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# Data Analysis And Fraud Prevention And Detection To Selected Money Deposit Bank In Nigeria

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**ABSTRACT**
This study empirically examined the Data analysis and fraud prevention and detection to selected money deposit bank in Nigeria. The objectives of this study are to; investigate the effect of machine learning on fraud prevention and detection; Evaluate the effect of data base management system on fraud prevention and detection; examine the effect of network analysis tools on fraud prevention and detection; examine the effect of data mining tools on fraud prevention and detection. four research questions and four hypotheses were formulated in line with the stated objectives. The variables used were sourced of from secondary source. Ex-post facto research design was used in this study, the study selected deposit money bank listed on the Nigerian Exchange Listing (NEL) while, the study used panel least square as a method of data analysis. The variables used are machine learning, data base management system, network analysis tools and data mining tools are the independent variables, while fraud prevention and detection are the dependent variable. The study finds out that Machine learning has significant effect on fraud prevention and detection to selected money deposit bank in Nigeria (t=3.583072=0.009). Base management system has no significant effect on fraud prevention and detection to selected money deposit bank in Nigeria (=0.569002, p=0.5721). Network analysis has significant effect on fraud prevention and detection to selected money deposit bank in Nigeria. (t=3.378671, p=0.0006). analysis tools has significant effect fraud prevention and detection to selected money deposit bank in Nigeria (t=2.896441, 0.0059). The study concludes that data analytics plays a vital role in enhancing fraud prevention and detection in selected deposit money banks. The study recommends that deposit money banks should increase investment in machine learning technologies to strengthen their fraud prevention and detection systems. This will enhance the ability to identify suspicious transactions, predict fraudulent activities, and minimize financial losses. Banks should integrate their database management systems with advanced analytics platforms, artificial intelligence, and machine learning applications rather than relying solely on traditional database functions .Banks should adopt and strengthen network analysis techniques within their fraud management systems. By analyzing transaction patterns and relationships among customers, accounts, and devices, banks can detect complex fraud networks more effectively and respond promptly to emerging fraud threats.
**Keywords:** Machine learning, data base management system, network analysis tools and data mining tools

## INTRODUCTION

### 1.1 Background to the Study

The banking industry plays a vital role in the economic development of every nation through financial intermediation, mobilization of savings, credit creation, and facilitation of business transactions (Abdulhamid , Abubakar 2024) In Nigeria, deposit money banks have become increasingly dependent on digital technologies and electronic banking systems to improve operational efficiency and customer satisfaction (Aduda, & Kingoo, 2012).. The adoption of information and communication technology (ICT), internet banking, mobile banking, automated teller machines (ATMs), and electronic payment systems has transformed banking operations and enhanced financial transactions. However, the increasing reliance on technology has also exposed banks to various forms of fraud and financial crimes (Agboola, 2010).)..

Fraud in the banking sector has become a major concern to stakeholders due to its negative impact on bank performance, customer confidence, and the stability of the financial system (Burns, & Burns, 2019).). Fraud refers to deliberate acts of deception, manipulation, or dishonesty carried out for personal or financial gain. Common forms of fraud in deposit money banks include identity theft, ATM fraud, cyber fraud, insider abuse, electronic payment fraud, phishing, money laundering, and unauthorized transactions. These fraudulent activities result in huge financial losses, reputational damage, reduction in profitability, and loss of public trust in the banking system (Chaffey, & Wood, 2017).). The increasing sophistication of fraudulent activities has made traditional methods of fraud detection inadequate.

Consequently, deposit money banks are now adopting data analysis techniques to improve fraud prevention and detection mechanisms. Data analysis involves the process of collecting, examining, interpreting, and transforming data to identify meaningful patterns, trends, and relationships for decision-making purposes (Chaia, Dalal,, Goland, Gonzalez, Morduch & Schiff, 2009). In the banking industry, data analysis helps financial institutions monitor customer transactions, detect unusual activities, predict fraudulent behavior, and respond promptly to potential threats. The application of data analysis in fraud prevention and detection has gained significant attention in recent years due to the rapid growth of digital banking and financial technology (Cockburn, Iain , Rebecca and Stern. 2018). Through the use of advanced analytical tools such as data mining, predictive analytics, machine learning, artificial intelligence, and statistical models, banks can identify suspicious transactions in real time and reduce the occurrence of fraud. These analytical techniques enable banks to process large volumes of financial data efficiently, thereby improving operational effectiveness and strengthening internal control systems (Cuoto, 2018).

