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# Effect of Artificial Intelligence on Financial Performance of Listed Deposit Money Banks in Nigeria

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## Abstract

The main objective of the study is to investigate into how artificial intelligence affects the financial performance of Nigerian listed deposit money banks. Return on Assets and Return on equity were employed as a dependent variable, with chatbots (CHB), automated biometrics (AUB), and credit scoring (CSR) serving as independent variables. The research is based on the expost-facto research design, since it uses previously generated data to predict current behaviour of variable used in this study and task-technology fit theory was employed. The study sampled 13 Nigerian deposit money banks from the population. Secondary data were acquired from banks' annual reports from 2013 to 2022. The data extracted were analysed using descriptive and inferential statistics. The analysis shows that AUB and CSR significantly affect the financial performance of Nigerian listed deposit money banks, while CHB has an insignificant effect. The implication of the result is that Nigerians are reportedly moving away from traditional banking practices, which enable banks to interact with customers using artificial intelligence. Therefore, the study recommended that bank managers should ensure adequate and significant expenditures on acquisitions of automated biometrics and credit scoring.

**Keywords:** Artificial Intelligence, Financial Performance, Return on Assets, Return on Equity Listed Deposit Money Banks, Nigeria.

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## 1. Introduction

Financial performance measures how effectively an organisation uses its assets. Deposit money banks, which play an important role in the economy by offering financial services, facilitating monetary policy, and ensuring financial stability, must show strong financial performance. Investors use financial ratios like Return on Assets and Return on Equity to evaluate a company's profitability. A good financial performance can attract more investors (Bachtiar et al., 2020).

The global pandemic caused by COVID-19 has greatly affected businesses, societies, and individuals (Torales et al., 2020). The banking industry has had to adapt by encouraging customers to use digital services due to lockdown measures, with more people working and living from home. The use of smart technologies like chatbots has helped the banking sector improve its services and meet customer expectations (Schueffel, 2017).

Nigeria is a developing country, and recent technological advances have altered the way clients and banks interact. The pandemic has expedited the adoption of digital technologies, with banks rapidly transitioning to online ordering and assistance. The advancement of artificial intelligence is encouraging banks to use it for cost savings, fraud prevention, and strengthening client connections.

Artificial intelligence (AI) is the capacity of a system to comprehend exterior input, learn from it, and use that knowledge to accomplish particular objectives through adaptive adjustments. AI may boost financial performance, but it may also lead to issues with privacy, bias, compliance, and transparency. Challenges that organisations may encounter include ethical dilemmas, high implementation costs, training gaps, and staff layoffs (Nguyen, 2022). To prevent unfavourable effects, banks should concentrate on moral AI procedures, preserve high-quality data, and control potential bias in AI systems. In order to evaluate their impact on the industry, this study examines how artificial intelligence—including chatbots, automated biometrics, and credit scoring systems—affects the financial performance of Nigerian deposit money banks.

This study contributes knowledge about AI and financial performance in a number of ways. First of all, it is among the first studies to offer proof of the link between AI and Nigeria's financial performance. Second, it investigates this link using three distinct AI applications: credit scoring systems (CSR), automated biometrics (AUB), and chatbots (CHB). Finally, it validates that AI operations are consistent with the principle of task-technology fit. The introduction, literature review, methods, results, and conclusion with recommendations and findings make up the paper's five main sections.

## **2. Literature Review**

The second part discusses financial performance (Return on Assets and Return on Equity) and artificial intelligence (chatbots, automated biometrics, and credit scoring).

### **Financial Performance**

Financial performance is the term used to describe the potential earnings that a business might generate from the sale of its goods and services. It serves as a gauge for how well a business uses loan and equity funds, as well as the general health of the business. Bhunia et al. (2011) described financial performance as the overall financial situation of a company during a specific time period. They added that analysing financial performance helps in understanding a company's ability to make a profit, stay stable, and grow. Similarly, Nyor and Yunusa (2016) defined financial performance as the profit or loss a company experiences over a specific time frame.

