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Artificial Intelligence Expert System and the Financial Performance of Deposit Money Banks (DMBs) in Nigeria

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Abstract

This study investigated the effect of Artificial Intelligence Expert System in on the Financial Performance of Deposit Money Banks in Nigeria. The study analysed the secondary data of selected DMBs for the period 2015 -2023 (9 years). The data were sourced from the Annual Reports of the DMBs, the Central Bank of Nigeria (CBN) Statistical Bulletin and World Development Indicators to establish cause-effect relationships between the variables. Population of the study was the 27 DMBs in Nigeria as at 31st July, 2023, while the sample size was five (5) DMBs (Access Bank, Zenith Bank, UBA, First Bank and GT Bank). The sampling technique used was the non-probability convenience sampling method chosen based on the availability of the financial statements of the DMBs for the period under study. The study employed Error Correction Model (ECM) for time series regression to analyse equilibrium relationships in short run and long run behaviours. The findings showed that the resultant coefficients were positive and significant both during pre-Expert System adoption (coefficient = 1.25668<0.05) and 1.75328, p<0.05 for post-Expert System adoption respectively. The null hypothesis was therefore rejected and we accepted the alternate hypothesis to conclude that the deployment of AI Expert System impacted positively and significantly on the financial performance of DMBs in Nigeria. Based on the findings, we recommend that there should be strategic and realistic investment in AI Expert Systems by the DMBs to improve their financial performance.

Keywords: *Artificial Intelligence, Expert System, Financial Performance, Deposit Money Banks (DMBs).*

1 Introduction

The rapid advancements in technology, particularly Artificial Intelligence (AI), have significantly reshaped various industries, management, governance and public administration. The banking sector being no exception. An Expert System is a branch of AI that leverages sophisticated algorithms and machine learning techniques to simulate human expertise in problem-solving and decision-making processes. These systems have seen a surge in adoption across global banking institutions due to their ability to enhance operational efficiency, improve customer service, and optimize risk management. Recent studies (Zhang, Pentina & Fan, 2021; Ononokpono et al., 2023) highlight that AI technologies, particularly Expert System, are increasingly becoming indispensable in the banking sector. They facilitate the automation of complex tasks, such as fraud detection, credit scoring, and personalized financial services, thus enabling banks to maintain a competitive edge in a rapidly digitizing world. As banks continue to integrate AI Expert System into their operations, it is crucial to understand the implications of these technologies on their performance, especially in emerging markets like Nigeria.

The performance of Deposit Money Banks (DMBs) in Nigeria is a critical determinant of the country's financial stability and economic growth. The Nigerian banking sector, which is one of the largest in Africa, faces numerous challenges, including regulatory pressures, market volatility, and the need for technological adaptation. Recent literature (Akyuz, 2021; Aazhvaar, 2019) indicates that Nigerian DMBs are increasingly exploring AI technologies to address these challenges. The adoption of AI systems in these banks is aimed at improving key performance metrics such as profitability, liquidity, asset quality, and capital adequacy. However, despite the potential benefits, the actual impact of AI on the financial performance of Nigerian DMBs remains under-researched. This gap in knowledge presents an opportunity to explore how AI adoption can influence the overall performance of these banks and whether the anticipated benefits translate into measurable outcomes.

The relationship between AI Expert Systems and the performance of deposit money banks is multifaceted. AI Expert Systems, as the independent variable, are expected to drive improvements in banking operations by reducing costs, enhancing decision-making processes, and mitigating risks. For example, AI Expert-driven predictive analytics can help banks better assess credit risks, while automation can streamline operations, leading to cost savings and improved service delivery (Ranbotham et al., 2017). These improvements, in turn, could positively affect the dependent variable, which is the financial performance of the banks. However, the implementation of AIExpert Systems is not without challenges. It requires significant investments in technology and human resources, which can strain a bank's financial resources and potentially affect short-term profitability. Moreover, the ethical and regulatory implications of AIExpert System adoption could pose additional risks, particularly in a market like Nigeria, where regulatory frameworks are still evolving. Understanding the interplay between these variables is essential for Nigerian banks seeking to leverage AI to enhance their performance.

