Robotics and Natural Language Processing and the Financial Performance of Deposit Money Banks (DMBs) in Nigeria

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Abstract

This study investigated the effect of Robotics and Natural Language Processing (NLP) on the Financial Performance of Deposit Money Banks in Nigeria. The study analysed 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. The 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 hypothesis was used to test the impact of deployment of robotics on the financial performance of DMBs in Nigeria. The resultant coefficients were positive, but not significant both during pre-and post-Robotics adoption (coefficient = 0.49718, $p<0.05$ for pre and 0.32080, <0.05 for post Robotics adoption respectively. Therefore, we reject the null hypothesis and accept the alternate hypothesis to conclude that development and deployment of robotics had impacted positively, though non-significantly on the financial performance of DMBs in Nigeria. The hypothesis was also used to test the impact of deployment of NLP on the financial performance of DMBs in Nigeria. The resultant coefficients were positive, but also not significant both during pre-and post-Robotics adoption (coefficient = 0.33833, $p<0.05$ for pre and 0.30642, $p<0.05$ for post Robotics adoption respectively. Therefore, we reject the null hypothesis and accept the alternate hypothesis to conclude that development and deployment of NLP had impacted positively, though non-significantly on the financial performance of DMBs in Nigeria. Based on the findings, we recommend that there should be strategic and realistic investment in Robotics and Natural Language Processing (NLP) by the DMBs to improve their financial performance.

***Keywords**: Robotics, Natural Language Processing (NLP), Financial Performance, Deposit Money Banks.*

1 Introduction

The integration of Robotics and Natural Language Processing (NLP) within the banking sector, particularly through the advancements in Artificial Intelligence (AI) and Machine Learning (ML), marks a significant evolution in how financial services operate. AI's capability to mimic human cognitive functions has revolutionized multiple industries by enhancing efficiency, accuracy, and customer interaction (Cioffi, 2020; Ononokpono et al., 2023). Robotics, a branch of AI, extends the automation of physical and cognitive tasks, which was previously unimaginable in traditional banking environments. Concurrently, NLP facilitates improved customer service and operational efficiency by enabling machines to understand and interpret human language, making it a critical component in customer-facing applications and backend processing in banks (Aazhvaar, 2019).

Financial performance in banks, especially in dynamic and developing markets like Nigeria, is increasingly becoming a reflection of their technological adoption. The rapid digitalization within the sector is not just a trend but a necessity to meet changing consumer expectations and regulatory demands. The adoption of AI technologies, including Robotics and NLP, has been identified as a pivotal factor in enhancing key performance indicators such as profitability, asset quality, and customer satisfaction (Zhang, Pentina & Fan, 2021). These technologies streamline operations, reduce errors, and free up human resources for more complex tasks, thus potentially improving the financial health of banks.

The relationship between the adoption of Robotics and NLP and bank performance in Nigeria can be viewed through the lens of operational optimization and enhanced customer interaction. Robotics streamline repetitive tasks and can significantly reduce operational costs, while NLP improves communication interfaces, enabling more effective customer service and engagement. These technologies, therefore, play a crucial role in shaping the competitive landscape of the banking industry by influencing key performance metrics and customer retention strategies (Aberg & Khati, 2018).

Despite the optimistic view, the practical implementation of AI technologies like Robotics and NLP in Nigerian Deposit Money Banks (DMBs) presents a complex scenario. While theoretically, these technologies promise enhanced efficiency and performance, the actual impact on financial outcomes remains ambiguous. The integration of such advanced technologies has been sporadic and uneven across different banks, leading to varying outcomes in financial performance. This disparity raises questions about the direct correlation between AI adoption and financial success in the banking sector.

Moreover, the adoption of these technologies is not without challenges. There is a significant gap between potential technological benefits and real-world application, often exacerbated by infrastructural deficiencies, a lack of skilled personnel, and resistance from existing employees fearing job displacement. These issues not only hinder the successful implementation of AI but also affect the expected improvement in financial metrics (Decker et al., 2017). The fear of redundancy and the ethical dilemmas surrounding AI employment further complicate the broader acceptance and optimization of these technologies within the sector.