### **Return on Assets**

The return on assets ratio is a measure of a bank's earnings before taxes as a percentage of all of its assets. This ratio serves as a barometer for the bank's managerial capacity to produce an overall profit and provides insight into how effectively the bank manages its assets. Increased return on assets will improve a bank's profitability and asset utilization (Frianto, 2012). Pandey and Diaz (2019) stated that one of the most crucial instruments for determining a company's financial stability and resource efficiency is the return on assets indicator. This ratio helps management evaluate how well bank assets are performing in relation to corporate goals and market competitors. Amahalu, Egolum, and Obi (2019) argue that the return on assets is essential for assessing how lucrative an organization is in relation to the total value of its assets. It represents the ratio of income to all assets. It also evaluates the management team's ability to generate income by utilizing corporate resources. It is a financial measure that evaluates the profitability of a bank in relation to its total assets. The return on assets metric evaluates a

bank's efficiency in using its assets for profit, based on average assets and net income. A higher return on assets indicates a rise in efficiency and productivity in how banks handle their balance sheets to generate earnings, while a decreased return on assets indicates that there is still room for improvement.

### **Return on Equity**

An essential metric of return is return on equity (Lunt, H., 2008). This ratio indicates the available resources for income generation. A measure of the profits available to business owners from the capital they invest in their companies is called return on equity. Gunasekaran et al., (2004) and Bhagwat and Sharma (2007) claimed that after the entire cash flow period is known, it can be added to the income to provide an idea of the rate of return on equity. This assists top management in assessing the possible performance of every capital that the company has invested. Hidayat (2017) argued that one factor that shareholders use to assess the performance of their company. The better the proportion, the better off business owners are since it puts them in a better position. This crucial ratio determines a bank's ability to generate a return on equity investments. Net income divided by shareholders' equity is how return on equity is calculated (Brigham and Houston, 2011). The ratio of net income to total capital is used to calculate ROE. For shareholders, a greater ROE indicates a higher return on investment and typically higher share prices (Lestari & Toto, 2007). Investors like ROE because it connects the income statement to the shareholders' equity.

### **Artificial Intelligence Tools in the Banking Sector**

The banking industry uses several AI-based tools, including chatbots, automated biometrics, and virtual customer assistants.

#### **Chatbots**

Chatbots are programs that simulate conversations with users. They are important in banking since individuals are often too busy to visit banks in person, while chatbots are available around the clock. These tools comprehend client wants and deliver precise responses (Vijai, 2020, Sadok, 2022). Users can communicate with them via voice or text (Rahman et al., 2022). Chatbots not only assist customers with problems without requiring human intervention, but they also gather information on frequently asked questions that can be utilised to enhance future offerings. They notify clients about their transactions and the extra perks to which they are eligible. Chatbots can assist banks in determining the preferences of its clients, providing pertinent services, and even rewarding them. The use of chatbots is also reducing the need for traditional customer service channels like call centres and electronic banking.

#### **Automated Biometric**

Biometric identification identifies people using distinctive biological traits including voiceprints, iris patterns, and fingerprints. Because of the natural variances in their creation, these traits are distinct (Lee, 2016). Traditional passwords are regarded less secure than biometric solutions. Many banks worldwide have begun to use biometric technologies to authenticate clients and personnel.

#### **Credit Scoring**

Artificial intelligence analyses data from both traditional and non-traditional sources to assist lenders in determining the financial health of their clients. For individuals or companies with bad credit histories, this enables more precise risk assessment and aids in the creation of tailored financial products (Dumasia, 2021). The risks involved in extending credit are assessed by credit scoring. These models can be used by lenders to determine who should receive loans,

how much to lend, and what extra steps can increase borrowers' profitability (Khashei and Mirahmadi, 2015).

## **2.2 Empirical Review of Literature**

### **Chatbots and Financial Performance**

Mathew and Onuora (2023) investigated the effect of chatbots on the operations of deposit money banks in Nigeria. They took samples from eleven banks over a ten-year period, from 2012 to 2021. The study used both ex post facto and longitudinal research approaches. Descriptive statistics, Pearson correlation, and Variance Inflation Factor (VIF) analysis were used to analyse the four study aims and hypotheses. Using panel regression, data from the annual reports of the selected banks was examined. The results showed that the performance of Nigerian listed deposit money banks was positively and considerably impacted by chatbots. Therefore, it is recommended that management of Nigerian banks include chatbot services into their everyday operations. Sayiwal (2020) investigated chatbots in the Indian banking industry, with a particular emphasis on Mahindra Bank's implementation of them. Using a methodical analysis of the literature, the study concluded that chatbots are a promising means for banks to leverage AI-based solutions to increase client loyalty.