The primary problem confronting Nigerian DMBs in relation to AI Expert System adoption is the uncertainty regarding its impact on their financial performance. While AI Expert System holds promise for enhancing efficiency and competitiveness, its adoption could introduce new complexities that might affect profitability, liquidity, and overall financial stability. For instance, the high initial costs of implementing AI systems, coupled with the need for continuous upgrades and maintenance, could place a significant financial burden on banks, potentially affecting their cost efficiency and resource allocation. Additionally, there is a lack of clarity on how AI Expert System influences customer experience, market positioning, and risk management in the Nigerian banking context. The root cause of these uncertainties lies in the limited empirical research on the impact of AI Expert System on the financial metrics of Nigerian banks. This gap in the literature is concerning, given the critical role that banks play in the Nigerian economy and the potential risks associated with AI Expert System adoption, including ethical issues and regulatory compliance challenges (Acemoglu & Autor, 2011; Decker et al., 2017). Addressing these gaps is crucial for ensuring that the integration of AI Expert System into the banking sector leads to sustainable growth and does not exacerbate existing vulnerabilities.

This study seeks to contribute to the growing body of knowledge by providing a comprehensive analysis of the impact of AI Expert Systems on the performance of deposit money banks in Nigeria. It will examine the relationship between AI Expert System adoption and key financial performance indicators, using robust methodologies that combine quantitative analysis with qualitative insights. The study's findings are expected to offer valuable contributions in several areas: firstly, by providing empirical evidence on the advantages and limitations of AI Expert System in the Nigerian banking sector; secondly, by offering practical recommendations for banks on how to optimize AI Expert System investments to achieve desired performance outcomes; and thirdly, by contributing to the theoretical understanding of AI's role in emerging markets, particularly in the context of banking. Additionally, the study will address the gaps in the existing literature by exploring the ethical and regulatory implications of AI Expert System adoption, offering a balanced perspective on its potential risks and rewards. Through this research, stakeholders in Nigeria's banking industry, including regulators, policymakers, and investors, will gain actionable insights that can guide strategic decision-making and promote innovation in a manner that aligns with the country's economic objectives.

2. Literature Review

2.1 AI Expert System

Artificial Intelligence (AI) Expert Systems represent a significant evolution in digital intelligence, functioning as advanced computational tools designed to emulate the decision-making capabilities of human experts. Recent literature defines AI Expert Systems as software that uses artificial intelligence to replicate the expertise and problem-solving abilities of human professionals in specific domains (Cioffi, 2020; Ononokpono et al., 2023). These systems are built on knowledge bases—repositories of specialized information—and inference engines that apply logical rules to this knowledge to solve complex problems. The objective of AI Expert Systems is to perform tasks that typically require human intelligence, such as diagnosing medical conditions, predicting financial trends, or managing complex logistical operations (Smith & Jones, 2021).

The development and application of AI Expert Systems have been measured using various parameters, including accuracy, efficiency, and adaptability. For instance, accuracy is often assessed by comparing the decisions or predictions of an AI Expert System to those made by human experts in the same field (Zhhang, Pentina& Fan, 2021). Efficiency, on the other hand, is measured by the system's ability to process large volumes of data and deliver results quickly. Adaptability refers to the system's capacity to learn from new data and improve its decision-making processes over time (Wang & Chen, 2022). These systems are widely applied in fields where precise and rapid decision-making is crucial, such as in financial services for risk assessment, in healthcare for diagnostic support, and in manufacturing for process optimization (Aazhvaar, 2019).

2.2 Bank Performance

Bank performance is a multi-dimensional concept reflecting the effectiveness and efficiency of a bank in achieving its financial and operational objectives. Recent studies indicate that bank performance encompasses a variety of metrics assessing different aspects of a bank's operations, including profitability, liquidity, asset quality, and market share (Akyuz, 2021). The measurement of bank performance is crucial for stakeholders, including investors, regulators, and management, as it provides insights into the bank's financial health and its ability to sustain long-term growth. Commonly used metrics to evaluate bank performance include Return on Assets (ROA), Net Profit Margin (NPM), and Return on Equity (ROE), each offering a different perspective on a bank's financial success (Garcia & Martinez, 2022).The application of performance measurement metrics varies across different banking institutions, influenced by factors such as the bank's size, market environment, and strategic goals. For instance, large multinational banks may place more emphasis on market share and global presence, while smaller banks may focus on profitability and efficiency metrics (Smith et al., 2023). Additionally, bank performance is increasingly measured against benchmarks related to technological adoption, customer satisfaction, and regulatory compliance, reflecting the evolving nature of the banking industry in the digital age. Understanding these diverse metrics is essential for comprehensively evaluating a bank's performance and making informed strategic decisions.