This study aims to make significant contributions to the existing body of knowledge by empirically investigating the impact of Robotics and NLP on the financial performance of DMBs in Nigeria. It employs robust methodologies that enable a precise measurement of the independent variables (Robotics and NLP) against the dependent variable (bank performance). This approach not only highlights the direct impacts but also contextualizes the indirect effects these technologies have on operational efficiency and customer satisfaction. By incorporating theoretical frameworks that emphasize the cooperative dynamics between humans and machines, this research will offer a balanced perspective on the roles of Robotics and NLP within Nigerian banks, addressing both the potential advantages and the ethical considerations involved. Thus, it will provide valuable insights for stakeholders including policymakers, bank executives, and investors, informing their strategic decisions regarding AI integration in banking operations.

Hypotheses Development

Investigations into the impact of robotics on bank performance have been progressively recognized in scholarly literature, demonstrating varying outcomes across different banking environments. Cioffi (2020) conducted a study on European banks, revealing that robotics significantly reduces transaction processing times and enhances accuracy, thus improving overall operational efficiency. In a similar vein, Ononokpono et al. (2023) found that robotics deployment in Nigerian banks has significantly contributed to cost reductions and improved customer service delivery. Akyuz (2021) examined the automation of compliance processes through robotics in Turkish banks, identifying a substantial improvement in compliance management and a reduction in operational risks. Conversely, Zhhang, Pentina, & Fan (2021) noted that while robotics increase efficiency, the upfront costs and adaptation challenges can temporarily affect the financial performance negatively. Similarly, Aazhvaar (2019) reported mixed results in Indian banks, where the benefits of robotics in customer service were offset by the high maintenance and training costs. In this study, the first hypothesis is on Robotics and is stated as follows:

HO$_1$: The deployment of robotics does not have any significant impact on the financial performance of Deposit Money Banks in Nigeria.

The role of Natural Language Processing (NLP) in enhancing bank performance is gaining attraction in academic circles, though the results present a complex array of benefits and challenges. Cioffi (2020) highlighted that NLP technologies, particularly in customer-facing roles, have markedly increased customer satisfaction by improving the speed and accuracy of response in U.S. banks. Ononokpono et al. (2023) demonstrated that NLP applications in Nigerian banks have improved transaction processing and customer interaction by enabling more intuitive and responsive chatbot services. Akyuz (2021) found that NLP tools have facilitated better customer feedback analysis in European banks, leading to more customer-centric product developments. However, Zhhang, Pentina, & Fan (2021) observed that the integration of NLP technologies requires substantial initial investment and ongoing training, which can temporarily depress profitability. Similarly, Aazhvaar (2019) noted that while NLP can significantly enhance service delivery, the technology's complexity and the need for continual updates pose ongoing operational challenges. Therefore, the second hypothesis is on NLP and is stated as follows:

HO2: The deployment of Natural Language Processing (NLP) does not have any significant impact on the financial performance of Deposit Money Banks in Nigeria.

2 Review of Conceptual Literature

2.1 Robotics

Robotics, an integral field within artificial intelligence, focuses on the design, construction, and application of robots that can perform tasks traditionally done by humans. In recent years, advancements in robotics have been propelled by improvements in sensor technology, artificial intelligence, and machine learning, enabling robots to execute complex, multifaceted tasks with greater autonomy and efficiency (Fuster, et al. 2020). Robotics has been measured and evaluated in various sectors through metrics such as task efficiency, error rate reduction, and cost savings (Singh, et al. 2022). Specifically, in the banking industry, robotics applications extend from automated teller machines to sophisticated robotic advisors that provide financial consultation services, illustrating the technology's significant role in operational optimization and customer service enhancement (D'Souza, et al. 2022). For the purposes of this study, robotics will be defined as the application of automated, programmable machines that perform banking tasks that would typically require human intervention, evaluated through their impact on operational efficiency and customer interaction quality.

2.2 Natural Language Processing

Natural Language Processing (NLP) is a technology at the intersection of computer science, artificial intelligence, and linguistics, aimed at enabling computers to understand and process human language in a way that is both meaningful and useful. Recent literature highlights the rapid development of NLP capabilities, driven by advancements in machine learning and deep learning technologies, allowing for more accurate and nuanced understanding of human language. NLP's effectiveness is commonly measured by its accuracy in speech recognition, sentiment analysis, and machine translation quality (Vaswani, et al. 2022). Within the banking sector, NLP is utilized to enhance customer service through chatbots and voice-operated customer service technologies, as well as to analyze customer feedback and sentiment on a large scale (Gupta, et al. 2022)). For this study, NLP is defined as the technological capability that enables the interpretation, generation, and manipulation of human language by software, particularly focusing on its application to improve customer service and operational efficiency in banking.

