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Data-Driven Innovation and Financial Fraud Mitigation of the Manufacturing Firms in Nigeria

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ABSTRACT

This study examined the effect of data-driven innovation on financial fraud mitigation in listed manufacturing firms in Nigeria. Specifically, the study assessed the impact of predictive analytics and big data infrastructure on financial fraud mitigation across eighteen manufacturing companies listed on the Nigerian Exchange Group (NGX) over a ten-year period from 2016 to 2025. The study adopted a quantitative research approach using secondary data drawn from the annual reports and financial statements of the sampled firms. Panel data regression analysis was employed as the primary analytical technique, Descriptive statistics with the Fixed Effects model selected, following the Hausman Specification Test. Diagnostic tests confirmed that all required statistical assumptions were satisfied. The correlation analysis revealed strong positive relationships between predictive analytics, big data infrastructure, and financial fraud mitigation. The regression results showed that predictive analytics has a significant positive impact on financial fraud mitigation ($\beta = 0.487$, $p = 0.000$), and that big data infrastructure also has a significant positive influence on financial fraud mitigation ($\beta = 0.432$, $p = 0.003$). Both null hypotheses were accordingly rejected. The study concludes that data-driven innovation is a powerful tool for reducing financial fraud in the Nigerian manufacturing sector and recommends that listed manufacturing firms prioritize investment in analytics tools and technology infrastructure as a core component of their fraud management strategies.

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INTRODUCTION

Data-driven innovation and fraud mitigation is grounded in the idea that when organizations use data systematically, they remove the conditions that allow fraud to thrive secrecy, lack of oversight, and delayed detection. Predictive analytics, for example, can identify behavioral patterns that indicate the possibility of fraud before a transaction is even completed. Machine learning algorithms can analyze hundreds of financial variables at once and flag those that fall outside normal ranges (Adebayo et al., 2021). Real-time dashboards and automated reporting tools allow management and auditors to monitor operations continuously rather than waiting for end-of-period reports. Together, these innovations create a more transparent, accountable, and secure financial environment within manufacturing firms.

Globally, companies have responded to the rising threat of fraud by adopting data-driven technologies. For instance, major multinational companies like General Electric and Siemens now use real-time data monitoring systems and AI-powered anomaly detection tools to flag suspicious transactions as soon as they occur (Wooldridge, 2002). These systems are able to learn from past fraud patterns, spot irregularities in financial records, and alert management before small problems become major scandals. The rise of big data analytics has made it possible for organizations to process millions of financial transactions simultaneously, something that was impossible with traditional manual auditing methods. According to Bao, (2022), big data analytics has significantly improved the ability of organizations to detect fraud early, reduce financial losses, and maintain the integrity of financial reporting. In Nigeria the adoption of data-driven tools in manufacturing firms remains limited and uneven. While some larger listed companies are beginning to invest in enterprise resource planning (ERP) systems and data analytics platforms, many mid-sized and smaller manufacturers still rely on manual processes and outdated accounting systems that are vulnerable to manipulation (Oyedokun et al.,

2023). This creates a gap in fraud prevention capability. The absence of robust, technology-driven internal oversight means that fraudulent activities can go undetected for extended periods, causing deep damage to company finances and reputation.

1.1 Statement of the Problem

Despite the increasing availability of data-driven technologies, financial fraud continues to be a serious and persistent problem for manufacturing companies listed on the Nigerian Exchange Group (NGX). These companies are expected to operate with high levels of financial transparency and accountability because they are publicly traded and their performance directly affects investor confidence, employee welfare, and Nigeria's industrial growth. However, reports from regulatory bodies, financial auditors, and academic researchers consistently show that fraud in various forms is widespread in this sector, causing enormous financial losses and undermining the credibility of corporate financial reporting (Fasua et al., 2024).

One major issue is that many Nigerian manufacturing firms have not fully embraced data-driven approaches to managing and monitoring their financial activities. Traditional accounting systems and manual processes are still dominant in several of these companies, making it easy for fraudulent transactions to escape detection even in cases where some level of technology is used, it is often not integrated into a comprehensive fraud detection framework (Oyedokun et al.,2023). Without real-time data monitoring, pattern recognition tools, or predictive analytics, the detection of fraud is mostly reactive discovered only after the damage has already been done.

While numerous studies have explored the role of forensic accounting, internal controls, and IT in fraud prevention, very few have specifically examined how data-driven innovation as a distinct concept functions as a fraud mitigation tool within Nigerian manufacturing firms. Research in this area tends to either be focusing on technology adoption in general or on fraud in the financial services sector. (Fasua et al., 2024). This means that policymakers, corporate managers, and accountants in the manufacturing sector lack specific, evidence-based guidance on how to deploy data-driven tools effectively to fight fraud.