Fraud prevention refers to the measures and strategies adopted by banks to minimize or eliminate the occurrence of fraudulent activities before they happen. Fraud detection, on the other hand, involves identifying and investigating fraudulent transactions or suspicious activities after they occur (Doumpos, Constantin, Dimitrios, Emmanouil, & Wenke 2023). Data analysis contributes significantly to both fraud prevention and detection by providing accurate information, enhancing monitoring systems, and improving decision-making processes. For instance, transaction monitoring systems powered by data analytics can flag abnormal customer behavior, unauthorized withdrawals, or unusual transaction patterns for immediate investigation (Eketu  Nwiyii, & Uelee, 2023)

Despite the benefits associated with data analysis, many deposit money banks in Nigeria still experience persistent cases of fraud due to inadequate technological infrastructure, poor internal control systems, lack of skilled personnel, and increasing cyber threats (Elegunde, & Shotunde, 2020).. In some cases, insider collaboration and weak regulatory compliance further contribute to the rising incidence of fraud in the banking sector (Festus, & Olabosipo, 2020). The continuous occurrence of fraud has raised concerns among regulators, bank management, customers, and other stakeholders regarding the effectiveness of existing fraud prevention mechanisms. Furthermore, the increasing volume of electronic transactions in Nigeria has intensified the need for effective data-driven fraud management systems (Franck, 2021).).. Regulatory authorities such as the Central Bank of Nigeria and the Nigeria Deposit Insurance Corporation

have emphasized the importance of strong risk management practices, cybersecurity frameworks, and technological innovation in combating fraud within the banking industry. Banks are therefore investing heavily in analytical tools and digital security systems to strengthen fraud prevention and enhance customer confidence (Frank, & Binaebi, 2019).)..

Against this background, this study seeks to examine the role of data analysis in fraud prevention and detection in selected deposit money banks in Nigeria. The study aims to determine how data analysis techniques contribute to identifying fraudulent activities, reducing financial losses, improving internal control systems, and enhancing the overall performance and security of banks. The findings of the study are expected to provide useful insights to bank management, policymakers, researchers, and other stakeholders on the importance of adopting effective data analytical systems in combating fraud in the Nigerian banking sector.

**1.2 Objectives of the Study**

The main objective of the study was to examine the Data analysis and fraud prevention and detection to selected money deposit bank in Nigeria.. The specific objectives were to:

I. To investigate the effect of machine learning on fraud prevention and detection
II. To Evaluate the effect of data base management system on fraud prevention and detection
III. To examine the effect of network analysis tools on fraud prevention and detection
IV. To examine the effect of data mining tools on fraud prevention and detection

**REVIEW OF RELATED LITERATURE**

**2.1 Conceptual Review**

**2.1.1 Data Analytics**

Big data analytics refers to the systematic process of examining large, complex, and diverse datasets to uncover hidden patterns, correlations, trends, and insights that can support effective decision-making effectiveness (Olumuyiwa, 2023), Big Data is commonly described using the "5Vs": volume, velocity, variety, veracity, and value (IBM, 2020). Volume relates to the massive amount of data generated from multiple sources such as transactions, social media, and digital platforms (Hassan, Rabbani, and Ali, 2020).. Velocity refers to the speed at which data are generated, processed, and analyzed, often in real time. Variety highlights the different forms of data, including structured, semi-structured, and unstructured data such as text, images, and videos.

Veracity concerns the accuracy, reliability, and quality of data, while value emphasizes the usefulness of data in generating meaningful insights. Furthermore, Big data analytics (BDA) has been defined by various scholars from different perspectives, reflecting its multidimensional nature (Hogan, & Okereke, 2023).. It is generally viewed as the process of examining large, complex datasets to uncover hidden patterns, correlations, and insights that support decision-making effectiveness. Also, big data analytics is defined as the application of advanced analytical techniques to large and diverse datasets in order to generate actionable insights (Jarek, & Mazurek, 2019).