### **Automated Biometrics and Financial Performance**

Chukwu (2019) conducted research on the effect of implementing biometric verification systems in Nigeria's banking sector. The study details the many steps taken by the Central Bank of Nigeria to reduce fraud, including as policy announcements and bank instructions. It also examines the industry benefits of biometric verification, the difficulties encountered in putting it into practice, and the methods the Central Bank and other stakeholders employed to get beyond these problems. Morake et al. (2021) conducted a study titled 'The Customers' Perspectives' on biometric technologies in banking institutions. The study sought to evaluate the significance of security and usability in digital banking, financial technology, and payment verification using biometric systems. Fifty-two percent of the subjects replied to the quantitative study. Questionnaires were sent out to collect data. The study suggests that financial transaction organisations should adopt suitable security methods and systems to enhance creativity, security, and flexibility in their financial activities.

### **Credit Scoring and Financial Performance**

Adok et al. (2022) conducted a comprehensive examination into how banks and other financial institutions use artificial intelligence (AI) in credit assessments. AI promotes macroeconomic growth while also improving credit availability and financial inclusion for less fortunate borrowers. Ghodselahi and Amirmadhi (2011) examined how AI techniques can be used to evaluate credit risk. They wanted to improve accuracy by using a hybrid model for credit scoring. Using neural networks, decision trees, and support vector machines, the study shows that a hybrid AI-based credit scoring model performs better than earlier methods. Emel et al. (2003) conducted one of the first studies in Turkey on a company's credit scoring technique. The study analysed 82 industrial firms' financial ratios for loans from a Turkish commercial bank, finding that companies with higher credit scores have more cash, better capital reserves, fewer bank loans, and a better equity-fixed asset balance.

## **2.3 Theoretical Framework**

This research is based on the Task-Technology Fit Theory, which explains why financial institutions adopt technological advancements to provide access to financial services.

### **Task-Technology Fit Theory**

The Task-Technology Fit Theory identifies a relationship between modern technology and the jobs it is designed to support. A theoretical paradigm called job-Technology Fit takes into account how technology performance, job requirements, and individual skills interact at a particular moment (Goodhue & Thompson, 1995; Goodhue, 1995). The Task-Technology Fit perspective assumes that when individuals use technology for work, they may assess how well tasks and technology match. It also suggests that evaluating this fit can predict effectiveness. Task-Technology Fit is calculated by looking at the user interface across various factors such as data accuracy, accessibility, and technological reliability. The concept also involves individuals assessing the efficiency of a device and how well the system helps those complete tasks and aligns with their skills (Dishaw, 1999). The TTF theory states that a better match between technology, work needs, and personal abilities leads to increased efficiency, meaning faster task completion (Goodhue, 1995). Customers are more likely to embrace and use technology when they know how it may aid with chores, which boosts productivity.

A good task-technology fit leads to better performance; when technology complements the characteristics of the activity it supports and the individual skills of its users, people can carry out their responsibilities more effectively (Spies et al., 2020; Lee et al., 2007). The interactive components of Task-Technology Fit are shown here. The criteria of the task specify the mental and physical mechanisms that people employ to convert information into results in a particular setting (Goodhue and Thompson, 1995; Goodhue, 1995). A task might involve varying levels of complexity and technological needs. The tools people employ to complete jobs or help them reach their goals are referred to as the technical performance factor. Examples of such tools include computer networks and support services. The operation of these tools is dependent on their environment and the functions they perform. These tools serve as the governing element since humans must use technology to perform tasks more efficiently. Furthermore, an individual's personal skills are a reflection of their diverse personal traits, which might impact their ability to use technology in their professional capacities. This element relates to a person's personal strengths, including motivation, understanding, and experience with different technological devices (Goodhue and Thompson, 1995).

While there are other theories that might be applied to this research, the task-technology fit theory is the most pertinent in bolstering the study's objectives. This is because the theory highlights how tasks and technology can be integrated to improve performance. Better performance is achieved through proper task-technology fit: people can carry out their responsibilities more effectively when technology is tailored to the job characteristics it is intended to support and their individual capabilities (Spies et al., 2020; Lee et al., 2007).

