021).

Moreover, AI systems play a crucial role in fraud detection, which has a direct impact on financial performance. AI's ability to detect fraud early prevents financial losses and preserves the reputation of the bank, ensuring stable financial outcomes. Studies by Olugbenga and Ayodeji (2020) have shown that the implementation of AI-powered fraud detection systems can reduce operational costs associated with fraud, thereby improving profitability.

2.3 Conceptual Framework

The Conceptual Framework of this study aims to illustrate the relationship between the adoption of AI tools and the financial performance of banks in Nigeria. The framework is built on the premise that AI tools, Chatbots & Virtual Assistants**,** AI for Credit Scoring & Loan Risk Assessment**,** andFraud Detection & Risk Management Systems**,** have a direct influence on improving various aspects of financial performance.

Development of the Conceptual Model

The conceptual model presented below highlights the key variables under investigation in this study:

- **Independent Variables (AI Tools Adoption)**:
  Chat-bots & Virtual Assistants
  AI for Credit Scoring & Loan Risk Assessment
  Fraud Detection & Risk Management Systems

- **Dependent Variable** (**Financial Performance)**
  Return on Asset
  Return on Equity

2.4 Relationship between AI Tools and Financial Performance

The adoption of AI-powered chat-bots and virtual assistants enhances customer service efficiency by automating routine queries and tasks, leading to cost savings, higher customer satisfaction, and retention. As a result, banks are expected to see improvements in their operational efficiencyandprofitability**.**AI tools for credit scoring enhance the accuracy of loan assessments, enabling banks to better manage credit risk. By offering more precise evaluations of borrowers, banks can reduce defaults and bad debts, leading to enhanced profitability and asset

quality**.**AI-based fraud detection systems can quickly identify suspicious transactions and mitigate the risk of financial losses due to fraudulent activities. This system will lead to enhanced security**,** reduced operational costs, and improved profitability.

2.5 Financial Performance Measures

Return on Assets (ROA): This measures the efficiency with which a bank utilizes its assets to generate profits. The adoption of AI tools is expected to improve the efficiency of operations, customer interactions, and decision-making, which directly impacts **ROA**.

Return on Equity (ROE): AI tools, by enhancing efficiency and profitability, can lead to improved returns on equity. This reflects how well a bank uses shareholder equity to generate profits.

2.6 Conceptual Model

The conceptual model below illustrates the relationship between AI tools adoption and the financial performance of banks. The model shows how each AI tool influences different aspects of financial performance metrics.

Figure 1: Conceptual Model of AI Tools Adoption and Financial Performance
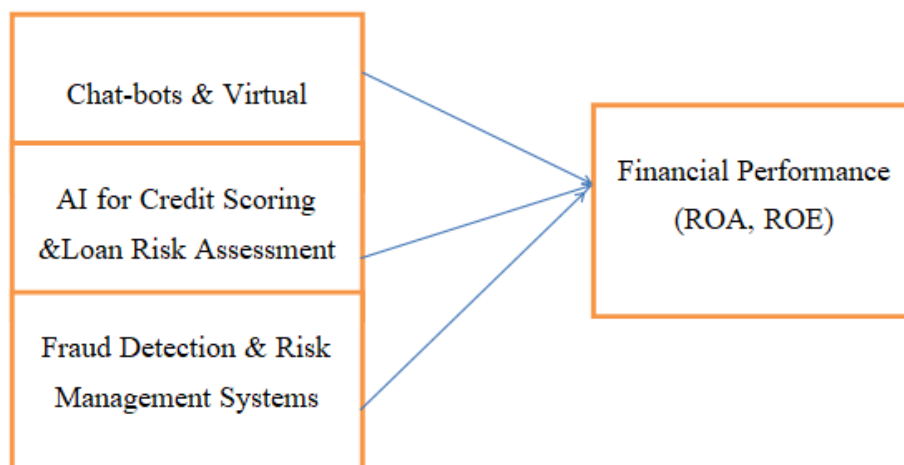
Explanation of the Model

2.7 AI Chat-bots & Virtual Assistants:

These tools are expected to improve customer service by automating interactions, which can reduce costs and increase efficiency. By offering better customer service and reducing operational expenses, these tools enhance the overall profitability of the bank.