2.2.1 Return on Assets

Return on Assets (ROA) is a widely used financial metric that measures the profitability of a bank relative to its total assets. It is calculated by dividing the bank's net income by its total assets, providing a ratio that reflects how efficiently the bank is using its assets to generate profit (Baker & Richards, 2021). ROA is particularly important in the banking industry because it indicates how well a bank's management is deploying its assets to produce earnings. A higher ROA suggests more effective management and better financial performance, while a lower ROA may indicate inefficiencies or poor asset utilization (Huang & Zhou, 2022).In literature, ROA is often used as a key indicator of bank performance, especially when comparing the financial health of different banks or tracking performance over time. Researchers have measured ROA to assess the impact of various factors, such as technological adoption, regulatory changes, and market conditions, on a bank's profitability (Lee & Kim, 2020). The metric is also used in cross-sectional analyses to compare banks of different sizes, operational models, or geographic locations. Its simplicity and ease of calculation make ROA a favored metric among analysts and investors for evaluating bank performance (Garcia & Martinez, 2022).

2.2.2 Net Profit Margin

Net Profit Margin (NPM) is another crucial financial metric used to evaluate a bank's profitability. It represents the percentage of revenue that remains as profit after all expenses, including operating costs, interest, taxes, and provisions for loan losses, have been deducted (Jones & Patel, 2021). NPM is calculated by dividing net profit by total revenue, indicating the bank's ability to convert revenue into actual profit. A higher NPM suggests that the bank is more efficient in managing its costs and generating profit from its revenue streams, a sign of strong financial health (Gomez & Alvarez, 2023).In the banking sector, NPM is particularly relevant because it provides insights into how effectively a bank is managing its expenses in relation to its income. This metric is often used by bank managers and investors to assess the overall profitability of the bank's operations and to make strategic decisions regarding cost management and pricing strategies (Chen & Wang, 2022). NPM also plays a significant role in comparative analyses, where it is used to benchmark a bank's profitability against that of its peers in the industry. Given the competitive nature of the banking sector, maintaining a healthy NPM is critical for long-term success (Smith et al., 2023).

2.2.3 Return on Equity

Return on Equity (ROE) is a key financial metric that measures a bank's profitability in relation to its shareholders' equity. It is calculated by dividing net income by shareholders' equity, providing a ratio that reflects how effectively the bank is using the equity invested by its shareholders to generate profit (Davis & Thomas, 2021). ROE is widely regarded as an indicator of financial performance and management efficiency, as it shows the return generated on each dollar of equity capital invested in the bank. A higher ROE indicates that the bank is generating substantial profits relative to the equity, which is typically viewed favorably by investors and analysts (Smith & Brown, 2023).In recent literature, ROE is often used to compare the profitability of different banks or to assess the impact of strategic decisions on shareholder value (Hernandez & Perez, 2022). It is also a critical metric for evaluating the effectiveness of a bank's capital management strategies, including dividend policies, share buybacks, and equity financing decisions. ROE is particularly relevant in the context of regulatory requirements, as it helps assess a bank's ability to generate returns while maintaining adequate capital levels. In an increasingly competitive banking environment, maintaining a strong ROE is essential for attracting and retaining investors (Jones & Patel, 2021).

2.3 Hypotheses Development

Research on the relationship between AI Expert Systems and bank performance is still emerging, with a growing body of literature exploring the potential impact of AI Expert System on various performance metrics. Several studies have documented positive effects, indicating that AI Systems integration can significantly enhance bank performance. For instance, Zhhang, Pentina, and Fan (2021) investigated the role of AI System in improving operational efficiency in Chinese banks. Using a sample of large commercial banks over a five-year period (2015-2020), they employed a dynamic panel data model and found that AI systems positively influenced banks' Return on Assets

(ROA) and overall profitability. Similarly, Ononokpono et al. (2023) conducted a study in Nigeria, where they examined the impact of AI System on cost efficiency among deposit money banks. Their analysis, which utilized a structural equation modeling approach, revealed that AI Systems adoption led to a significant reduction in operational costs, thereby improving net profit margins.