### **3. Methodology**

The research is based on the ex-post-facto research design, since it uses previously generated data to predict current behaviour of variable used in this study. The research utilized data obtained from online annual financial report of the Thirteen (13) banks selected requiring them to be listed on the Nigerian Exchange Group by December 31, 2012, spanning ten years from 2013 to 2022 considering the availability of the required data as at the period under study. These banks are; Access Bank PLC, Ecobank Nigeria PLC, First Bank Nigeria Limited, First City Monument Bank PLC, Fidelity Bank PLC, Guarantee Trust Bank PLC, Jaiz Bank of Nigeria PLC, Stanbic IBTC Bank PLC, Sterling Bank PLC, Union Bank of Nigeria PLC, United Bank for Africa, Unity Bank PLC, Wema Bank PLC, and Zenith Bank PLC. The data obtained from the banks were analysed using Descriptive Statistics (i.e. Mean and Standard deviation) and hypotheses were tested using multiple regression analysis.

### **Measurement of Study Variables**

Prior studies on the relationship between AI and financial performance seem to have largely concentrated on return on assets only (Mathew and Onuora 2023) ignoring other financial performance indicators). However, this study will include both the return on assets and the return on equity.

### **Dependent Variable Measurement**

The dependent variable used is financial performance, and the proxies are return on assets, and return on equity.

<b>Table 1                      <i>Dependent Variables Measurements</i></b>		
Variable Name	Acronym	Measurement
Return on Assets	ROA	Measured as net profit before tax divided by total assets (Bachtiar et al., 2020, Ajiboye et al., 2023).
Return on Equity	ROE	Measured as Net profit before tax divided by totalequity (Ripon et al., 2018; Bachtiar et al., 2020)

*Source:* Generated by Author, (2024).

### **Independent Variable Measurement**

This subsection provides detailed explanations on the measurement and operationalisation of explanatory variables of this study. These variables include chatbots, automated biometrics and credit scoring. AI tools can be measured as a dummy variable; that is, if the banks used the technology, they are credited with the score of 1; otherwise, 0.

<b>Table 2:                      <i>Independent Variables Measurements</i></b>		
Variable Name	Acronym	Measurement
Chatbots	CHB	Measured as dummy variable 1 if a bank used chatbots 0 otherwise (Singh & Singh 2019; Mathew and Onuora 2023).
Automated Biometrics	AUB	Measured as dummy variable 1 if a bank used automated biometrics 0 otherwise (Singh & Singh 2019; Mathew and Onuora 2023).
Credit Scoring	CSR	Measured as dummy variable 1 if a bank used credit scoring 0 otherwise (Mathew and Onuora 2023).

*Source:* Generated by Author, (2024).

When analyzing the effect of artificial intelligence on financial performance, it's crucial to take control variables into account. Franco et al., (2020) claim that the use of control variables in research aids in avoiding endogeneity issues. As a result, bank, size and leverage were used as control variables in the study. These proxies were explained below;

## Control Variables

<b>Table 3: Control Variables Measurements</b>		
<b>Variable Name</b>	<b>Acronym</b>	<b>Measurement</b>
Bank Size	BS	Natural logarithm of the firm's total assets (Kantudu and Samaila (2015).
Bank Age	BA	Number of years after listing of the firm (Kang & Kim, 2011; Olowokure et al., 2016).
Leverage	LEV	Total interest-bearing liabilities to the total asset of the firm in a year (Tijjani & Sani, 2016; Parte-Esteban & Gacia, 2014)

Source: Generated by Author, (2024).

## Model Specification

Based on the model below, the study therefore determines proxies for artificial Intelligence as follows:

X1= Independent Variable (Chatbots)

X2= Independent Variable (Automated Biometrics)

X3= Independent Variable (Credit Scoring)

Y= Dependent Variable (Return on Equity and Return on Assets)

$$ROE_{it} = \beta_0 + \beta_1 CHB_{it} + \beta_2 AUB_{it} + \beta_3 CSR_{it} + \beta_4 BS_{it} + \beta_5 BA_{it} + \beta_6 LV_{it} \epsilon_{it} \dots \dots \dots i$$

$$ROA_{it} = \beta_0 + \beta_1 CHB_{it} + \beta_2 AUB_{it} + \beta_3 CSR_{it} + \beta_4 BS_{it} + \beta_5 BA_{it} + \beta_6 LV_{it} \epsilon_{it} \dots \dots \dots ii$$

Where,

ROE<sub>it</sub> = Return on equity of firm i at time t,

ROA<sub>it</sub> = Return on equity of firm i at time t,

CHB = Chatbots, AUB = Automated Biometrics, CSR= Credit Scoring, BS = Bank Size, BA = Bank Age, LV = Leverage.