**2.2 Theoretical Review**

This study was anchored on Resource-Based View (RBV) Barney (1991). The theory states that firms achieve and sustain competitive advantage through the effective utilization of internal resources and capabilities. According to the RBV, not all resources contribute equally to firm performance; rather, only those resources that are valuable, rare, inimitable, and non-substitutable (VRIN) can generate sustained competitive advantage. Valuable resources enable firms to exploit market opportunities or neutralize threats, while rarity ensures that such resources are not widely possessed by competitors. Inimitability refers to the difficulty competitors' face in copying or replicating these resources, and non-substitutability implies that no alternative resources can perform the same function effectively.

Big Data Analytics capability is a strategic organizational resource for effective decision-making purposes. This capability encompasses the firm's technological infrastructure, skilled personnel, data management processes, and analytical culture required to transform raw data into actionable insights.

When effectively developed, Big Data Analytics enables firms to understand customer needs, anticipate market trends, and make superior marketing decisions regarding product development, pricing, promotion, and distribution. The insights are often firm-specific and embedded in organizational routines, making them difficult for competitors to imitate. Resource-based view theory assumes that investing in analytics capabilities can strengthen firm competitiveness, even in resource- constrained environments. This theory is very relevant to the present study. Therefore, this study anchors on it for theoretical foundations, hypotheses formulation and empirical grounding. Thus, by leveraging on data-driven insights, SMEs can differentiate themselves, improve marketing effectiveness, and achieve sustainable performance even in highly competitive markets.

**2.3 Empirical Studies**

Junghare and Sachin (2026) reviewed and provide a conceptual reconsideration of the interconnection between data-analytic adoption and the financial performance of firms. It questions the ability of predictive analytics, business intelligence, and live data processing to enable a greater quality in decision-making, increased cost-effectiveness, improved financial planning, and increased profitability. Based on the recent research conducted in the period between 2014 and 2024, the paper outlines the key financial metrics that are affected by the analytics, especially the return on investment (ROI), profit margins, and operational productivity. According to the empirically proven benefits, however, SMEs still face implementation limitations like the lack of technical infrastructure, poor human resources, challenging data integration, and cybersecurity threats. As a result, some promising future routes are noted in the review, such as the introduction of low-cost analytics or a focus on developing digital skills and the development of policy frameworks that would encompass the needs of SMEs.

Mensa and Owolabi, (2026) evaluated how standardized algorithmic governance frameworks and explainable artificial intelligence architectures can substantiate public trust in automated fraud detection systems operating within the U.S. financial infrastructure. A mixed-methods research design was employed, which combines systematic literature review, comparative policy analysis, and empirical data synthesis from real-time monitoring environments to assess how formal verification workflows, drift monitoring protocols, and third-party audit mechanisms translate into measurable institutional accountability. The findings demonstrate that hybrid ensemble models augmented with post-hoc interpretability tools such as SHAP and LIME achieve F1-scores of 92.2% and AUC-ROC values of 0.97, as well as maintaining high regulatory alignment, which outperform opaque deep learning architectures across both predictive and compliance dimensions. Institutions deploying layered governance architectures incorporating federated learning, cryptographic audit trails, and continuous drift monitoring record compliance scores of 94%, compared to 41% for systems with no formal governance structure. Furthermore, the integration of contestable AI mechanisms and stakeholder inclusion protocols significantly reduces perceived institutional bias and strengthens procedural fairness.

Parmar, (2026) examined the impact of AI-driven data analytics on fraud detection effectiveness in selected firms. Using primary data collected from accounting and audit professionals and secondary data from published reports, the study analyzes improvements in detection accuracy, reduction in investigation time, and prevention of financial fraud. The findings indicate that AI-based forensic tools significantly improve fraud detection effectiveness and contribute to proactive fraud prevention.

