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Neural Network and Financial Performance of Deposit Money Banks

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ABSTRACT: This study investigated the neural network and financial performance of deposit money banks in Nigeria, using data for the period of 2012-2022. The objectives of this study were to: Determine the effect of digital payment on financial performance of deposit money banks. Ascertain the effect of digital remittance on financial performance of deposit money banks. Panel least squared (OLS) method of data analysis was adopted because of its Best Linear Unbiased Estimators (BLUE) properties. The data for the variables used was sourced from annual report of the selected deposit bank. The variables were on digital payment, digital remittance and financial performance. The study adopted the descriptive statistics, correlation approach, as well as panel least square. E- View software was used for the analysis. The study found that Digital payment has significant effect on financial performance of deposit money banks. (t=2.002328=0.001). Digital remittance has significant effect on financial performance of deposit money banks. (t=3.452278=0.000).The study recommends that Deposit money banks should ensure adequacy of Digital payment services, regardless of location to enhance customer access. They should also ensure availability of Digital remittance services so that customers can have seamless and round-the-clock access.

Keywords: Neural network, financial performance, digital payment, digital remittance

INTRODUCTION

In modern finance, organizations face high-frequency, high-dimensional data from transactions and market ticks to customer interactions that strain traditional econometric models. Neural networks (NNs), the workhorse of deep learning, have emerged as flexible, data-driven function approximators that can capture complex nonlinear relationships without pre-specifying rigid functional forms (Dim, & Arinze, 2025). In today's data-driven economy, organizations are increasingly relying on advanced computational models to improve decision-making, efficiency, and profitability (Zhang et al., 2024), Among these models, artificial neural networks (ANNs), a subset of artificial intelligence (AI) and machine learning-have emerged as a powerful tool for analyzing complex data patterns, predicting outcomes, and enhancing financial decision-making.

Neural networks mimic the structure of the human brain by processing information through interconnected nodes, allowing them to recognize patterns and relationships that

traditional statistical methods often overlook (Eriki, & Udegbunam, 2013).

The integration of neural networks into financial systems has revolutionized key areas such as credit risk assessment, fraud detection, portfolio management, stock market forecasting, and customer relationship management (Dim, & Arinze, 2025). For instance, banks and other financial institutions apply neural network models to assess creditworthiness more accurately than conventional scoring systems, thereby reducing default risks. Similarly, investment firms employ neural networks to predict stock prices and detect market anomalies, which enhance portfolio returns and minimizes risks. In accounting and auditing, neural networks are increasingly used to detect irregularities and fraudulent activities that can significantly affect a firm's financial performance (Wang et al., 2021.

Financial performance is a critical indicator of the health, stability, and long-term sustainability of business organizations. It reflects how efficiently firms utilize their resources to generate profits, create value for shareholders, and remain competitive in dynamic markets (Ifechukwu-Jacobs, Arinze, & Nwangwu, & Atueyi, (2025)..

Traditionally, financial performance has been evaluated through measures such as return on assets (ROA), return on equity (ROE), earnings per share (EPS), net profit margin, and other accounting-based or market-based indicators (Kaplan & Norton, 1996). However, the growing complexity of global financial systems, increased market volatility, and the influence of both structured and unstructured data sources have created challenges for conventional financial analysis and forecasting methods (Egbunike, Anachedo, Echekoba, & Ubesie, 2022).

In response to these challenges, scholars and practitioners have turned to advanced computational techniques, particularly artificial intelligence (AI) and machine learning (ML), for more accurate prediction, evaluation, and decision-making in finance. Among these techniques, artificial neural networks (ANNs) have gained significant prominence. Neural networks, inspired by the functioning of the human brain, are designed to process vast amounts of data, identify hidden patterns, and adaptively learn from complex, nonlinear relationships (Egbunike, & Ibeanuka, 2015). Unlike traditional statistical methods, ANNs excel at handling noisy, incomplete, and multidimensional financial data, making them highly suitable for analyzing financial performance. The linkage between financial performance and neural networks is also evident in corporate decision-making (Nwangwu, Arinze,. & Nwangwu, 2025).

Neural networks support managers, investors, and policymakers by providing predictive analytics that enhance risk management, resource allocation, and investment strategies. In emerging economies such as Nigeria, where financial markets are often characterized by volatility, limited transparency, and data irregularities, the application of neural networks can provide a more robust mechanism for evaluating organizational performance beyond conventional accounting figures (Ani, & Ugwunta, (2012). Therefore, the integration of neural networks into financial performance analysis represents not only a methodological innovation but also a practical tool for improving forecasting accuracy, reducing uncertainty, and enhancing the competitiveness of firms in a rapidly evolving financial environment.