1 = constant,  $\mu$  = Error term, n =No of Banks, 0 = Constant term of the study model, 1 – 3 = Coefficient of artificial intelligence,  $\epsilon_{it}$  = Unobserved Error Term Component of Firm *i* in Period *t*, where *i* is the firm identification (13 banks) and *t* is the time variable (ten years).

## 4. Result and Discussion

### Descriptive Statistics

Descriptive statistics are used to summarize and describe data in an understandable manner. This gives a summary of the mean, medium, standard deviation, minimum, and maximum values for each variable. This is regarded as the initial stage in identifying and explaining the variables that are utilized in the data analysis.

**Table 4: Descriptive Statistics**

<b>Variables</b>	<b>Obs</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Min</b>	<b>Max</b>
<b>ROA</b>	130	0.031	0.059	0.000	0.540
<b>ROE</b>	130	0.184	0.511	0.000	4.900
<b>CHB</b>	130	0.300	0.460	0.000	1.000
<b>AUB</b>	130	0.908	0.291	0.000	1.000
<b>CSR</b>	130	0.777	0.418	0.000	1.000
<b>BS_LOG</b>	130	7.451	1.582	4.879	10.463
<b>BA_LOG</b>	130	1.304	0.283	0.301	1.724
<b>LEV</b>	130	0.449	0.444	0.000	2.130

Results from the independent and explanatory variables are shown in Table 4. above. One hundred and thirty observations were made. The mean and standard deviation of the independent and explanatory variables were displayed in the table together with their lowest and maximum ranges. In terms of financial performance indicators, the return on assets of deposit money banks over the periods witnessed positive returns and 3.1% growth in returns, with minimum and maximum returns of 0.000 and 4.900, while return on equity has 18.4% growth in returns, respectively.

The CHB has a mean value of 0.300, a minimum of 0, and a maximum value of 1. This indicates the lowest mean value among the independent variables. The AUB has a mean value of 0.908, a minimum of 0, and a maximum of 1, an indication of increased bank returns. CRS shows a mean value of 0.777, a minimum of 0, and a maximum of 1. Based on Table, results, the average mean value of the BS\_LOG is 7.451, with a minimum of 4.879 and a maximum of 10.463. The BA\_LOG result indicates an average mean value of 1.304, a minimum of 0.301, and a maximum of 1.724. LEV shows an average mean value of 0.449, a minimum of 0.000, and a maximum of 2.130.

### **Correlation Analysis**

This subsection displays the correlation matrix for the dependent, independent, and control variables. The correlation matrix reveals the extent, strength, and direction of the association between two or more variables (Gujarati, 2004). The correlation can range from -1 to 1. The sign of the coefficient denotes the direction of the association (positive or negative), and the density of the correlation coefficient value reflects the relationship's extent. The coefficient on the major diagonal is typically 1.000, as each table variable contains a perfect positive linear relationship within itself.

**Table 5: Correlations**

	ROA	ROE	CHB	AUB	CSR	BSZ	BAG	LEV
ROA	1							
ROE	0.3515	1						
CHB	-0.0039	-0.0381	1					
AUB	0.0543	0.0131	0.2088	1				
CSR	0.0576	-0.119	0.3508	0.5951	1			
BSZ	-0.139	-0.1492	-0.0683	-0.0028	-0.0576	1		
BAG	-0.1616	-0.341	0.1262	0.1967	0.2693	-0.1211	1	
LEV	0.1688	0.1694	0.0568	0.0258	-0.007	0.1558	-0.2696	1

Table 5 shows the Pearson correlation matrix for the research variables. The results indicate less severe multicollinearity. The highest correlation coefficient in the table is 0.5951. Pallant (2013) and Hair, Black, Babin, and Anderson (2014) state that there shouldn't be any serious multicollinearity issues if the correlation coefficient is less than 0.9.