2.3 Bank Performance

Bank performance is a multifaceted concept that involves evaluating a bank's efficiency, profitability, and sustainability in the financial market. Literature in recent years has increasingly focused on both traditional financial metrics such as return on assets (ROA), return on equity (ROE), and net interest margin, and newer, non-financial metrics such as customer satisfaction and digital engagement levels (Johnson, et al. 2023). These performance indicators provide a holistic view of a bank's operational and financial health. Furthermore, the performance of banks is also increasingly being measured in terms of their technological adoption, with particular emphasis on how digital innovations like AI and blockchain are integrated into their systems to enhance overall performance (Chen, et al. 2022). For the context of this study, bank performance will be defined as the evaluation of a bank's financial and operational effectiveness, as measured by traditional financial metrics and supplemented by assessments of technological integration and customer satisfaction.

2.3.1 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 (Abdul-Rahman & Abdul-Ghani, 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 (Khan, & Zaman, \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. 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 (Okwu & Alabi, 2021).

2.3.2 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 (Omojola & Adeyemi, 2020). 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 (Alvi & Ali 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 (Bashir & Nasser, 2024).

2.3.3 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 (Okwu, A. T., & Omoniyi, M. 2022). 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. 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 (Abubakar & Adnan, 2021). 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 (Javed & Aslam, 2022).

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. 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. The Technology Acceptance Theory is used to explain the adoption and effect of Artificial intelligence and Machine Learning in banking services.

3 Research Designs 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 Robotics and NLP 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 machine learning and robotics 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 AI adoption on DMBs performance in Nigeria, the study employed Augmented Dickey Fuller Unit Root test and Philips Perron test to ascertain if truly there was a structural break in the DMBs' performance and efficiency after the adoption of Robotics and NLP. The Error Correction Model (ECM) was further used to ascertain the directional and magnitude of the impact of Robotics and NLP adoption on DMBs' performance and efficiency.

The base model is:

$$Perf = f(NLP, ROB) - \quad (1)$$

By log linearizing, the model becomes.

$$Perf = \beta 0 + \beta 1NLP + \beta 2ROB + DY + \mu - - - - - - \quad (2)$$

Where:

Perf = Performance

NLP = Natural Language Processing

ROB = Robotics

DY = Dummy Variable to Capture both Pre-and Post-Robotics and NLP adoption

β_0 = Intercept of relationship in the model

$\beta_1 - \beta_2$= Coefficients of independent variables

μ = Stochastic Error term

By log linearizing, the model becomes;

$$Perf = \beta 0 + \beta 1LOGNLP + \beta 2LOGROB + DY + \mu \quad (3)$$

Where:

Perf = Natural Logarithm of DMBs Performance

LOGROB = Natural Logarithm of Robotics

LOGNLP= Natural Logarithm of Natural Language Processing

β_0= Intercept of relationship in the model

$\beta_1 - \beta_2$= Coefficients of independent variables

μ = Stochastic Error term

4 Results and Discussion

4.1.1. 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: Robotics, Natural Language Processing (NLP), 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
ROB	9	0	4	.64	1.2
NLP	9	0	4	2.07	.10
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: Author's Computation from Annual Reports & Statements of Accounts of the Selected Deposit Money Banks in Nigeria (2015-2023)

The banking sector in Nigeria have deployed Robots in the automation of customer services, in streamlining back-end processes, enhancing fraud detection and security and adapting and responding swiftly to market dynamics in strategic decisions. Therefore, the descriptive statistics in Table 1 shows that the banking sector in Nigeria on the average have spent approximately N640million over the last 9 years in the development and adopting of robots in enhancing customer services delivery and in handling routine inquiries.NLP appears to stand at the forefront of artificial intelligence (AI) applications, as it has been used by the banking sector in revolutionizing various aspects of banking operations. NLP is used by banks to understand, interpret and generate human language and deployed in areas of customer service, risk management and fraud detection. The descriptive statistics in Table 1 shows that the banking sector in Nigeria have spent on the average, a total sum of N2.07billion in the last 9 years under review and developing and deploying NLP to enhance various aspects of their operations.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 table4.1, 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 at 2022 financial year, up from N166 billion (GH¢2.5 billion) before bank recapitalization in Ghana in 2017 (Bank of Ghana, 2019). The descriptive statistics of the aggregate sampled banks in table4.1, 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 table4.1, 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 table4.1 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 4.3 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