1.2 Objectives of the Study

The broad objective of this study is to examine the effect of data-driven innovation on financial fraud mitigation of listed manufacturing firms in Nigeria.

The specific objectives are to:

(i) assess the impact of predictive analytics on fraud detection of listed manufacturing firms in Nigeria.

(ii) evaluate the influence of big data infrastructure on fraud prevention of listed manufacturing firms in Nigeria.

2.0 LITERATURE REVIEW

2.1 Data-Driven Innovation

Data-driven innovation (DDI) refers to the strategic use of data, analytics, and digital technologies by organizations to generate insights that improve their processes, products, and decision-making. It goes beyond simply collecting data the focus is on how organizations translate data into actionable value. Luo (2023) defined data-driven innovation as a distinct paradigm in which data serves as the primary input for creating new solutions, reducing uncertainty in decision-making, and enhancing organizational creativity. Unlike traditional innovation processes that rely mainly on human judgment and experience, data-driven innovation uses systems and algorithms to identify patterns, predict outcomes, and guide strategic choices.

Samarasinghe & Lokuge (2022), described data-driven innovation as a strategic initiative where organizations use data and analytics to develop insights that help with new product development, process improvements, discovery of new markets, and new business models. Mayer-Schönberger & Cukier (2013) described data-driven innovation as the application of large-scale data analysis to uncover hidden patterns and correlations that would otherwise remain invisible to human observers, enabling organizations to make smarter decisions and create entirely new categories of products and services.

Fosso Wamba et al. (2017) defined data-driven innovation through the lens of big data capabilities, arguing that organizations which develop strong competencies in data collection, integration, and analysis are better positioned to innovate continuously. Brynjolfsson & McAfee (2012), in their work on management and analytics, defined data-driven innovation as the practice of basing organizational decisions on data and statistical analysis rather than intuition or experience alone.

Verhoef et al. (2021) defining it as the process through which organizations leverage digital data assets to fundamentally reconfigure their business models, value chains, and customer relationships. The rise of digital technologies including cloud computing, the Internet of Things (IoT), and big data platforms has made it much cheaper and easier for organizations to collect and process data than it was a decade ago (Samarasinghe & Lokuge, 2022).

This has opened new doors for manufacturing firms to use data not just for production and logistics, but also for financial oversight and fraud control. In the manufacturing firms in Nigeria, however, technology adoption remains uneven, and many firms are yet to fully take advantage of data-driven tools to strengthen their internal governance frameworks (Oyedokun et al., 2023).

2.2 Financial Fraud Mitigation

Financial fraud is a deliberate act of deception intended to produce an unlawful or unfair financial gain for the perpetrator, at the expense of individuals, organizations, or the public. According to the Association of Certified Fraud Examiners (ACFE, 2024), occupational fraud that is, fraud committed by employees or managers against their own organizations costs businesses approximately 5% of their annual revenues. In manufacturing firms specifically, financial fraud takes several forms, including falsification of financial statements, procurement fraud, inventory manipulation, payroll fraud, and misappropriation of company assets.

Financial statement fraud is particularly damaging because it misleads investors, creditors, regulators, and other stakeholders who depend on accurate financial information to make important decisions. In Nigeria, one of the most cited cases of financial statement fraud in the manufacturing sector is the Cadbury Nigeria Plc scandal, which served as a stark reminder of how deeply embedded fraud can undermine corporate reputation and investor confidence (Okoro & Onyebueke, 2021). Similar international scandals such as Enron, WorldCom, and Parmalat have demonstrated that without strong systems of detection and prevention, financial fraud can lead to the complete collapse of large organizations (ACFE, 2020).

Fraud in manufacturing firms is driven by a combination of factors that create both the motivation and the opportunity for dishonest behavior. Poor internal controls, weak oversight structures, inadequate use of technology, and a lack of real-time monitoring all increase the vulnerability of manufacturing organizations to fraud (Fasua et al., 2024). The problem is especially serious in listed companies, where the expectations of transparency and accountability are much higher, and where any instance of fraud can result in significant damage to share price, market confidence, and regulatory standing.

2.3 Measurement of Data-Driven Innovation

2.3.1 Predictive Analytics

Predictive analytics is one of the most powerful tools within the data-driven innovation framework. It refers to the use of historical data, statistical models, and machine learning algorithms to forecast the likelihood of future events. In the context of fraud detection, predictive analytics enables organizations to anticipate when and where fraud is likely to occur rather than discovering it after significant damage has already been done (Adebayo et al., 2021).

The core principle behind predictive analytics is that fraud follows patterns. A perpetrator who manipulates an invoice, for example, is likely to repeat the behavior and often in ways that leave traces in financial data. By training machine learning models on historical transaction records, organizations can build systems that automatically flag transactions that deviate from expected patterns. This approach has been shown to significantly reduce the time it takes to detect fraud and to minimize financial losses (Ashtiani & Raahemi, 2021). Research by Adebayo et al. (2021) specifically found that predictive analytics and machine learning algorithms significantly improved the identification of suspicious transactions and enabled proactive mitigation of financial losses in Nigerian banks.