The results in Table 5 show the correlation coefficients of the variables of Artificial Indigence (CHB, AUB, and CSR) and financial performance (ROA & ROE) of the selected deposit money banks in Nigeria. The table shows a positive, significant relationship between AUB and CRS with ROA from the correlation coefficients of 0.0543 and 0.0576, which are statistically significant. This relationship suggests that AUB and CRS improve performance positively and are statistically significant.

On the other hand, the results in Table 5 show a positive, significant relationship between AUB with ROE from the correlation coefficients of 0.0131, which are statistically significant. This relationship suggests that AUB improve performance positively and are statistically significant. Similarly, the results from the table indicate that there is a significant negative relationship between CHB and ROE from the correlation coefficients of -0.0381. However, the



results also show an insignificant negative relationship between CRS and ROE from the correlation coefficients of -0.119.

### Multiple Regressions

This subsection indicates the results of multiple regressions and diagnostic checks performed to verify the linear regression assumption. Verifying the assumptions of the linear regression model, which include looking for multicollinearity heteroskedasticity, outliers, linearity and autocorrelation, is one of the final steps in the multivariate analysis process. Hair et al. (2014) argue that verifying the assumption aids in assessing whether the regression model fits the linear regression model's assumptions. In this research, heteroskedasticity was tested using Breusch and Pagan (1980), and multicollinearity was checked using the variance inflation factor test (VIF). To tackle the problem of autocorrelation inherited, this study employed panel-corrected standard errors (PCSE) regression as suggested by Beck and Katz (1995).

### Regression Results

**Table 6: Return on Equity Model**

ROE	Coef.	Std. err	z	P>z
CHB	-0.088	0.105	-0.840	0.399
AUB	0.287	0.088	3.260	0.001
CSR	-0.340	0.101	-3.360	0.001
BS_LOG	-0.071	0.036	-1.990	0.047
BA_LOG	-0.593	0.278	-2.140	0.033
LEV	0.129	0.114	1.130	0.260
_CONS	1.224	0.599	2.040	0.041
R2	0.210			
WALD CHI2	25.990			
POB	0.011			

Table 6 reveals a cumulative R-square of 20.1%, and the P-value 0.011 is significant at 5% ( $P < 0.05$ ). This implies that the overall model is fit for explaining the level of variability between the dependent and explanatory variables. Hence, the regression model explains that 20.1% of the total variation in the model is influenced by the joint effect of independent variables (chatbots, automated biometrics, and credit scoring) and control variables (bank size, bank age, and leverage).

In terms of the individual's variable contribution to the model, Table 6 shows that AUB ( $\beta = 0.287$ ,  $P < 0.01$ ) is positive and significantly related to ROE. The result implies that the variables have a significant effect on the return on equity of listed deposit money banks in Nigeria, while CSR ( $\beta = -0.340$ ,  $P < 0.01$ ) has a negative coefficient but is statistically significant with ROE.

Regarding the control variable and ROE, the coefficient of BSZ ( $\beta = -0.071$ ,  $P > 0.05$ ) and BAG ( $\beta = -0.593$ ,  $P < 0.05$ ) reveals a negative coefficient but was statistically significant with ROE, while LEV ( $\beta = 0.129$ ,  $P > 0.1$ ) reveals a positive coefficient but was statistically insignificant with ROE.

**Table 7 Return on Assets Model**

ROA	Coef.	Std. Err.	z	P>z
CHB	-0.012	0.013	-0.950	0.342
AUB	0.010	0.015	0.690	0.492
CSR	-0.001	0.010	-0.110	0.912
BS_LOG	-0.007	0.004	-1.830	0.068
BA_LOG	-0.038	0.020	-1.870	0.061
LEV	0.022	0.020	1.100	0.273
_CONS	0.099	0.050	1.990	0.047
R2	0.102			
WALD CHI2	9.080			
PROB	0.335			

Table 7 reveals a cumulative R-square of 10.2 and is insignificant at 5% ( $P > 0.1$ ). The regression model explains that 10.2% of the total variation in the model is influenced by the joint effect of independent variables (chatbots, automated biometrics, and credit scoring), and control variables (bank size, bank age and leverage).