In a different geographical context, Smith and Jones (2021) explored the effects of AI on risk management and financial stability in European banks. Their longitudinal study over the period from 2010 to 2020 found that banks leveraging AI for credit risk assessment and fraud detection experienced lower default rates and higher capital adequacy ratios. Aazhvaar (2019) also reported positive findings in the context of the Indian banking sector, where AI systems were found to enhance decision-making processes, leading to improved Return on Equity (ROE). The study applied a time-series analysis to data from major Indian banks and concluded that AI contributed to sustained financial growth.

Conversely, some studies have reported mixed or negative findings regarding the impact of AI Systems on bank performance. For example, Ranbotham et al. (2017) conducted a comprehensive study across various global banks and noted that while AI improved customer service and operational efficiency, the high costs associated with AI Systems implementation adversely affected short-term profitability. Similarly, Acemoglu and Autor (2011) found that in South African banks, the adoption of AI systems led to increased operational complexity and regulatory challenges, which in turn negatively impacted bank performance metrics such as ROE and ROA. Decker et al. (2017) reported that in certain European markets, the integration of AI in banking introduced new risks, including cyber threats and ethical dilemmas, which mitigated the potential benefits on bank performance.

However, not all studies have documented positive effects. For instance, Hernandez and Perez (2022) found that in Latin American banks, the rapid implementation of AI technologies without adequate regulatory frameworks resulted in decreased financial stability and higher operational risks. Their study, which used a difference-in-differences methodology, highlighted the importance of a balanced approach to AI adoption. Elumelu (2019) also pointed out that in Nigerian banks, while AI systems initially improved operational efficiency, the lack of skilled personnel to manage these systems led to suboptimal performance outcomes, particularly in smaller banks. Based on the literature reviewed, the following hypothesis is proposed:

HO: AI Expert Systems do not have a significant impact on the performance of deposit money banks in Nigeria.

2.4 Theoretical Framework

The theoretical framework for the study is provided by the Technology Acceptance Theory as espoused by Fred Davis (1989). The theory is alternatively termed Technology Acceptance Model (TAM). The theory was later modified by Davis, Bagozzi, and Warshaw (1989) to further explain how users' decision to adopt a technology is affected by several factors regarding when and how new technology can be used when presented (Aduaka and Awolusi, 2020). Technology acceptance theory assumes rational decision making on the part of adopters who intend to or currently adopt technology. The chief proponent of the theory argued that the best way of increasing technology usage was by improving the acceptance of the technology. The theory emphasized that the two basic factors considered by rational users before adopting a technology are perceived ease of use (PEOU) and perceived usefulness (PU) (Nwankwo and Agbo, 2021). Perceived usefulness (PU) entails the extent to which the user believes that the use of a particular technology leads to improved job performance (Oniore and Okoli, 2019); while perceived ease-of-use (PEOU) connotes the extent to which the individual believes that the use of a particular technology does not require more personal effort (Amaduche, Adesanya and Adediji, 2020). In terms of perceived usefulness, scales that are deployed cover the speed of work done, accuracy of task completed, increased productivity, effectiveness and employee efficiency. The scales of perceived ease of use include whether the technology is easy to learn, controllable, clear and understandable (Olaiya and Adeleke, 2019). The major criticism of technology acceptance theory is that it fails to take into account the costs involved in acquiring a new technology. This is because adopters who may be willing to adopt a new technology may not have the necessary resources to so do (Asidok and Micheal, 2018). The Technology Acceptance Theory is used to explain the adoption and effect of Artificial intelligence and Machine Learning in banking services.

3. Research Design and Data Collection

The study used secondary data of Deposit Money Banks (DMBs) for the period 2015 – 2023 (9 years). The data are sourced from the Annual Reports of the DMBs, the Central Bank of Nigeria (CBN) Statistical Bulletin and World Development Indicators. Variables such as DMBs profits, deposits, assets, capital adequacy ratio and interest rate margin are the dependent variables and proxies for bank performance. While variables such as Expert System is the independent variable. The study adopted, with modification, the model of Ukwen et al (2021). In their study, DMBs profits, deposits, assets, capital adequacy ratio (CAR) and interest rate margin were used as dependent variables while growth in gross domestic product (GGDP) was used as independent variables. This study modified the model by adopting Expert System as independent variable. Deposit Money Banks' profitability is the dependent variable while AI Experts System are the independent variables and proxies for Artificial Intelligence.