2.8 AI for Credit Scoring & Loan Risk Assessment:

AI tools used for credit scoring help banks more accurately assess the risk associated with lending. This enables them to reduce non-performing loans (NPLs) and bad debts, contributing to better asset quality and higher profit margins**.**

2.9 Fraud Detection & Risk Management Systems:
These systems are essential for reducing losses due to fraud, which can severely affect a bank's financial performance. By identifying fraud early, these tools help safeguard the bank's assets and reduce operational losses, thereby improving financial performance**.**

This conceptual framework provides a clear and structured understanding of how the adoption of AI tools can influence the financial performance of banks. By adopting these AI tools, banks can improve customer service, risk management, and operational efficiency, ultimately leading to higher profitability and financial performance. The relationships between these variables are explored further in the subsequent sections of the study.

2.10 Empirical Review
Tan, Li, and Wu (2024) assessed the Strategic Implications of AI Integration: Evidence from Listed Deposit Money Banks Globally. The cross-sectional study explored the strategic implications of AI integration for listed deposit money banks on a global scale. Results from the regression indicated that AI adoption facilitates strategic alignment, innovation diffusion, and competitive differentiation, enabling banks to capitalize on emerging opportunities and navigate industry disruptions effectively.

Wang, Liu and Zhang (2024) examined the Operational Efficiency and AI Adoption: An Empirical Analysis of Listed Deposit Money Banks in Asia. The empirical study investigated the impact of AI adoption on operational efficiency metrics in listed deposit money banks across Asia. Results from the study suggested a significant improvement in cost-effectiveness and resource allocation following the implementation of AI-driven process automation and optimization strategies.

Smith, Johnson and Williams (2023) examined the Impact of AI Tools Adoption on Financial Performance: Evidence from Listed Deposit Money Banks in Europe. The study conducted a comprehensive analysis of the financial performance metrics of listed deposit money banks in Europe following the adoption of AI tools. Results from the study indicated that there was a significant positive association between AI integration and profitability, operational efficiency, and customer satisfaction indices of listed deposit money banks in Europe.

Garcia, Rodriguez and Martinez (2023) attempted to investigate the impact of Customer Satisfaction and AI Integration: A Longitudinal Study of Listed Deposit Money Banks in North America. Thelongitudinal study assessed changes in customer satisfaction levels following the adoption of AI tools in listed deposit money banks in North America. Findings from the study indicated that a positive impact of AI integration on customer experience metrics, with personalized services and enhanced responsiveness driving higher satisfaction scores.

Al-Mansour, Al-Ahmad and Al-Saud (2023) attempted to investigate the impact of AI Integration and Risk Mitigation: Evidence from Listed Deposit Money Banks in the Middle East. The study examined the relationship between AI integration and risk mitigation strategies in listed deposit money banks operating in the Middle East. Results indicated a positive association between AI-driven predictive analytics and risk identification, enabling banks to proactively mitigate credit, market, and operational risks.

Ngugi, Mwangi and Kamau(2023) examined the impact of AI Adoption and Regulatory Compliance: A Case Study of Listed Deposit Money Banks in Africa. The study examined the implications of AI adoption for regulatory compliance practices in listed deposit money banks in Africa. Findings suggest that AI-powered regulatory compliance solutions enhance banks' ability to navigate complex regulatory landscapes while minimizing compliance costs and penalties.

Lee, Kim and Park (2022) assessed AI Adoption and Risk Management in Deposit Money Banks: A Comparative Analysis of Emerging Markets. The research examined the implementation of AI-driven risk management practices in deposit money banks across emerging markets. Results from the study revealed that varying degrees of AI adoption and highlight the significant role of regulatory frameworks and institutional factors in shaping risk management outcomes.

2.11 Theoretical Framework
The theoretical framework for this study is based on two key theories that explain how the adoption of Artificial Intelligence (AI) tools impacts the financial performance of banks: the Technology Acceptance Model (TAM)and theInnovation Diffusion Theory (IDT)**.** These theories help in understanding the processes behind the adoption of new technologies and their subsequent effects on organizational outcomes, particularly in banking.