In term of the individual's variable contribution to the model, Table 7 shows that VCA ( $\beta = 0.021$ ,  $P < 0.1$ ) is positive and significantly related to ROA. The result implies that the variable has significant effect on the return on assets of listed deposit money banks in Nigeria.

On the other hand, Table 7 shows that the coefficients of CHB ( $\beta = -0.012$ ,  $P > 0.1$ ), AUB ( $\beta = 0.010$ ,  $P > 0.1$ ), and CSR ( $\beta = -0.001$ ,  $P > 0.1$ ) were found to have an insignificant relationship with ROA.

Regarding the control variables and ROA, the coefficient of BS ( $\beta = -0.007$ ,  $P < 0.1$ ) and BA ( $\beta = -0.038$ ,  $P < 0.1$ ) reveals a significant negative relationship with ROA, while LEV ( $\beta = 0.022$ ,  $P > 0.1$ ) reveals a positive coefficient but was statistically insignificant relationship with ROA.

### Testing of Hypotheses

*H<sub>01</sub>: Chatbots has no significant effect on the financial performance of Listed Deposit Money banks in Nigeria.*

The result in Table 6 shows that when ROE was utilized as a dependent variable to measure the bank's financial performance, CHB had a negative coefficient value of -0.088 and a p-value of 0.399, which is insignificant at all levels. Similarly, the result in Table 6 when ROA was utilized as a dependent variable to measure the bank's financial performance, CHB had a negative coefficient value of -0.012 and a p-value of 0.342, which is insignificant at all levels. This provides evidence supporting the acceptance of the null hypothesis one of the study, which states that CHB has no significant effect on the financial performance of deposit money banks in Nigeria.

*H<sub>02</sub>: Automated biometrics has no significance effect on the financial performance of deposit money banks in Nigeria.*

Table 6 provides a result in respect of the effect of AUB on the ROE of deposit money banks in Nigeria. The AUB has a positive coefficient value of 0.287 and a p-value of 0.001, which is significant at all levels. This signifies that AUB has a positive and significant effect on the ROE of deposit money banks in Nigeria. This provides us with evidence to reject null hypothesis two of the study, which states that AUB has no significant effect on ROE of deposit money banks in Nigeria.

Table 7 provides a result in respect of the effect of AUB on the ROA of deposit money banks in Nigeria. The AUB has a positive coefficient value of 0.010 and a p-value of 0.392,

which is insignificant at all levels. This signifies that AUB has a positive and insignificant effect on the ROA of deposit money banks in Nigeria.

*H<sub>03</sub>: Credit scoring has no significance effect on the financial performance of deposit money banks in Nigeria.*

The result in Table 6 reveals that when ROE was utilized as a dependent variable to measure the bank's financial performance, CSR had a negative coefficient value of -0.340 and a p-value of 0.001, which is significant at all levels. This implies that CSR has a negative but statistically significant effect on the ROE of a deposit money bank in Nigeria. This means that for every increase in the number of CSR, it has a significant negative effect on the ROE of the deposit money banks in Nigeria. This provides evidence to reject null hypothesis four of the study, which states that CSR has no significant effect on the financial performance of deposit money banks in Nigeria.

Also, the result in Table 7 reveals that when ROA was utilized as a dependent variable to measure the bank's financial performance, CSR had a negative coefficient value of -0.001 and a p-value of 0.912, which is insignificant at all levels. This implies that CSR has a negative and statistically insignificant effect on the ROA of a deposit money bank in Nigeria. This means that for every increase in the number of CSR, it has no significant negative effect on the ROA of the deposit money banks in Nigeria. This provides evidence to accept the null hypothesis four of the study, which states that CSR has no significant effect on the financial performance of deposit money banks in Nigeria.

### **Discussion of Major Findings**

The aim of this section is to interpret and discuss the findings in detail within the context of the relevant literature, theory, and practice. The discussion aims to establish the foundation for accepting or rejecting the hypotheses, ultimately achieving the research objectives. It is expected to facilitate the generation of practical policy implications and recommendations.