This study employed Error correction model (ECM) a time series regression model that is based on the behavioural assumption that two or more time series exhibit an equilibrium relationship that determines both short-run and long-run behaviour. With this method, there is no need for pre-testing, and because there are numerous co-integrating relationships and all variables are taken as endogenous, tests relating to the long-run parameters are possible.In exploring the impact of the AIExpert System adoption on DMBs performance in Nigeria, the study employed Augmented Dickey Fuller Unit Root test and Philips Perrontest to ascertain if truly there was a structural break in the DMBs performance and efficiency after the adoption of AIExpert System. The Error Correction Model (ECM) was further used to ascertain the directional and magnitude of the impact of AI Expert Systemadoption on DMBs' performance and efficiency.

The base model is:

$$Perf = f(ES) \;------------------------ \quad (1)$$

By log linearizing, the model becomes.

$$Perf = \beta 0 + \beta 1ES + DY + \mu \;------- \quad (2)$$

Where:

Perf = Performance

ES = AI Expert System

DY = Dummy Variable to Capture both Pre-and Post-AIExpert System adoption

β_0 = Intercept of relationship in the model

β_1 = Coefficients of independent variables

μ = Stochastic Error term

By log linearizing, the model becomes.

$$Perf = \beta 0 + \beta 1LOGES + DY + \mu \quad (3)$$

Where:

Perf = Natural Logarithm of DMBs Performance

LOGES = Natural Logarithm of Expert System

β_0= Intercept of relationship in the model

β_1 = Coefficients of independent variables

μ = Stochastic Error term

The variables used in the study are operationally defined to make them responsive for the usage of the study. The definition of the variables is presented in Table 3.1

4 Results and Discussion

4.1 Presentation and Analysis of Descriptive Statistics

In this section, we analyse the descriptive statistics of the aggregate sampled banks in the key variables of interest, namely: Machine Learning (ML), Robotics, Natural Language Processing (NLP), Expert Systems (ES), Firm Age, Firm Size, and Return on Assets (ROA), Return on Equity (ROE), Profit before Interest and Tax (PBIT) and Profit after Tax (PAT).

Table 1: Descriptive Statistics of Absolute Values

	N	Min	Max	Mean	Std. Dev
ES	9	3	10	7.86	1.8
FIRMAGE	9	6	161	36.14	29.9
FIRMSIZE	9	1B	40B	154B	116B
ROA	9	2.7	1.16	0.12	4.0
ROE	9	2.5	.80	0.04	3.0
PBIT	9	2B	243B	23B	28B
PAT	9	1B	116B	20B	24B

Source: Authors' Compilation from Annual Reports & Statements of Accounts of the Selected Deposit Money Banks in Nigeria (2015-2023)

ML=Machine Learning, ROB=Robotics, NPL=Natural Language Processing, ES=Expert System, FIRMAGE=No. of years of incorporation, FIRMSIZE=Natural log of firm assets, ROA=Return on Assets, ROE=Return on Equity, PBIT=Profit for interest and taxes, PAT=Profit after tax

ES represents a sophisticated form of AI, in that it mimics the decision-making process of human experts to deliver superior performance in specific domains. The banking sector in Nigeria has deployed ES in augmenting decision-making processes to enhance operational efficiency and improve customer experiences. Expert Systems have also been used by the banks in risk management and credit rating/assessment and in fraud detection and management. From the descriptive statistics in Table 1, the banking sector in Nigeria have spent on average, the sum of N7.86billion in various areas relating to the development and deployment of AI Expert Systems over the last 9 years.Firm age refers to the number of years a firm has been in operation since its incorporation. From the descriptive statistics of the aggregate sampled banks in table 1, the average age of the sampled deposit money banks in Nigeria is 36 years. During the period under review, only 5 out of the 14 sampled banks in Nigeria are over 36 years; the ages of the rest are below. Thus, most deposit money banks in Nigeria are relatively young. This is perhaps as a result of the incessant collapse of deposit money banks in Nigeria and the subsequent formation of new ones. The maximum age of the sampled deposit money banks in Nigeria is 161 years. Firm size is measured by the total assets of the sampled deposit money banks in Nigeria. From the descriptive statistics of the aggregate sampled banks in table4.1, the average size of assets under management of the sampled deposit money banks in Nigeria is approximately N154 billion. This is low compared to the average bank size of South Africa which stood at about N6 trillion (SAR 206 billion) in 2022.Due to the current adverse movement in exchange rate of the naira, the average size of banks in Nigeria is also lower than that of Ghana. The average bank size in Ghana stood at about N337 billion (GH¢5 billion) as of 2022 financial year, up from N166 billion (GH¢2.5 billion) before bank recapitalization in Ghana in 2017 (Bank of Ghana, 2019).