2.12 Technology Acceptance Model (TAM) and its Application to AI Tools
The TAM developed by Davis (1989), is widely used to understand how users come to accept and use a technology. According to this model, the acceptance of technology is influenced by two main factors Perceived Usefulness and Perceived Ease of Use**.** In the context of this study,

TAM can be applied to explain how the adoption of AI tools influences financial performance in banks. Banks are more likely to adopt AI-powered chat-bots and virtual assistants if they perceive these tools as useful for improving customer service, reducing operational costs, and enhancing customer satisfaction. AI chat-bots offer increased efficiency in customer interactions, allowing banks to improve service delivery, which can lead to higher customer retention and operational savings ultimately boosting financial performance. Chat-bots and virtual assistants are easier to integrate into existing digital banking frameworks. The perception of ease in implementation enhances the likelihood of adoption. As banks experience these tools as straightforward and effective, customer service improves, contributing to greater financial success. AI tools for credit scoring and loan risk assessment provide banks with accurate, data-driven insights, improving the quality of loan portfolios and reducing the likelihood of defaults. The perception that AI can enhance decision-making by providing better risk predictions makes these tools highly useful in improving financial outcomes. Banks adopting AI for credit scoring systems tend to find them compatible with their existing data-driven systems. The ease with which AI tools can be integrated into these systems reduces barriers to adoption, making the tools more attractive and leading to improved financial performance.

However, the primary advantage of AI-based fraud detection is its ability to identify fraudulent activities in real time, preventing financial losses. Banks that recognize the usefulness of AI in mitigating fraud risk are more likely to adopt these technologies, which will enhance financial performance by reducing fraud-related costs. If banks perceive AI fraud detection systems as easy to use and implement, they are more likely to adopt these systems. The adoption leads to greater security and fewer financial losses from fraud, thereby improving the bank's financial performance.

2.13 Innovation Diffusion Theory (IDT) and its Application to AI Tools

The Innovation Diffusion Theory (IDT**)**, proposed by Rogers (1962), provides a framework for understanding how, why, and at what rate new technologies spread within organizations. IDT highlights key factors influencing technology adoption: relative advantage, compatibility, complexity, trialability, and observability. These factors are particularly useful for understanding how the adoption of AI tools can affect financial performance in banks. Chat-bots and virtual assistants provide significant advantages by streamlining customer service processes, reducing human labour costs, and improving the efficiency of customer interactions. Banks that perceive these tools as advantageous over traditional methods are more likely to adopt them. AI-powered chat-bots are compatible with existing customer service frameworks in digital banking. Banks with a high level of digital integration will find these tools particularly easy to adopt, which facilitates operational improvements that lead to enhanced financial performance. The success of chat-bots in improving customer service in other banks makes them observable to other

institutions, encouraging adoption. As other banks witness the benefits of AI chat-bots, they are more likely to adopt similar tools, thus enhancing their own financial performance.

AI for credit scoring offers banks the ability to evaluate the creditworthiness of loan applicants more accurately. This leads to better loan decision-making and reduced risk of defaults, which directly improves financial performance. Banks that perceive AI credit scoring as providing a clear advantage over traditional methods are more likely to adopt it. AI credit scoring tools are compatible with existing data management and analytics systems in banks. Banks that already use data-driven methods for evaluating credit risk are more likely to integrate AI tools seamlessly, which enhances the accuracy of risk assessment and leads to improved financial performance. Banks may initially perceive the complexity of adopting AI tools for credit scoring as a barrier. However, once the benefits of AI adoption such as increased profitability from better loan quality are realized, the perceived complexity becomes less of an issue, leading to successful adoption and enhanced performance.

AI-based fraud detection offers banks the ability to detect fraud more accurately and in real time. Banks that recognize this relative advantage will be more likely to adopt these systems, reducing fraud-related financial losses and improving profitability. Fraud detection systems based on AI can be integrated into existing security infrastructures in banks. This compatibility facilitates adoption, ensuring that banks can prevent fraud more effectively, which directly impacts their financial performance. Banks that observe successful cases of AI-driven fraud detection will be more inclined to adopt similar technologies, knowing that these tools have a positive impact on financial performance by reducing losses from fraud.