Objectives of the study

The main objective of this study is to examine the neural network and financial performance of deposit money banks. The specific objectives are to:

1. Determine the effect of digital payment on financial performance of deposit money banks.
2. Ascertain the effect of digital remittance on financial performance of deposit money banks.

LITERATURE REVIEW

2.1 Conceptual Framework

2.1.1. Neural Network (NN)

An artificial neural network (or simulated neural network) is a network or circuit of artificial neurons or nodes that uses a mathematical or computational model for information processing based on a connection's approach to computation. The connections of the biological neuron are modeled as weights between nodes. A positive weight reflects an excitatory connection, while negative values mean inhibitory connections (Kruse et al. 2022; Alkhawaldeh et al. 2019, 2022; Alkhawaldeh 2021). Artificial Neural Networks are mathematical representations inspired by the human brain nerve cells and their communication and processing information techniques. The Neural Network is ideally composed of three layers, the input layer, the hidden layer, and the output layer. The input layer consists of input nodes which represent the system's variable. The hidden layer consists of nodes which facilitate the flow of information from the input to the output layers.

The flow is controlled by weight factors associated with each connector. The output layer consists of nodes which represent the system's classification decision. The value of the output nodes is compared with cut-offs to determine the output and classify each case. The weight adjustment is known as training. The training process consists of running input values over the network with predefined classification output nodes. This process runs until the weight values are minimized to an error function. Testing samples are used to verify the performance of the trained network. In the context of credit scoring, numerous studies have proven that Neural Network perform remarkably better than any other statistical approach, such as logistic regression or discriminant analysis (Hu & Ansell 2007).

2.1.2 Financial Performance

Financial performance is a critical measure of how well an organization can use its assets to generate revenues and manage its financial obligations. It reflects the overall health of the business and provides insights into its operational efficiency, profitability, and growth prospects. In the context of the study on the relationship between capital structure and financial performance of listed deposit money banks in Nigeria, understanding financial performance is pivotal. According to Mohammed, et al. (2023), financial performance helps stakeholders understand the economic viability of an organization, guiding investment and management decisions. The study adopted return on asset (ROA) that provides insight into how efficiently banks are using its assets to improve financial performance. The choice of return on asset (ROA) is helps managers, stakeholders, investors, analysts, and regulators, assess the bank's financial performance relative to its

Financial performance is the single most important factor in assessing growth potential, earnings capacity and overall financial strength. Nelly (2020) observed that financial performance measures mainly serve three purposes. One they serve as a tool of financial

management, two they serve as major objectives of business and three they serve as a mechanism for motivation and control in an organization. Pandey (2018) defines financial performance as a subjective measure of how well a firm uses assets from its primary mode of business to generate revenues. He further says that the term can also be used as a general measure of a firm's overall financial health position over a given period of time, and can be used to compare similar firms across the same industry or to compare industries or sectors in aggregation.

2.2 Theoretical Framework

Classical Theory of Artificial Intelligence (CTAI)

The Classical Theory of Artificial Intelligence serves as the foundation for this research (CTAI). The theory, according to Muller (2012), is focused on the question of whether artificial intelligence (AI) is even conceivable. It prompts inquiries like, "Can a machine think?" and "Can a machine do x?" According to one theory, artificial intelligence (AI) will likely never completely replace human intelligence. However, Super Artificial Intelligence (SAI) machines, which were developed quickly, are in a serious race with Human inventors, according to Zohuri and Rahmani (2020).

Thus, while this theory stands on the premix that humans will still provide the necessary transactions for artificial intelligence (AI) to operate, it is still a matter of argument that several operations of humans have not been totally taken over by artificial intelligence (AI) in the recent years. Despite the advancement in artificial intelligence (AI), however, this theory is still relevant as to the limitations of what machines can perform, asserting that artificial intelligence (AI) is fundamentally limited and should be replaced with other methods (Muller, 2012). While this study focused on the link between artificial intelligence and accounting practice, this theory creates more awareness as to the continued relevance of accountants on accounting activities but with dimensional changes in approach.