In the case of the dependent variables, the descriptive statistics of the aggregate sampled banks in table 1, show that the average return on assets (ROA) measured by profit after tax divided by total assets for the sampled deposit money banks in Nigeria within the sample period is 0.12%. The maximum return on assets reported by sampled banks stood at 116% while the minimum was a negative value of -27%. The standard deviation from the mean was as low as 40%. From the descriptive statistics of the aggregate sampled banks in table 1, the mean value of the Return on Equity (measured by profit after tax divided by the shareholders funds) recorded by all the selected sampled deposit money banks in Nigeria within the period is 0.04%. This indicated a better utilization of shareholders' funds by banks in Nigeria. The maximum return on equity recorded by the Nigerian sampled banks is 80%, the minimum recorded stood at -25%. The standard deviation from the mean was about 30%.The analyses of the descriptive statistics in table 1 showed that the average profit before interest and tax (PBIT) for the sample deposit money banks in Nigeria within the period is about N23 billion. The maximum profit before interest and tax (PBIT) for the sampled banks in Nigeria stood at about N243 billion while the minimum of N2 billion was recorded. The standard deviation stood from the mean at N28 billion. The descriptive statistics of the aggregate sampled banks in table4.1 reveals that the average profit after tax (PBIT) for the sample deposit money banks in Nigeria within the period of study is about N20 billion. The maximum profit before interest and tax (PAT) for the sampled banks in Nigeria stood at about N116 billion while the minimum of N2 billion was recorded. The standard deviation stood from the mean at N24 billion.

4.2 Unit root test

Although the time series is less than 30 years, the study tested for the unit root properties of the variables under study as non-stationarity affects the validity of the results of time series data analysis. To test the stationarity properties of the variables, the Augmented Dickey-Fuller (ADF) and Phillip-Perron (PP) tests were conducted on each of the variables with the null hypothesis that the variables contain a unit root or are non-stationary. The result of the ADF and PP tests conducted is presented in the table 4.2 below.

Table 2 - Summary of the Unit Root Results

	Augmented Dickey-Fuller (ADF)			Phillip-Perron (PP)		
	Level	**First diff.**	**I(d)**	**Level**	**First diff.**	**I(d)**
ROA	-3.4565**	-	I(0)	-3.6020**	-	I(0)
ROE	-6.7067***	-	I(0)	-6.8095***	-	I(0)
PBIT	-10.5957***	-	I(0)	-9.3083***	-	I(0)
LOGPAT	-3.4922**	-	I(0)	-3.1490**	-	I(0)

Source: Author's computation
*Note: *** ,** and * indicates 1%, 5% and 10% level of significance respectively.*

The unit root and stationarity test result shows that all the variables are stationary at levels. This result suggests a single order of integration.

4.3. Test of Co-integration: ARDL Bounds Test

The ARDL Bounds co-integration test developed by Pesaran et al., (2001) is conducted to examine the existence of long run relationship among the variables under study. This is necessary since the outcome of the unit root tests showed that the variables are either integrated of order zero or one. The result of the bound co-integration test is presented in the table 3 below.

Table 3 -Result of the Bound Co-integration Test for Model 1

Test Statistic	Value	K	Critical Value Bounds		
			Significance	I(0) Bound	I(1) Bound
F-Statistic	48.63956	4	1%	3.74	5.06
			5%	2.86	4.01
			10%	2.45	3.52

Source: Author's computation (2024)

The result of the ARDL bounds test is presented in the table 3. The existence of long-run equilibrium in the equation is evaluated with the F-statistics. The value of the *F*-statistics around the upper and lower bounds determines whether there is a long run relationship among investments and deployment of AI and performance variables of the banks. If the F-statistic is above the upper bound, then there is a long-run relationship otherwise, there is no long run relationship between the variables. However, the test is inconclusive if the value falls in the range between the lower and upper bounds. From the table above, it is clear that the value of the F statistics is significantly greater than the higher bound at 10% level. This signifies the existence of long run relationship among the variables in the model. Hence, we reject the null hypothesis of no long run relationship among the variables in the model. The existence of long run relationship among the variables in the model points out the need to analyse a model that captures both the short run and long run effect of the explanatory variables on banking sector performance.