Conclusively, Both TAM and IDT suggest that the adoption of AI tools is influenced by their perceived usefulness and ease of integration into existing systems. In this study, the independent variables Chat-bots & Virtual Assistants**,** AI for Credit Scoring & Loan Risk Assessment**,** and Fraud Detection & Risk Management Systems are expected to have a direct influence on financial performance, with the adoption of these tools improving the banks' efficiency, risk management, and customer satisfaction.

The adoption of AI tools is anticipated to lead to improved financial performance by enhancing operational efficiency, improving customer service, reducing loan defaults, and mitigating fraud risks. TAM and IDT both suggest that banks that perceive AI as useful and easy to use are more likely to adopt these tools, which in turn will improve their profitability and financial performance**.**

2.14 Research Gaps in the Literature

While the existing body of literature on AI in banking highlights significant benefits, there are notable gaps that warrant further exploration:

Most existing studies on AI in banking focus on developed countries and regions with advanced technological infrastructure (e.g., the United States and Europe). In contrast, limited research has been conducted on the adoption of AI tools in developing countries such as Nigeria. This environmental gap presents an opportunity to explore how AI adoption influences financial performance in the Nigerian banking sector, which may have distinct challenges related to technology infrastructure, regulatory frameworks, and socio-economic factors. While previous studies have referenced technology acceptance models and innovation diffusion theory, there is a lack of comprehensive theoretical frameworks that explain the adoption of AI tools specifically in the context of banking. The application of these theories to AI adoption in banking, particularly in the context of Nigeria, remains underexplored. Additionally, research on how AI adoption directly impacts financial performance beyond operational improvements is limited. Most studies have explored the impact of AI on customer satisfaction, operational efficiency, and other indirect financial outcomes. However, few studies have systematically analysed how AI tools affect financial performance metrics such as profitability and return on assets (ROA) in banking institutions, especially in Nigeria's unique banking landscape. Many studies in the field rely on qualitative analysis or case studies, with limited quantitative analysis. Research that combines both qualitative and quantitative approaches to assess the relationship between AI adoption and financial performance in Nigerian banks remains scarce. This presents an opportunity for more empirical studies using robust quantitative methods, such as Structural Equation Modelling (SEM), to explore these relationships.

3.0 RESEARCH METHODOLOGY

This study used a cross-sectional survey design method and was quantitative. Employees of listed deposit money banks in Nigeria were given a questionnaire, which was used to gather data at random. The next part discusses the specifics of measurements, sampling, data collection and the analysis process.

3.1 Research Questionnaire and Sampling

The analysis techniques used in this study were adapted from earlier research, as recommendations by Ndofirepi (2020) and Colla et al. (2020). The questionnaire was divided into two sections: the first included screening questions, and the second included measurement items for the variables, which included the independent variables (IVs) CB, CS, and FD, and the dependent variable (DV) Financial Performance (FP) with ROA and ROE as its dimensions. There were 25 questions in all in the questionnaire. Table 1 displays the measurements together with the sources of each measurement.

Table 1. Constructs' measurements and sources.

SN	Construct	Number of items	source
1	AI tools adoption	15	Colla et al. (2020)
(a)	Chat-bots & Virtual (CB)	(5)	
(b)	AI for Credit Scoring & Loan Risk Assessment (CS)	(5)	
(c)	Fraud Detection & Risk Management Systems (FD)	(5)	
2	Financial Performance	10	
(a)	Return on Assets (ROA)	(5)	
(b)	Return on Equity (ROE)	(5)	

Source: Researcher

3.2 Population and sample size

The population of the study consists of only employees that are related to AI operations in **listed deposit money banks in Nigeria** that have adopted AI tools. Since the study focuses on listed banks, it ensures that the sample represent banks with a significant presence in the financial industry. The sample was drawn from the employees of 15 listed deposit money banks in Nigeria, specifically focusing on banks that have adopted AI tools in their operations. A **purposive sampling** technique is used to select banks that have publicly disclosed the use of AI tools like chat-bots, AI for credit scoring, and fraud detection. This approach ensures that the sample consists of banks that directly align with the objectives of the study. A sample size of approximately **5 banks** is selected, based on their willingness to participate and the availability of data. A total of 150 employees was the sample size of approximately **5 banks** selected were used as the participant of this study