Abubakar, Adebisi and Mlanga, (2025) examined the effect of forensic data analysis on fraud detection in listed firms in Nigeria. Fraudulent activities pose a significant threat to corporate governance, financial transparency, and investor confidence. With the rising complexity of corporate fraud, forensic data analysis has emerged as a critical tool in fraud detection. This study employs a quantitative research design, analyzing financial data from listed firms using statistical and forensic techniques. The findings reveal a significant positive relationship between forensic data analysis and fraud detection, indicating that the adoption of forensic tools enhances the ability to identify and prevent fraudulent activities. The results underscore the necessity for organizations to integrate forensic data analytics into their risk management frameworks. Furthermore, the study recommends increased investment in forensic

technologies, capacity building for auditors, and stricter regulatory oversight to enhance fraud detection effectiveness.

Onuoha, et al. (2025) examined the effectiveness of forensic data analytics in detecting fraudulent claims within Nigeria's health insurance sector.. The study adopts a quantitative research design using secondary data obtained from five major health insurance companies in Nigeria—Hygeia HMO, Leadway Health, Zenith HMO, Avon HMO, and Mutual Benefits HMO. A total of 1,200 health insurance claims covering the period 2019–2024 were analyzed. Descriptive statistics, multiple regression analysis, and other inferential statistical tools were employed to evaluate the relationship between forensic data analytics techniques and fraud detection effectiveness. Findings reveal that forensic data analytics significantly improves fraud detection rates in the Nigerian health insurance sector. The regression results indicate that data analytics techniques, machine learning models, forensic accounting integration, and artificial intelligence collectively explain approximately 78% of the variation in fraud detection effectiveness ($R^2 = 0.78$, $F = 34.21$, $p < 0.01$). Among the firms studied, Leadway Health recorded the highest detection rate. . It recommends that insurance companies invest in advanced analytical tools, strengthen staff capacity, and adopt proactive fraud monitoring systems. Regulatory bodies are also encouraged to support the adoption of these technologies through policies and incentives.

Odeh and Usman, (2026) explored how big data analytics affects the performance of multinational companies in Nigeria with reference to Guinness Nigeria Plc. The research design was a cross-sectional survey. A total of 839 employees in Guinness in Benin City, Lagos and three regional divisions were used to obtain a sample of 325 employees through the Krejcie and Morgan formula with a 20 percent non response adjustment. There was the use of the cluster sampling method that would provide representation within operations units. A structured questionnaire was used to gather primary data, and regression analysis was used to analyse data with the assistance of SPSS version 27. The results indicated that text analytics, video analytics, and audio analytics positively and statistically impacted the performance of organisations.. It was advised that Guinness Nigeria Plc ought to enhance its analytics by using context-sensitive text processing systems to improve operational optimisation, real-time video surveillance on customer engagement, and high-end audio analytics tools to improve customer engagement.

## METHODOLOGY

### 3.1 Research Design

*An ex-post facto* research design was employ in this study. The time period was from 2014 to 2025. The selection of an *ex-post facto* research design is on the presumption that the author's cannot manipulate the data as they are available in public domain vide established and regulated government agencies.

### 3.2 Nature and Sources of Data

The data was secondary in nature and on annual basis, while the Nigeria Deposit Insurance Corporation (NDIC) annual reports of the selected bank served as the source of data collection for the return on asset (ROA), While Machine learning, Data base management, Network analysis and Data mining adopted Dummy variables which 1 & 0

### 3.3 Population of the Study

The population of this study consists of fourteen (14) deposit money bank quoted in Nigeria exchange limited from 2014-2025

### 3.4 Sample Size and Sampling Technique

This study selected ten (10) deposit money banks in Nigeria. The researcher used purposive sampling techniques in selecting the chosen banks.