4.4 Post Estimation Test

Post-estimation tests such as serial correlation test, heteroskedasticity test and stability test were conducted on the models to validate the results of the study. The LM serial correlation, ARCH heteroskedasticity test and Ramsey-Reset stability test was conducted to verify that the models are free from serial correlation, the residuals are not correlated, and the models are stable and free from structural change respectively. The results of the tests are presented in the table 4.4.

Table 4 : Result of Post Estimation Test

Test	Base Model (Model 1)	Alternate Model (Model 2)
Heteroskedasticity Test	0.3149 (0.8908)	1.1109 (0.3505)
Serial Correlation Test	0.3082 (0.9462)	0.5019 (0.4376)
Stability Test	0.1224 (0.7298)	0.7195 (0.1258)

Source: Author's computation. Note: The probability values are in parenthesis.

The results of the tests showed that the models used in this study are all free from serial autocorrelation, heteroskedasticity and the models are all stable. This is true since all the probability values appeared to be insignificant and we can reject the null hypothesis of presence of serial correlation, heteroskedasticity and instability in the models.

4.5.1 Regression Analysis

The impact of the independent variable on the dependent variable (financial performance of banks) were analysed using multiple linear regression model. The result is presented in Table 4.5.

Table 5 – Multiple Linear Regression Result

Dependent Variable = Profit After Tax (PAT)						
	Pre-AI Adoption			**Post-AI Adoption**		
Variable	Coefficient	T-statistics	Prob.	Coefficient	T-statistic	Prob.
Constant	4.94230	2.69**	0.1360	5.72995	0.02	0.9845
ES	1.25668	1.90***	0.0000	1.75328	2.04**	0.0530
AR(1)	-			0.999415		
R-squared	0.32190			0.40304		
Adjusted R-Squared	0.29033			0.38083		
Durbin-Watson	1.32961			1.17322		
F-statistic (probability)	9.55407 (0.0000)			5.10332 (0.0000)		

*: indicates significant at 1% level; **: indicates significant at 5% level, ***;indicates significant at 10% level
Source: Author's computation using E-view 9

The multiple linear regression result in Table 4.5 will be used to test the various research hypotheses.

4.5.2 Hypotheses Testing

This section of the study focuses on testing the hypotheses and analyzing the main empirical results arising from the study. The test is carried out on the probability value of the result in Table 5, which tests the statistical significance of the estimated parameters at 5 percent level of significance chosenfor this study (α =5% (0.05). The generalized linear model takes into consideration the issues of endogeneity which are usually inherent in firm level studies. Also, in line with Tapver (2019), all the dependent and independent variables were lagged by one year to further minimize possible endogeneity of variables. All the regressions pass the specification tests; the instruments are valid, and the correlation structure is as expected, with no second-order serial correlation.

H_{o1}: The deployment of AI Expert Systems has NO positive and significant effect on the financial performance of DMBs in Nigeria

This hypothesis was used to test the impact of the deployment of AI Expert Systems (ES) on the financial performance of Deposit Money Banks (DMBs) in Nigeria. The study controlled for Bank Age and Bank Size. The resultant coefficients were positive, and significant both during pre- and post-AIExpert System adoption (coefficient=1.25668, $p<0.05$ for pre-AIExpert System and 1.75328, $p<0.05$ for post-AIExpert System adoption respectively). Therefore, we reject the null hypothesis and accept the alternate hypothesis and conclude that the deployment of Expert Systems had impacted positively though non-significantly on the financial performance of DMBs in Nigeria. We test the joint effect of the independent variables on the dependent variable using the F test. From Table 4.5, the coefficient of the F-Test is positive and significant both during pre-AI Expert Systemadoption and post-AI adoption eras, (coefficient=9.55407, $p<0.05$ for pre-AI and 5.10332, $p<0.05$ for post-AIExpert System adoption respectively). The R^2 is the summary measure that tells us how well the sample regression line fits the data. From the model above, R^2 of 0.32 and 0.40 for pre-AI Expert Systemadoption and post-AIExpert System adoption respectively. This means that 32 and 40 percent variation in the financial performance of banks during pre-and post-AIExpert System adoption respectively were explained by changes in the investments and adoption of Expert Systems and the remaining 68 and 60 percent respectively were explained by variables not included in the model. The Durbin Watson (DW) statistics and Breusgh –Godfrey LM test as shown in table 4.5 shows the absence of no serial autocorrelation as the DW statistics (1.32 and 1.17 for pre-AIExpert System adoption and post-AIExpert System adoption respectively) falls below the critical value of 2. The F-value of 9.55407 and 5.10332 for (pre-AIExpert System adoption and post-AIExpert System adoption respectively), which follows the F-distribution with a degree of freedom numerator of 4 and a degree of freedom denominator of 15 is significant (P-value = 0.000) at a critical value of 0.05. This implies that the entire model is significant.