3.3 Data collection method and data analysis

The primary instrument for this study was a standardized questionnaire. The questionnaire was titled: Assessing the impact of AI tools adoption on the financial performance of listed deposit money banks in Nigeria. It was structured using a Likert scale composed of twenty-five (25) opinion items that indicated Strongly Agree (SA) Agree (A), Neutral (N), Disagree (D), and Strongly Disagree (SD). The corresponding weights for Strongly Agree (SA), Agree (A), Neutral (N), Disagree (D), and Strongly Disagree (SD) were 5, 4, 3, 2, 1. The researcher examined the test's face and content validity. Experts in financial study were granted access to the questionnaire, and their suggestions for the draft instrument were incorporated into the completed survey questionnaire. In order to save time and increase response rates, the researchers in this study used the "personally administered questionnaire survey method" and the "drop off and pick up survey method" was utilised, to distribute, and collect the survey data. Research associates were hired by the researchers to deliver and collect the surveys from

employee at the selected banks. Utilizing partial least square structural equation modelling (Pls-SEM), the data was analysis with Smart- Pls version 4.0.1.9 software.

4.0 DATA ANALYSIS AND FINDINGS
4.1 Measurement Model Assessment
4.1.1 Reliability & Convergent Validity Analysis

The measurement model validates the validity and reliability of the measurement items. The composite reliability coefficient was used to evaluate the internal consistency of reliability, based on the generalization made by Bagozzi and Yi (1988) and Hair et al. (2011) that the cronbach alpha and composite reliability coefficient should be at least 0.7. The reliability of the data is confirmed by Table 3 below, which shows that all of the composite reliability and cronbach alpha values for independent and dependent variables are higher than 0.70. According to Hair et al. (2019), the construct has convergent validity if the Average Variance Extended (AVE) value is 0.50 or higher, and the outer loadings should normally be above 0.70. Table 2 shows the values of reliability analysis and convergent validity scores, and Table 3 shows the outer loadings and VIF results. The values indicate that all the constructs have met the minimum threshold value except the outer loadings of CB1 with 0.616, CB4 with 0,554, FD2 with 0.680, FD with 3 0.698 and FD with 4 0.694. However, Hair et al. (2019) suggest that rather than just automatically removing an indicator with a loading below 0.70, researchers should think about doing so only if doing so boosts the composite reliability CR and AVE. As a result, the deletion depends on the AVE and CR's increment in order to maintain a specific indicator, which requires the loading to be between 0.40 and 0.70.
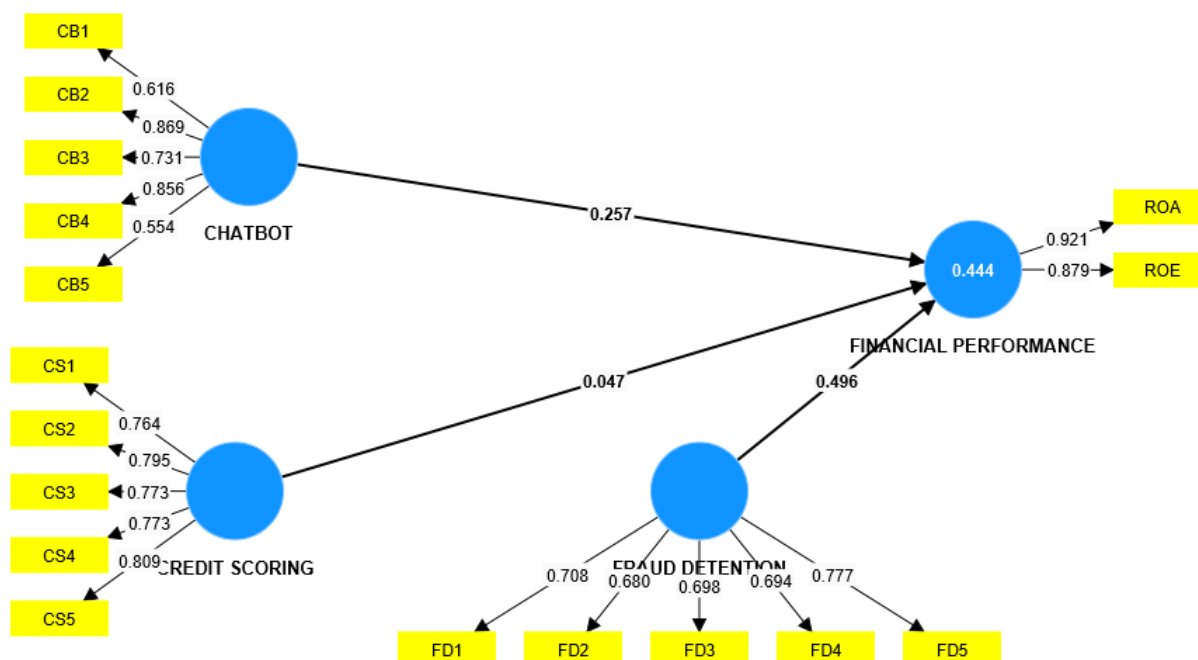