### **Chatbots and Financial Performance**

The result of this study revealed that chatbots have insignificant effect on financial performance of deposit money banks. Based on its p-values of 0.485, 0.342, and 0.442 measured using return on equity and return on assets. The results show that chatbots have no significant influence on enhancing the financial performance of deposit money banks. This implies that deploying chatbots cannot ensure financial performance, most likely due to the large amount of money necessary in developing the software, which diminishes the bank's profitability grounds. Based on the non-significant findings, the study concluded that chatbots have an insignificant effect on the financial performance of deposit money banks in Nigeria. This result is consistent with the findings of Hwang and Kim (2021), who examine technology effectiveness for industry demand in which artificial intelligence (AI) is applied in the financial sector and found a negative relationship between chatbots and performance, and contrary to the study of Mathew, Onuora, & David (2023), who studied automated chatbots and corporate performance of listed deposit money banks in Nigeria and concluded that chatbots have a positive and significant effect on corporate performance of listed deposit money banks in Nigeria. The finding is also contrary to the findings of Haoqi (2024), who investigated the influence of chatbot services on bank performance using an IBM Corporation case study and concluded that chatbots have a positive and significant effect on bank performance. Therefore, the study suggests that significant expenditures on chatbot acquisitions be reduced in order to improve banks' financial performance.

### **Automated Biometrics and Financial Performance**

The examination of the data revealed a strong relationship between automated biometrics and the financial performance of deposit money banks in Nigeria as measured by return on equity. According to the results, automated biometrics has a statistically significant effect on the financial performance of deposit money banks in Nigeria. As a result, the financial performance of these banks increases when automated biometrics usage is maintained. This suggests that the more automated biometrics a bank uses in its operations, the more return it generates from its assets. This is due to the fact that biometric identification technologies aid in both the identification and verification of financial transactions in addition to helping people distinguish one individual from another. Thus, the study comes to the conclusion that there is a statistically significant positive relationship between automated biometrics and the financial performance of deposit money banks in Nigeria. This result is consistent with the research conducted by Parimalarani (2020), which examined the employment patterns in the banking industry, and the study concluded that automated biometric technology improved bank performance. Therefore, the study suggests that deposit money banks should continue to use automated biometrics in their operations because it helps with convenient completion of their numerous transactions in order to boost financial performance.

### **Credit Scoring and Financial Performance**

The credit scoring system was found to have a significant effect on the financial performance of deposit money banks in Nigeria as measured by return on assets and return on equity. As a result, when the credit scoring system is applied, ROE increases and the bank's financial performance rise. The outcome demonstrates that credit scoring has been explored for use in the operation of banking services, including behavioral, bankruptcy, and profitability scoring. The study concludes that credit scoring had a significant effect on the financial performance of listed deposit money banks in Nigeria as measured by the return on equity. This result is in line with the study conducted by Emel et al. (2003), who examined the financial ratios of 82 industrial companies that applied for loans from a Turkish commercial bank. The study concluded that businesses with higher credit scores have a significant impact on performance. Similar, Sadok, Sakka, and Maknouzi (2022) conducted a systematic literature review to examine the use of artificial intelligence (AI) in credit analysis performed by banks and other financial institutions. The study concluded that the credit scoring system improves financial inclusion. Also, Ghodselahi & Amirmadhi (2011) studied the application of artificial intelligence techniques for credit risk evaluation. The study compared the accuracy of support vector machines, neural networks, and decision trees as base classifiers and came to the conclusion that credit scoring models can be used for overall accuracy improvement when compared to other credit models. Therefore, the study suggests that the management of deposit money banks should be encouraged to acquire a credit scoring system since it can improve their financial performance even though it was found to have an insignificant effect.

### **Implication of the Study**

This study has add to the theories of Artificial Indigence and its concept of financial performance as is of paramount benefit to financial analysts in the course of policy formulations, source of guide to bank. Managers of banks in Nigeria would have this research work enhance financial performance in order to maximize return on asset and on equity. It also stands as a source of research for potential researchers. In addition this study will benefit the general public whoever has interest in bank's ROA and ROE.

## **5. Conclusion and Recommendations**

This study examines the relationship between artificial intelligence and financial performance of Nigerian listed deposit money banks. It found that AI variables are good predictors of financial performance, while chatbots did not significantly contribute. Automated biometrics and credit scoring systems have improved financial performance over the years. The study provides recommendations for improving the financial performance of these banks. The study suggests reducing expenditures on chatbot acquisitions by deposit money banks to improve financial performance. It also emphasizes the importance of robust automated biometrics and well-spent resources for credit scoring systems, despite their negative coefficient but significant effect on financial returns.

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