2.3 Empirical Review

Al Omari, Alkhawaldeh, and Jamil (2023) examined artificial neural network for classifying financial performance in Jordanian insurance sector. The study classified insurance companies' financial performance in Jordan's Amman Stock Exchange (ASE). The sample size is 15 out of 22 selected insurance firms from 2008 to 2020. We apply the Multi-Layer Perceptron (MLP) model for the detection of (high/low) total asset turnover (TAT) as output, while we select the subrogation (SB), claims paid (CP), market capitalization (MC), and total shareholders' equity (SE) as input to the MLP model. The performance of the MLP model is evaluated using different criteria, namely the false positive rate (FP rate), false negative rate (FN rate), F-measure, precision, and accuracy (ACC). The results show that MLP is efficient and performs well in multiple criterion tests through iteration growth. Based on our knowledge, the paper assesses the financial performance of Jordanian insurance firms, which has not been investigated previously. Furthermore, this study gives valuable information to regulators and policymakers to improve asset management efficiency in the insurance sector.

Egbunike, et al. (2022) compared two models developed using AI techniques, the genetic algorithm (GA) and neural network on a sample of quoted manufacturing firms in Nigeria. This study adopts a quantitative approach and utilizes a sample of sixty-six (66) companies listed on the Nigerian Stock Exchange (NSE), after excluding firms from

the financial, natural, and oil & gas sectors. The study relied on secondary data from annual financial statements. The McNemar test was utilized to compare the accuracies of the two models. The model results showed a significant difference in the classification accuracies of the GA (96.94%; 97.85%) compared with the neural network (92.2%; 94.4%) models. In other words, the GA model outperformed the neural network model in corporate bankruptcy prediction. The inclusion of selected corporate governance variables also improved the accuracy of the models. The results demonstrate the practicality of using GA in a different context from prior western studies with different regulatory and institutional regimes.

Osman (2020) examined the viability of adopting artificial neural network (ANN), an aspect of machine learning in the analysis of monetary data for the design and validation of monetary policy from both optimistic and normative approach. Methodologically, the research is motivated by the work of [which used the Greenbook real time data of the U.S. Federal Reserve's in the analysis of monetary policy reaction functions in forecasting performance using ANN. Following the work on the adoption of this technique, we tried to develop a framework based on machine learning for policy rate forecasting by analysing macroeconomic data with the aim of guiding and aiding monetary authority in making monetary policy decisions. From the results, the ANN perform better in predicting the monetary policy rate compared to the linear models and the univariate process. It also revealed the non-linearity in the behavior of the monetary policy rate in Nigeria during the study period. While the work does not mean to advocate that machine will replace human-being in policy rate determination in the monetary policy- making process; we believe that the development and implementation of this system would support building effective prediction system which can be validated. The result from the designed system is expected to enhance credibility, confidence and transparency of central banks in making an independent decision (s) based on objective forecasts and implied analysis in setting policy through a well-structured comparison of results.

Mayabi, (2019) showed that an ANN model is able to capture adequate number of directions of monthly price fluctuations as compared to models that employ the linear approach. It has also been observed that feeding the model with lagged observation of the same variable (univariate form) leads to more accurate forecasts than its performance in its multivariate form (Feeding it with different variables). Most models reviewed during this study, showed little effort in development of research tools, therefore this study has purposed to develop a user- friendly ANN prototype based on the proposed model.

Suleiman, Burodo and Garba (2018) examined the efficiency of the Artificial Neural Network to predict the credit risk of customers of the First Bank Nigerian Plc. The computations have been done by using MATLAB software. Number of samples was 131 including 81 creditworthy customers and 50 non creditworthy customers. In this paper, 11 independent (attribute) variables were used and 1 dependent variable. The result of the neural network model shows that out of 50 non creditworthy cases, 78.0% are correctly predicted as non creditworthy and 22.0% are predicted as creditworthy. Out of 81 creditworthy cases, 95.1% are correctly predicted as creditworthy and 4.9% are classified as non creditworthy. Overall, 88.5% of the predictions are correct and 11.5% are wrong classifications.

Seokwoo, et. Al. (2025) investigated the impact of network capabilities and deep learning techniques on companies' financial performance within buyer-supplier networks. It broadens the scope by incorporating network measures such as closeness and network constraint, whereas previous studies have primarily focused on suitable buyer-supplier relationships. The analysis evaluates the effects of these network measures on companies' financial performance metrics, including asset growth rate, return on assets, and more. In addition, this study explores the impact of extended networks on company performance using deep learning techniques. The results show that companies' network capabilities are positively associated with their financial performance, highlighting the critical role of network positions in driving success. Furthermore, the findings suggest that extending the network through deep learning offers significant benefits for companies.