**Table 3.1 Selected Deposit Money Banks**

| | |
|---|---|
| 1 | Fidelity bank plc |
| 2 | FCMB plc |
| 3 | First bank plc |
| 4 | Access bank plc |
| 5 | United bank of Africa (UBA) |
| 6 | Sterling bank plc |
| 7 | GT Bank |
| 8 | ECO Bank |
| 9 | Zenith Bank |
| 10 | Union Bank |

### 3.4 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 in the following equation below
Algebraically, therefore
FPD =F (MAL, DBM, NTA, DTM)
$FPD=\beta o+\beta_1 MAL + \beta_2 DBM + \beta_3 NTA + \beta_4 DTM$
Where
FPD= Fraud prevention and detection
MAL= Machine learning
DBM= Data base management
NTA= Network analysis
DTM= Data mining
Bo= constant
$\beta_1$-$\beta_3$ is parameters to be estimated

**Panel Regression**

In this study, the regression approach of data analysis was used. Specifically, the connection between the independent variables data analysis and dependent variable (fraud prevention) 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.

### 3.5 Variables and Measurement

| Variable | measurement | Authorities |
|---|---|---|
| **Dependent Variable**<br>Fraud prevention and detection | Firm‘s net income to total assets in the same year | (Setiawan&Gestanti, 2022) |
| **Independent Variable**<br>Machine learning | ‘1’ if disclosed, ‘0’otherwise | Zhang & Lucey (2022); Rahi, Akter, & Johansson (2022) |
| Data base management | ‘1’ if disclosed, ‘0’otherwise | Zhang & Lucey (2022); Rahi, Akter, & Johansson (2022) |
| Network analysis | ‘1’ if disclosed, ‘0’otherwise | Zhang & Lucey (2022); Rahi, Akter, & Johansson (2022) |
| Data mining | ‘1’ if disclosed, ‘0’otherwise | Zhang & Lucey (2022); Rahi, Akter, & Johansson (2022) |

## DATA PRESENTATION AND ANALYSIS

### 4.1: See appendix 1 for Data Presentation.

Complete set of data from selected bank sector for all the analysis was presented at the appendix 1 for your reference.

### 4.2: Preliminary Data Tests

#### 4.2.1 Descriptive Statistics Analysis

Table 4.2.1, which displays the number of observations, mean, standard deviation, minimum and maximum values of the explained variable, and each of the explanatory variables, provides the descriptive statistics for all the variables in the model. The descriptive data of the chosen service sector that comprise our sample are displayed in the table below.

**Table 1 Descriptive Statistics**

| | FPD | MAL | BMS | NTA | DTM |
|---|---|---|---|---|---|
| Mean | 0.102727 | 16.26176 | 17.57151 | 16.38742 | 8.493355 |
| Median | 0.030000 | 17.44278 | 19.43901 | 17.63820 | 9.406934 |
| Maximum | 0.610000 | 20.12964 | 30.43941 | 19.73981 | 11.55281 |
| Minimum | 0.010000 | 7.414573 | 10.21899 | 7.440734 | 3.001217 |
| Std. Dev. | 0.127638 | 3.172703 | 3.777851 | 3.610735 | 2.531564 |
| Skewness | 1.604184 | -0.843594 | -0.448847 | -1.007445 | -1.002340 |
| Kurtosis | 5.214986 | 2.387396 | 2.969313 | 2.509920 | 2.691636 |
| Jarque-Bera | 69.66568 | 14.76699 | 3.697816 | 19.70815 | 18.85506 |
| Probability | 0.000000 | 0.000621 | 0.157409 | 0.000053 | 0.000080 |
| Sum | 11.30000 | 1788.794 | 1932.866 | 1802.616 | 934.2691 |
| Sum Sq. Dev. | 1.775782 | 1097.199 | 1555.665 | 1421.077 | 698.5610 |
| Observations | 120 | 120 | 120 | 120 | 120 |

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

The mean values for each variable, along with their maximum and lowest values, standard deviation, and Jarque-Bera values—which indicate the data's normality and nature—are displayed in the descriptive statistics result in table 4.2.1 above. The outcome sheds some light on the characteristics of the chosen listed financial sector from Nigeria that were employed in the research. The objective of the descriptive statistics was to characterize the overall distributional characteristics of the data and to pinpoint any anomalous observations or anomalous patterns of observations that would pose issues for the data's further analyses. The data generated for the study was thus described and summarized by an initial analysis of the data using basic descriptive methods. According to the study's goal, the descriptive statistics are provided in this part. The liquidity 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 liquidity suggests that the chosen components artificial intelligence vary widely from one another, and this implies that the firms are not homogenous across the period under examination. The financial service standard deviation was 0.12. The return on asset's skewness was 1.60, suggesting that the data were skewed to the right and that most values were therefore clustered to the BMS of the distribution. The kurtosis for performance was 5.21 that are more than 3 hence the distribution is said to be leptokurtic hence it may have few outliers.