Figure 1. PLS Measurement Model.

Table 2: Item loadings, CA, CR and AVE values.

Items	Loading	VIF
CB1	0.616	1.471
CB2	0.869	2.496
CB3	0.731	1.637
CB4	0.856	2.448
CB5	0.554	1.102
CS1	0.764	1.816
CS2	0.795	1.829
CS3	0.773	1.625
CS4	0.773	1.689
CS6	0.809	1.756
FD1	0.708	2.433
FD2	0.68	2.412
FD3	0.698	2.517
FD4	0.694	2.342
FD5	0.777	1.064
ROA	0.921	1.641
ROE	0.879	1.640

Source: Smart-PLS Output (2025)

Table 3: Construct Reliability and Validity

Construct	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
CB	0.783	0.814	0.542
CS	0.844	0.854	0.613
FD	0.769	0.791	0.811
FP	0.828	1.075	0.507

Source: Smart-PLS Output (2025)

4.2 Discriminant Validity

The HTMT scores and the Fornell-Lacker criteria were examined in order to assess the discriminant validity. The Fornell–Lacker criterion is used to determine if the square root of the AVE of a certain construct is larger than that of other constructions (Fornell & Larcker, 1981). According to Table 4, a given construct satisfies the Fornell–Lacker criterion since all of its diagonal values are higher than those of other constructions. Additionally, the discriminant validity is checked using the HTMT scores. Henseler et al. (2016) state that the confidence interval for the HTMT statistic for every construct combination shouldn't have the value 1.

Consequently, all of these results indicated that the model's constructs met the criteria for discriminant validity listed in Table 5.

Table 4: Fornell-Lacker criteria.

Construct	CB	CS	FP	FD
CB	0.736			
CS	0.209	0.783		
FP	0.497	0.171	0.901	
FD	0.465	0.144	0.622	0.712

Source: Smart-PLS Output (2025)

Table 5: Heterotrait-Monotrait Ratio (HTMT).

Construct	CB	CS	FP	FD
CB				
CS	0.247			
FP	0.592	0.207		
FD	0.429	0.116	0.524	

Source: Smart-PLS Output (2025)

Structural Model Assessment

In addition to determining significance and relevance, the coefficient of determination, also known as the assessment of the degree of R-square, is another often used metric for evaluating the relationships in the Pls-SEM model. The R2 value is a representation of the combined impact of the exogenous latent variables on the latent endogenous variable (Hair et al., 2014). Table 6 shows the coefficient of determination data. The study's exogenous latent constructs chat-bot (CB), Credit scoring (CS), and fraud detention (FD), account for 44.4% of the variation in financial performance (ROA, ROE), as indicated in Table 6. Furthermore, following the execution of the Q2 predict, Q2 values was 0.247 higher than 0. This indicates that the model is predicatively relevant.