METHODOLOGY

3.1 Research Design

In this study, *an ex-post facto* research design was employ in this study. The time period was from 2014 to 2024.

3.2 Nature and Sources of Data

The data was secondary in nature and on annual basis, while the Central Bank of Nigeria (CBN) banking and supervision and Nigeria Deposit Insurance Corporation (NDIC) annual reports of the selected bank served as the source of data collection.

3.3 Population of the Study

The population of this study consists of the fourteen (14) deposit money banks quoted on the Nigerian Exchange Group (NGX). The study covers twelve years annual reports and accounts of these banks from 2014 to 2024.

3.4 Sample Size and Sampling Technique

This study selected all the ten (10) deposit money banks in Nigeria for the study. The banks were chosen because of availability of data and they are Fidelity bank plc, FCMB plc, First bank plc, Access bank plc, united bank of Africa (UBA), Sterling bank plc, GT Bank, ECO Bank, Zenith Bank, and Union Bank

3.5 Model Specification

This study adapted and modified the model of Ibenta and Anyanwu (2017). The original model of Ibenta and Anyanwu (2017) is stated as:

$$EFR = f(VTATM,\ VTWEB, VTPOS, VTMOB, MPR, CRR) \quad 1$$

Where:
EFR = Efficiency Ratio
VTATM = Value of Transaction on Automated Teller Machines
VTWEB = Value of Transaction on Web/Internet
VTPOS = Value of Transaction on Point of Sale,
VTMOB = Value of Transaction on Mobile Banking
MPR = Monetary Policy Rate
CRR = Cash Reserve Ratio

The model is modified to in the following equation below

Algebraically, therefore
ROA = F (DIP, DGR)
Where
ROA = Return on asset
DIP = Digital Payment
DGR = Digital Remittance
F= Functional Notation

Our model is now restated in an econometric form as:
ROE - $B_O + B_1DIP + \beta_2DGR + u$ ----------(2)
ROA = Return on equity (proxy of performance of bank)
DIP = Digital Payment
DGR = Digital remittance
Bo = constant

Panel Regression

In this study, the regression approach of data analysis was used. Specifically, the connection between the independent variables (Neural Network) and dependent variable (performance) in the model was analyzed using Panel Least Square regression techniques. The three main statistical techniques employed to analyze the data were multiple regression analysis, descriptive statistics, and correlation analysis.

3.6 Variables and Measurement

Variable	Measurement	sources
Dependent Variable Return on Assets	Firm's net income to total assets in the same year	(Setiawan&Gestanti, 2022)
Independent Variable Digital payment	Measured by the total amount of transactions done through Digital payment on an annual basis	Hafez, B., Kaddumi, T. A., Nassar, M.D. & Muqattash, R. S. (2023).
Digital remittance	This is measured by the annual turnover on the total number of transactions carried out via remittance channels.	Ibenta and Anyanwu (2017).

RESULTS AND DISCUSSION

4.1.1 Descriptive Statistics Analysis

The descriptive data of the chosen deposit money bank that comprise our sample are displayed in the table below.

	ROA	LDIP	LDGR
Mean	0.022273	15.15931	15.71976
Median	0.020000	16.03895	15.76858
Maximum	0.060000	20.12964	20.57762
Minimum	0.010000	7.414573	10.21899

Std. Dev.	0.014336	3.621987	3.675114
Skewness	0.953064	-0.131348	-0.070116
Kurtosis	2.894759	1.551415	1.312787
Jarque-Bera	10.02210	5.960376	7.882468
Probability	0.006664	0.050783	0.019424
Sum	1.470000	1000.514	1037.504
Sum Sq. Dev.	0.013359	852.7214	877.9202
Observations	110	110	110

Source: Researcher's summary of descriptive result (2026) using E-view 10

First, the dependent variable was the return on assets. 22% was the average return on assets. It was noted that the sampled banks' average positive digital payment over the review period was 22%. The bank' return on assets had a maximum value of 0.61% and a minimum value of 0.01% throughout the review period. The significant variance between the highest and lowest return on assets suggests that the chosen banks' neural network vary widely from one another, and this implies that the firms are not homogenous across the period under examination. The kurtosis for stock price was 2.89% that are less than 3 hence the distribution is said to be leptokurtic hence it may have few outliers.