Table 4.1.2 above presents the descriptive analysis of Real Time Gross Settlement (MAL), 16.26% was the minimal number for the machine learning (MAL), additionally, it can be seen that the machine learning (MAL), reached a level of 16.26%. The standard deviation was 3.17, indicating that the available resources or size of the ten listed financial service in Nigeria were dispersed around the mean by around 3.17%. With a skewness of -0.84, the machine learning (MAL), was negatively skewed, suggesting that

the majority of its values were clustered to the Base management system. The kurtosis for point of sales was 2.38% which are less than 3 hence it is platykurtic and may have few outliers.

Base management system (BMS) which is 17.57 % of their average value. The mean of Base management system (BMS) was 17.57 % suggesting that the average value of Base management system (BMS) for the 10 listed financial sector studied was about 17%, implying that the Base management system (BMS) were exactly quarter of the profit. The standard deviation of 3.77% suggests that there is high return on Base management system(BMS) amongst the meNTAer selected financial service, with a minimum and maximum value of about 10.21% and 30.43% respectively.

In a similar vein, network analysis, 16.38% was the average network analysis . It was noted that the tested enterprises had an average positive network analysis of 16.38% during the review period. The bank has a minimum network analysis income value of 7.44 and a maximum value of 19.73 for the evaluation period. The substantial variation between the maximum and minimum network analysis suggests that the bank vary significantly among the chosen firms and during the reviewed period, demonstrating the heterogeneity of the enterprises. The standard deviation for network analysis was 3.61 The skewness for network analysis was -1.00 implying that the data on network analysis were skewed to the right hence most values were bunched to the right of the distribution. The kurtosis for network analysis was 2.50% that are less than 3 hence the distribution is said to be leptokurtic hence it may have few outliers.

In addition, the JB Probability values of 0.0000 demonstrate that, with the exception of the Base management system (BMS), 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.

### 4.2.2: Pearson Correlation Matrix

In order to ascertain the nature or degree of association, i.e., positive or negative correlation, as well as the magnitude of the correlation between dependent variable (fraud prevention and detection) and independent variables with other explanatory variables, Pearson's correlation matrix was used to assess the degree of association between data mining and fraud prevention and detection. The direction and strength of the relationship between two or more variables are measured by the correlation coefficient. At this stage, it is important to remember that correlation quantifies association rather than causation. Positive (>0) or negative (<0) correlations are both possible. When two variables have a positive correlation, they are moving in the same direction; when they have a negative correlation, they are moving in the other way. As a consequence, we used the Pearson correlation coefficient (correlation matrix) to investigate the relationship between the variables, and the outcomes are shown in table 4.2. below.

**Table 2: Correlation Analysis Result**

| | FPD | MAL | BMS | NTA | DTM |
|---|---|---|---|---|---|
| FPD | 1.000000 | 0.309547 | 0.359617 | 0.287201 | 0.292822 |
| MAL | 0.309547 | 1.000000 | 0.860353 | 0.866790 | 0.768127 |
| BMS | 0.359617 | 0.860353 | 1.000000 | 0.880013 | 0.809822 |
| NTA | 0.287201 | 0.866790 | 0.880013 | 1.000000 | 0.773757 |
| DTM | 0.292822 | 0.768127 | 0.809822 | 0.773757 | 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 data mining component and the fraud prevention of deposit money bank in Nigeria 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 demonstrates that the majority of correlation coefficients between the variables are quite low. The aforementioned findings indicate that the data mining component and fraud prevention have a very weak but positive correlation. 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.