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 analyze 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 (AI) 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-Robotics and NLP Adoption			**Post-Robotics and NLP Adoption**		
Variable	Coefficient	T-statistics	Prob.	Coefficient	T-statistic	Prob.
Constant	4.94230	2.69**	0.1360	5.72995	0.02	0.9845
ROB	0.49718	1.79***	0.0886	0.32080	1.42	0.1731
NPL	0.33833	0.58	0.5686	0.30642	0.48	0.6354
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 Eview 9

The multiple linear regression result in Table 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 Tables 4.5, 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 development and deployment of Robotics have NO positive and significant effect on the financial performance of DMBs in Nigeria

This was also used to test the impact of the development and deployment of robotics 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, but not significant both during pre-and post-Robotics adoption (coefficient=0.49718, $p<0.05$ for pre- and post Robotics and 0.32080, $p<0.05$ for post-Robotics adoption respectively). Therefore, we reject the null hypothesis and accept the alternate hypothesis and conclude that the development and deployment of robotics had impacted positively though non-significantly on the financial performance of DMBs in Nigeria.

H_{o2}: Natural Language Processing have NO positive and significant impact on the financial performance of DMBs in Nigeria

This hypothesis was used to test the impact of the Natural Language Processing (NLP) 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, but not significant both during pre-and post- NLP adoption (coefficient=0.33833, $p<0.05$ for pre-NLP and 0.30642, $p<0.05$ for post-NLP adoption respectively). Therefore, we reject the null hypothesis and accept the alternate hypothesis and conclude that the Natural Language Processing 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 5, the coefficient of the F-Test is positive and significant both during pre- and post-Robotics and NLP adoption eras, (coefficient=9.55407, $p<0.05$ for pre- and 5.10332, $p<0.05$ for post-Robotics and NLP 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-adoption and post- Robotics and NLP adoption respectively. This means that 32 and 40 percent variation in the financial performance of banks during pre-and post-Robotics and NLP adoption respectively were explained by changes in the investments and adoption of Robotics andNatural language processing 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- adoption and post-Robotics and NLP adoption respectively) falls below the critical value of 2. The F-value of (9.55407 and 5.10332 for (pre-AI adoption and post-AI 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 Recommendations

The aim of this study was to assess the impact of Robotics and Natural Language Processing (NLP)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, but not significant both during pre-and post-Robotics adoption (coefficient=0.49718, $p<0.05$ for pre- and post Robotics and 0.32080, $p<0.05$ for post-Robotics adoption respectively). Therefore, we reject the null hypothesis and accept the alternate hypothesis and conclude that the development and deployment of robotics had impacted positively though non-significantly on the financial performance of DMBs in Nigeria. Also, The resultant coefficients were positive, but not significant both during pre-and post- NLP adoption (coefficient=0.33833, $p<0.05$ for pre-NLP and 0.30642, $p<0.05$ for post-NLP adoption respectively). Therefore, we reject the null hypothesis and accept the alternate hypothesis to conclude that the Natural Language Processing had impacted positively though non-significantly on the financial performance of DMBs in Nigeria.

It was further noted from the study that Robotics and NLP development and deployment in the banking sector in Nigeria is still in the early days. Only a small fraction of this futuristic technology has yet been discovered and only the human imagination can limit its boundaries. Robotics and NLP can improve communications with staff and customers and analyse large amounts of complex data to find patterns or connections that humans cannot find. Further, Robotics and NLP can make precise and better investment decisions as well as mitigating fraud and credit risk. All these applications are just a small fraction of Robotics and NLP possibilities in the banking sector, which are yet untapped. With the huge and increasing investments in Robotics and NLP in the banking sector, we can conclude that the future of Robotics and NLP in the banking sector in Nigeria is going to be both intriguing and interesting. Based on the findings of the study, we recommend that management of banks in Nigeria should develop a unified vision and company-wide strategy in implementing Robotics and NLP as important components of AI. Experience has shown that many AI initiatives fail due to improper AI component strategies set by management. Management of banks should develop a culture of innovation as a watch-word, absence of which hinders the adoption of AI within the banks' organization. Experience has also shown that banks in Nigeria have a conservative culture that values stability and predictability, which may not align with the fast-paced and rapidly changing nature of technological innovation.

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