Table 4.1.1 above presents the descriptive analysis of digital payment (DIP), 20.12% was the minimal number for the digital payment. The standard deviation was 3.62%, indicating that the available resources or size of the ten listed bank in Nigeria were dispersed around the mean by around 363%. With a skewness of -0.13, the neural network was negatively skewed, suggesting that the majority of its values were clustered to the left. The kurtosis for neural network was 1.55%% which are less than 3 hence it is platykurtic and may have few outliers.

The mean of Digital remittance (DGR) was 17.51 % suggesting that the average number of Digital remittance for the 10 listed bank studied was about 17.51%, implying that the Digital remittance were exactly quarter of the profit. The standard deviation of 3.67% suggests that there is high return on Digital remittance amongst the member selected banks, with a minimum and maximum value of about 10. % and 20% respectively.

In addition, the JB Probability values of 0.0000 demonstrate that, with the exception of the financial technology, which is not normally distributed, all the variables are normally distributed at the 1% level of significance. This suggests that the variables are distributed according to the Gaussian standard distribution. This suggests that the distribution of all the variables is roughly normal. This indicates that there are no outlier-containing variables, or if there are, they are not expected to affect the outcome and can thus be trusted when making generalizations. This further supports the application of panel least squares estimation methods. Therefore, recommendations that are provided in a significant way will reflect the traits of the actual research population.

4.1.2: Pearson Correlation Matrix

	ROA	LDIP	LDGR
ROA	1.000000	0.309547	0.359617

LDIP	0.309547	1.000000	0.860353
LDGR	0.359617	0.860353	1.000000

Source: researcher's summary of correlation result (2026) using E-view 10

The correlation coefficient's result revealed a mixed correlation. The finding of this link supports the idea that there is a linear relationship between our variables. Additionally, the Pearson product-moment correlation, which measures the strength of the relationship between variables, revealed that the association between the variables is relatively small and falls below the 0.80 threshold, indicating that multicollinearity is not a problem for the predictor variables. The pairwise correlations between the variables of the neural network component and the performance of deposit money bank are presented and discussed in this section. Although there are still some reasonably strong correlations between some of the study's variables, Table 4.2.2 demonstrates that the majority of correlation coefficients between the variables are quite low. The correlation table above revealed that none of the explanatory variables were completely or highly correlated, ruling out the possibility of an outlier when the study was looking for multicollinearity. This suggests that the model utilized for the analysis does not have a multi-collinearity issue. This further supports the application of panel regression analysis.

4.3 Fixed and Random Effect Test (Hausman Test)

To choose between these two regressions models, Hausman test can be run to examine whether the difference between the random effects regression and the fixed effects regression is zero. In other words, H0: random effect is preferred. Based on the present analysis, Hi was strongly rejected (p-value= 0.000) which means that the random effects model was preferred.

4.3.1 Fixed and Random Effect Test

Correlated Random Effects - Hausman Test
Equation: Untitled
Test period random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Period random	0.080746	2	0.9604

** WARNING: estimated period random effects variance is zero.

Period random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
LDIP	-0.000093	0.000002	0.000000	0.7780
LGR	0.001478	0.001401	0.000000	0.7799

Source: researcher's summary of Hausman Test (2026) using E-view 10

The pooled OLS model is applicable if the Hausman test's p-value is less than the significance level, which allows you to reject the null hypothesis. You should apply the Random effects model and cannot reject the

null hypothesis if the p-value exceeds the significance level.

4.4: Test of Hypotheses/ Regression Results

Since the data had both time series (2014–2024) and longitudinal properties (Ten Deposit Money Bank), we used a panel least square regression analysis to investigate the relationship between the dependent variable (ROA) and the independent variables (LDIP, LDGR,) and to test our hypothesis. Our analysis is shown in the following table 4.3.1:

Table 4.3.2 Panel Least Regression Result

Dependent Variable: ROA
Method: Panel EGLS (Period random effects)
Date: 04/2/26 Time: 10:17
Sample: 2014 2024
Periods included: 11
Cross-sections included: 10
Total panel (balanced) observations: 110
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.100217	0.508134	0.026632	0.9788
LDIP	0.286706	0.220979	2.002328	0.0001
LDGR	0.101401	0.300965	3.452278	0.0000

Effects Specification		
	S.D.	Rho
Period random	0.000000	0.0000
Idiosyncratic random	0.014568	1.0000

Weighted Statistics			
R-squared	0.729324	Mean dependent var	0.022273
Adjusted R-squared	0.701684	S.D. dependent var	0.014336
S.E. of regression	0.013588	Sum squared resid	0.011631
F-statistic	4.678800	Durbin-Watson stat	0.962091
Prob(F-statistic)	0.000749		

Unweighted Statistics			
R-squared	0.729324	Mean dependent var	0.022273
Sum squared resid	0.701684	Durbin-Watson stat	1.962091

Source: Researcher's summary of regression result (2026).