### 4.2.4 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.

**Table 6: Hausman Test**

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

| Test Summary | Chi-Sq. Statistic | Chi-Sq. d.f. | Prob. |
|---|---|---|---|
| Period random | 2.786894 | 5 | 0.0749 |

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

Period random effects test comparisons:

| Variable | Fixed | Random | Var(Diff.) | Prob. |
|---|---|---|---|---|
| MAL | 0.055175 | 0.051913 | 0.000156 | 0.7942 |
| BMS | 0.126403 | 0.114009 | 0.000321 | 0.4890 |
| NTA | 0.052997 | 0.036933 | 0.000187 | 0.2403 |
| DTM | 0.235261 | 0.222191 | 0.000897 | 0.6626 |

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

The pooled PLS 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.

### 4.2.5: Test of Hypotheses/ Regression Results

Since the data had both time series (2014–2025) and longitudinal properties (Ten deposit money bank), we used a panel least square regression analysis to investigate the relationship between the dependent variable (FPD) and the independent variables (MAL, BMS, NTA, DTM) and to test our hypothesis. Our analysis is shown in the following table 4.3.1:

**Table 7: Panel Least Regression Result**

Dependent Variable: FPD
Method: Panel Least Squares
Date: 06/25/26 Time: 05:40
Sample: 2014 2025
Periods included: 12
Cross-sections included: 10
Total panel (balanced) observations: 120

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.502159 | 0.019774 | 0.109194 | 0.9135 |
| MAL | 0.160554 | 0.000950 | 3.583072 | 0.0009 |
| BMS | 0.290588 | 0.001033 | 0.569002 | 0.5721 |
| NTA | 0.560348 | 0.000919 | 3.378671 | 0.0006 |
| DTM | 0.491620 | 0.001807 | 2.896441 | 0.0059 |

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

| | | | |
|---|---|---|---|
| R-squared | 0.616141 | Mean dependent var | 0.022273 |
| Adjusted R-squared | 0.557591 | S.D. dependent var | 0.014336 |
| S.E. of regression | 0.010558 | Akaike info criterion | 6.018756 |
| Sum squared resid | 0.005128 | Schwarz criterion | 5.355224 |
| Log likelihood | 218.6189 | Hannan-Quinn criter. | 5.756563 |
| F-statistic | 9.886092 | Durbin-Watson stat | 2.117084 |
| Prob(F-statistic) | 0.000085 | | |

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

The panel regression study of ten quoted financial services is displayed in table 7 above. The aforementioned table indicates that the model was well-specified in explaining data mining as seen by the F-statistics value of 9.886092 and their P-value of 0.000085, 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 0.616141 (61%) and the R-squared value was 0.557591 (55%). The coefficient of determination, or R-squared, was found to be 61%. This indicates that 61% of the systematic fluctuations in the individual dependent variables could be described by the model, with the other 39% being explained by the stochastic error factor. This shows that over a twelve year period, the data mining 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 39% of the overall variations. Furthermore, the data mining model that was employed for the analysis was statistically significant at the 1% level, as indicated by the F-statistics value of 9.886092 and its probability value of 0.00085. 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**

$Ho_1$: **Machine learning has no significant effect on the fraud prevention and detection of deposit money bank in Nigeria.**

Table 4.3.2 above's panel regression result revealed that the Machine learning had a positive coefficient value of 0.160554 and a P-value of 0.0009. Based on the model's outcome, the Machine learning of Nigeria's quoted deposit money bank showed a statistically significant and positive correlation with the liquidity, which indicated the value of performance ratios. This implies that the Machine learning has a

positive correlation with fraud prevention and detection of deposit money bank, as indicated by the positive coefficient and likelihood, but that this correlation is statistically negligible and sufficient to influence the fraud prevention and detection of deposit money bank of Nigerian bank. This suggests that a 1% increase in the machine learning causes a 5% increase in fraud prevention and detection of deposit money bank, supporting the idea that raising the Machine learning is crucial for fraud prevention and detection of deposit money bank. The Nigeria Exchange Group's increased level of inspection and monitoring is generally predicted to improve fraud prevention and detection of deposit money bank 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 Machine learning has significant effect on the fraud prevention and detection of deposit money bank in Nigeria