With a 5000 sample size and a confidence interval upper limit (Ul) of 97.5% and lower limit (LL) of 2.5%, the study used a bias-corrected and accelerated (Bca) bootstrapping approach in SMART Pls 4.0.1.9. This made it possible for the researchers to examine the significance level and the standardized path coefficients. Below is a discussion of the direct correlations between independent variables (IVs) and the dependent variable (DV). The Pls-SEM structural model is displayed in Figure 2, and the path co-efficient values are displayed in Table 7.

Table 6: Coefficient of determination.

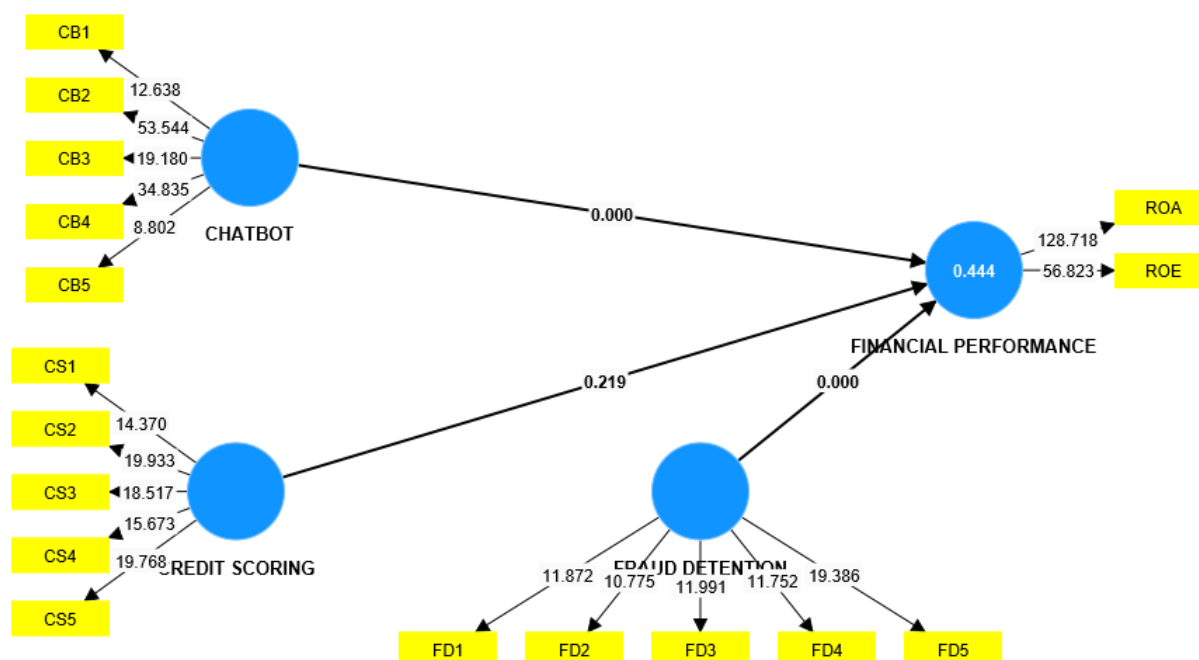|	R square	R square adjusted	Q2
Financial Performance	0.444	0.439	0.247

Source: Smart-PLS Output (2025)

Figure 2. PLS Structural Model.

4.3 Hypotheses Testing for Direct Correlations

Table 7: Direct path co-efficient results. original sample (O)

Path - coefficient	Original sample (O)	Sample mean (M)	(STDEV)	T statistics	P values
CB -> FP	0.257	0.258	0.051	5.038	0.000
CS -> FP	0.047	0.051	0.038	1.230	0.219
FD -> FP	0.496	0.499	0.042	11.836	0.000

Source: Smart-PLS Output (2025)

Figure 2 and Table 7 show the correlations between the latent variables, P values, T statistic values, and the values of all path coefficients, as shown in Table 7 above. The results of the analysis show that chatbot (CB) with β = 0.257, T statistics = 5.038, p = 0.000 have a significant effect on financial performance (FP). Also, credit scoring (CS) with β = 0.047, T statistics = 1.230, p = 0.219 has an insignificant effect on financial performance (FP). Furthermore, the

result shows that fraud detection (FD) with β = 0.496, T statistics = 11.836, *p* = 0.000 has a significant impact on financial performance (FP).