The panel regression study of ten quoted deposit money bank is displayed in table 4.3.2 above. The aforementioned table indicates that the model was well-specified in explaining neural network as seen by the F-statistics value of 4.678800 and their P-value of 0.000749, which indicate that the total analysis of our variables in the regression model was generally significant at the 1% level of significance. Based on the aforementioned findings, the study found that the R-squared adjusted value was 0.729324 (72%) and the R-squared value was 0.701684 (70%). The coefficient of determination, or R-squared, was found to be 72%. This indicates that 72% of the systematic fluctuations in the

individual dependent variables could be described by the model, with the other 28% being explained by the stochastic error factor. This shows that over a eleven-year period, the neural network of our sampled banks in Nigeria can be explained by the independent variables together to the extent that they account for around 61% of the system variation. The stochastic error term captures the remaining 28% of the overall variations. This attests to the suitability of our model for the analysis. The Durbin Watson statistics value of 2.1 showed that the model is well spread since the value is approximately 2 and that there have not been self or auto correlation problem and that error are independent of each other.

Hypotheses

H_{01}: Digital payment has no significant effect on financial performance of deposit money banks.

Table 4.3.2 above's panel regression result revealed that the Digital payment had a positive coefficient value of 0.286706 and a P-value of 0.0001. Based on the model's outcome, the Digital payment of Nigeria's quoted deposit money bank showed a statistically significant and positive correlation with the financial performance, which indicated the number of performance ratios. This implies that the Digital payment has a positive correlation with performance of deposit money bank, as indicated by the positive coefficient and likelihood, but that this correlation is statistically negligible and sufficient to influence the performance of Nigerian bank. This suggests that a 1% increase in the Digital payment causes a 2% increase in performance, supporting the idea that raising the Digital payment is crucial for performance in deposit money bank. The Nigeria Exchange Group's increased level of inspection and monitoring is generally predicted to improve bank performance when the point of sales rises. We accepted our alternative hypothesis as a result of the strong link we found, and as a result, we can say that the Digital payment has significant effect on financial performance of deposit money banks..

H_{02}: Digital remittance has no significant effect n financial performance of deposit money banks.

In Nigeria, the Digital remittance of the listed deposit money bank is positively and significantly impacted on the performance, as demonstrated by the study's 0.101401 positive coefficient value and 0.000 p-value ($\beta 2$=-0.101401, $p = 0.0000 > \alpha = 0.05$). The positive coefficient value of $\beta 2$ indicates that the Digital remittance is positively impacted on performance. As a result, performance rises by 10% units for every 1% increase in bank performance. This indicates that, is statistically significant among Nigerian banks, performance has a favorable impact on the level of banks performance of businesses. The analysis's findings led the study to accept the second null hypothesis, which leads it to the conclusion that Digital remittance has significant effect n financial performance of deposit money banks.

Summary of Findings

The study examined effect of neural network on financial performance of deposit money banks in Nigeria. Based on a sample of 10 selected deposit money bank from Nigeria Exchange Group for ten fiscal year from 2014-2024 and using two measures of Neural networks (LDIP, LDGR). The study found that:

1. Digital payment has significant effect on financial performance of deposit money banks.
   (t=2.002328=0.001)
2. Digital remittance has significant effect on financial performance of deposit money banks.

(t=3.452278=0.000)

CONCLUSION

Neural networks can provide valuable insights into bank performance in Nigeria by predicting factors that impact profitability, risk management, and customer service. The predictive accuracy of neural networks can be improved by incorporating a wider range of variables, including macroeconomic factors and customer behavior, into the model. The adoption of neural networks in the banking sector can lead to more informed decision-making, better risk management, and enhanced customer service, leading to improved overall performance. However, the recommendations of the study are as follows:

1. Deposit money banks should ensure adequacy of Digital payment services, regardless of location to enhance customer access.
2. They should also ensure availability of Digital remittance services so that customers can have seamless and round-the-clock access. Adequacy and availability of FinTech services are essential elements of performance.

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