**$H_{o_2}$: Base Management System has no significant effect on the fraud prevention and detection of deposit money bank in Nigeria**

In Nigeria, the base management system of the fraud prevention and detection in deposit money bank is positively and significantly impacted as demonstrated by the study's 0.569002 positive coefficient value and 0.5721 p-value ($\beta 2$=-0.290588, $p = 0.5721 > \alpha = 0.05$). The positive coefficient value of $\beta 2$ indicates that the base management system is positively impacted on fraud prevention and detection of deposit money bank. As a result, base management system rises by 29% units for every 1% increase in fraud prevention and detection. This indicates that, although being not statistically significant among Nigerian financial sector has a favorable impact on the level of fraud prevention and detection. The analysis's findings led the study to accept the second null hypothesis, which leads it to the conclusion that base management system has no significant effect on the fraud prevention and detection of deposit money bank in Nigeria

**$H_{o_3}$: Network analysis has no significant effect on the fraud prevention and detection of deposit money bank in Nigeria**

The analysis of the impact of Network analysis expressed on fraud prevention and detection of deposit money bank in Nigeria revealed a 0.0006 P-value, a t-value of 3.378671, and a positive coefficient value of 0.560348. According to table above, the Network analysis of Nigeria's listed deposit money bank has a positive and significant relationship with liquidity of financial sectors. A rise in Network analysis may result in a 0.56% increase in the fraud prevention and detection of deposit money bank, according to the coefficient value of 0.560348. Network analysis has a positive impact on the fraud prevention and detection of deposit money bank, as indicated by the t-value of 3.378671. At the 1% level of significance, the probability value of 0.0006 suggests that the impact of Network analysis on the fraud prevention and detection of deposit money bank is statistically significant. This study accepts the third alternative hypothesis and comes to the conclusion that Network analysis has significant effect on fraud prevention and detection of deposit money bank

**$H_{o_4}$: Data mining tools (DTM) has no significant effect on the fraud prevention and detection of deposit money bank in Nigeria.**

From the regression Table 7 above, the result of data mining tools shows fraud prevention and detection of deposit money bank in Nigeria has a positive coefficient value of 0.491620 and P-value of 0.0059. The result of the analysis from the model indicates that data mining tools has positive but significant influence on fraud prevention and detection of deposit money bank. This implies that a 1% increase in the proportion of Data mining tools will lead to a magnificent increase in the financial sectors in Nigeria. The probability value showed that the effect is statistical significant. As a result of this significant effect we documented, we accepted our fourth hypothesis and therefore conclude that Data mining tools (DTM) has significant effect on the fraud prevention and detection of deposit money bank in Nigeria.

## CONCLUSION AND RECOMMENDATION

### 5.1: Conclusion

The study concludes that data analytics plays a vital role in enhancing fraud prevention and detection in selected deposit money banks. The significant effects of machine learning, network analysis, and data analytics tools demonstrate that advanced analytical technologies are critical for improving the efficiency, accuracy, and timeliness of fraud detection. Therefore, deposit money banks should continue to invest in modern data analytics technologies, strengthen their analytical capabilities, and integrate intelligent fraud detection systems into their operational processes to minimize fraud risks, protect customers' assets, and improve overall banking performance.

### 5.2 Recommendations

The recommendations of the study are as follows:

i Deposit money banks should increase investment in machine learning technologies to strengthen their fraud prevention and detection systems. This will enhance the ability to identify suspicious transactions, predict fraudulent activities, and minimize financial losses.

ii.Since the database management system was found to have no significant effect on fraud prevention and detection, banks should integrate their database management systems with advanced analytics platforms, artificial intelligence, and machine learning applications rather than relying solely on traditional database functions

iii.Banks should adopt and strengthen network analysis techniques within their fraud management systems. By analyzing transaction patterns and relationships among customers, accounts, and devices, banks can detect complex fraud networks more effectively and respond promptly to emerging fraud threats.

iv.Management of deposit money banks should continuously upgrade and deploy advanced data analytics tools capable of processing large volumes of transactional data in real time. Regular updates and staff training should accompany these investments to ensure the tools are used effectively for fraud detection and prevention.

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