5.0 DISCUSSION

Hypothesis 1 proposes no significant relationship between the adoption of chat-bots and virtual assistants and the financial performance which was not supported with prior findings. The result indicates that adoption of chat-bots has a significant relationship on financial performance. The same outcome applies to the research that Rani and Kaur (2022) reported. This finding implied that investing heavily on chatbot technology will enhance capabilities and efficiency and it will equally make client have satisfaction, happiness, and will improve revenue generation for banks. The finding is in alignment with technology acceptance model (TAM) and innovation diffusion theory (IDT).According to TAM, chatbot usage will rise if people believe they are practical and simple to use. These requirements will be satisfied, which would result in better performance. In accordance to IDT, innovations that are compatible and have a relative benefit have a higher chance of being implemented. Chatbots may be seen as providing definite benefits (such as round-the-clock assistance), promoting uptake, and increasing financial performance of banks.

The acceptance of H2 also shows there is no significant effect between the use of AI for credit scoring and loan risk assessment on financial performance. The same conclusions were drawn by (Kumar & Raj, 2021). This indicates that there are issues and challenges with data quality, legal restrictions, and opposition to adoption of AI for credit scoring and loan risk assessment for it use in these banks. The result is consistent with the innovation diffusion theory (IDT) and the technological acceptance model (TAM). Low perceived utility or simplicity of use may be the cause of the negligible effect, which would restrict user acceptability. This suggests that usability or awareness concerns may need to be addressed by banks. According to IDT, innovations must have definite advantages; adoption and impact will be low if credit scoring systems are difficult or do not provide a relative benefit which was express by the result.

The not acceptance of hypothesis 3 is supported by the study of Oluwaseun and Oyetola (2020) that 'fraud detection has a significant effect on financial performance'. This implied that banks investing in cutting-edge security fraud prevention equipment's will help in reducing losses, improve client trust and it will improve integrity in operationalisation which will equally lead to having a favourable effect on financial performance of banks. Innovation diffusion theory (IDT) and the technology acceptance model (TAM) are consistent with the findings. Given their importance, fraud detection systems are probably more likely to be accepted and integrated into operations since they are seen as beneficial. Fraud detection supports IDT elements that can improve adoption and performance impact, such as trialability (testing systems prior to full adoption) and observability (visible advantages in less fraud).

6.0 CONCLUSION AND RECOMMENDATIONS

The study concludes that chatbots (CB) and virtual assistants have a significant effect on financial performance, this demonstrates the ability that chatbot been significant can improve the experience of user, lead to low operational cost, and enhance quality service to clients. The study also, conclude that credit scoring (CS) has an insignificant effect, highlighting minimal effect on financial performance, is largely due to poor implementation, lower adoption cost, or inadequate in the appraisal of credit process. Lastly, the study does conclude that fraud detection (FD) has a significant effect on financial performance, indicating the significance of technologies in risk management and safeguarding properties/cash, this enhances trust and increase overall financial performance of banks and improve client loyalty to these banks.

The study recommends that banks should energise in investing in chatbot, they should carry on with adoption and refine chatbot systems to improve the interaction of client efficiency in operationalisation. Improvement in the capacity of employees will improve user interfaces which can result in enhancing effectiveness and satisfaction by user. Furthermore, the study recommend banks should give more prioritise in investing in fraud detection systems. Equally, they should continue training of employees and updating of algorithms to improve and boost efficiency and guarantee sustained performance. Regulators and policymakers should as matter of urgency stimulate digital transformation for financial institutions most especially the banking sector by creating acceptable rules, regulations, standards and initiating capacity building.

Suggested Areas for Further Study

This study investigated assessing the impact of AI tools adoption on the financial performance of listed deposit money banks in Nigeria. Future studies could consider conducting a comparative study across industries to analyse if chatbot, credit scoring and fraud detection effects can be different by sectors. Further study can also, explore adding a mediating variable such as technology readiness, user competence and data quality to access it mediating role between the relationship of AI tools adoption (chatbot, credit scoring and fraud detection) on financial performance.

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