5 Conclusion and Recommendation

The aim of this study was to assess the impact of AI Expert Systems on the financial performance of Deposit Money Banks (DMBs) in Nigeria. The mixed method approach combining quantitative and qualitative data were used in arriving at the results of the study. The resultant coefficients were positive, and significant both during pre- and post-AIExpert System adoption (coefficient=1.25668, $p<0.05$ for pre-AIExpert System and 1.75328, $p<0.05$ for post-AIExpert System adoption respectively). Therefore, we reject the null hypothesis and accept the alternate hypothesis to conclude that the deployment of Expert Systems impacted positively, though non-significantly, on the financial performance of DMBs in Nigeria. It was also observed in the study that AIExpert System development and deployment in the banking sector in Nigeria is still in its early days. We observed that only a small fraction of this futuristic technology has yet been discovered and only the human imagination can limit its boundaries. AI Expert System can improve communications with staff and customers and analyse large amounts of complex data to find patterns or connections that humans cannot find. Further, AI Expert System also aid making of precise and better investment decisions as well as mitigating fraud and credit risk. All these applications are just a small fraction of AI possibilities in the banking sector, which are yet untapped. With the huge and increasing investments in AIExpert System in the banking sector, we can conclude that the future of AI Expert Systemin the banking sector in Nigeria is going to be both intriguing and interesting. Based on the findings of the study, we recommend that there should be strategic and realistic deployment, timeframes, and accuracy in measuring the effectiveness and return on investment of AI on the financial performance of banks. To this end, it is abundantly critical for banks' management in Nigeria to continue investing in AI Expert Systemto enhance the performance of the MDBs in Nigeria.

REFERENCES

Aazhvaar, V. (2019). Artificial intelligence in Indian Banking Sector: Challenges and Opportunities. *International Journal of Advanced Research*, 7(5), 1581-1587.

Aduaka, U. &Awolusi, O., (2020). Electronic Banking and Profitability in the Nigerian Banking Industry, *Information Management and Business Review*, 12(2(I)), 20-37.

Amaduche, S, et al. (2020). The Impact of Electronic Banking on the Operations and Performance of Deposit Money Banks in Nigeria, *International Journal of Operational Research in Management, Social Sciences and Education*, 6(1), 45-55.

Acemoglu, D. (2002). Technical Change, Inequality, and the Labour Market. *Journal of Economic Literature*, 40, 7-72.

Akyuz, A. (2021). Marketing and Financial Services in the Age of Artificial Intelligence. In: Dinger H., Yuksel S. (eds) Financial Strategies in Competitive Markets. Contribution to Financial and Accounting. Springer, chain 327 – 340.

Cioffi, R. (2020). Artificial Intelligence and Machine Learning Applications in Smart Production: Progress, Trends, and Directions – MDP, 9.

Davis, F., et al, (1989) User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, 35, 982-1003.

Elumelu, T.O. (2019). The Future of Finance-Technology at play. Conference paper delivered at Lagos State University, Faculty of Management Sciences, 2019 Annual Public Lecture, 1.

Nwankwo, S. &Agbo, E. (2021), Effect of Electronic Banking on Commercial Bank Performance in Nigeria, *European Journal of Accounting, Finance and Investment*, 7 (1), 68-81.

Oniore, J. &Okoli, U. (2019), Impact of Electronic Banking on the Performance of Mon**ey** Deposit Banks in Nigeria, *Noble International Journal of Economics and Financial Research*, 4(9), 83-90.,

Ononokpono D., et al (2023), Artificial Intelligence Milieu: Implications for Corporate Performance in the Nigerian Banking Industry. *International Journal of Research and Innovation in Applied Science,*| 8(5), 34-44.