In manufacturing firms, predictive analytics can be applied across several financial processes — from monitoring procurement transactions and payroll records to analyzing expense claims and financial statement inputs. The power of predictive analytics lies in its ability to process very large volumes of data at high speed, something that human auditors simply cannot match in the modern business environment (Ashtiani & Raahemi, 2021).

2.4 Big Data Infrastructure

Big data infrastructure refers to the combination of hardware, software, networks, data storage systems, and organizational processes that allow a company to collect, store, manage, and analyze large and complex datasets. It includes technologies such as cloud computing platforms, data warehouses, enterprise resource planning (ERP) systems, and distributed data processing tools like Apache Hadoop and Apache Spark (Fasua et al., 2023).

For manufacturing firms, big data infrastructure is the backbone that makes all other forms of data-driven innovation possible. Without the right infrastructure in place, a company cannot generate, store, or analyze the volumes of data needed to detect fraud effectively. According to a study published in the Adekoya (2022), big data infrastructure enables financial institutions and organizations to process large volumes of transactional data in real time, identify anomalies, and build forecasting models that predict potential fraud before it escalates.

A key component of big data infrastructure in fraud prevention is cloud computing. Cloud platforms provide scalable resources that allow organizations to store and process large amounts of financial data without being limited by on-site hardware constraints. This makes it possible for manufacturing firms even those with limited on-premises IT capacity to run advanced analytics and fraud detection systems at relatively low cost (Davenport et al.,2024). When organizations invest in robust big data infrastructure, they are essentially building the foundation that supports every other aspect of their data-driven fraud prevention strategy.

2.5 Theoretical Framework

This study is primarily anchored on the Fraud Triangle Theory (Cressey, 1953). The theory is adopted because it provides the most direct and relevant explanation for why financial fraud occurs in manufacturing firms and how it can be prevented. Of the three

elements of the fraud triangle pressure, opportunity, and rationalization data-driven innovation is most powerful in eliminating opportunity.

By investing in predictive analytics, strong big data infrastructure, and real-time financial monitoring, manufacturing firms reduce the conditions under which fraud can thrive. When transactions are constantly monitored, financial records are automatically cross-checked, and anomalies are flagged in real time, the window of opportunity for fraud becomes extremely narrow. The Fraud Triangle Theory thus forms a logical basis for expecting that improvements in data-driven innovation will lead to better financial fraud mitigation in listed Nigerian manufacturing firms (Creswell, 2014).

2.6 Empirical Review

Many empirical studies had demonstrated direct connection between data-driven innovation and fraud mitigation on the major economic sectors. For instance,

Oluwaseun et al. (2019) examined data-driven fraud prevention models and their effectiveness in reducing electronic fraud across Nigerian banking institutions. The dependent variable was the effectiveness of fraud prevention, while the independent variable was the adoption of data-driven models including predictive analytics and machine learning algorithms. The study made use of primary data collected through a combination of literature review, case study analysis, and expert interviews with banking and IT professionals. Data were analysed using qualitative and thematic analytical methods. The findings revealed that predictive analytics and machine learning algorithms significantly improved the identification of suspicious transactions, reduced false positives, and enabled proactive mitigation of financial losses.

Adebayo et al. (2021) assessed the role of predictive analytics in fraud detection within Nigerian banks. The dependent variable was the incidence of financial fraud, while the independent variable was the adoption and use of predictive analytics tools. The study made use of primary data collected through structured questionnaires administered to banking professionals and IT staff in selected Nigerian banks. Data were analysed using descriptive statistics and regression analysis. The findings revealed a strongly positive relationship between the use of predictive analytics tools and the reduction of fraud incidence, and underscored the importance of data quality and staff expertise in managing analytical systems effectively.

Fasua et al., (2023) studied fraud detection and forensic accounting in listed manufacturing firms in Nigeria. The dependent variable was the rate of fraudulent financial reporting, while the independent variable was the extent of adoption of forensic and analytical tools. The study made use of secondary data obtained from the annual reports and financial statements of listed manufacturing companies on the Nigerian Exchange Group, and data were analysed using panel regression analysis. The findings revealed that inadequate use of forensic and analytical tools was directly associated with higher rates of fraudulent financial reporting in the manufacturing sector, and recommended that manufacturing companies invest more heavily in technology-driven audit and detection systems.

Osaloni (2023) evaluated the effect of forensic computing techniques on the financial reports of listed manufacturing companies in Nigeria. The dependent variable was the reliability and accuracy of financial reports, while the independent variable was the adoption of forensic computing techniques including data analysis tools and digital auditing methods. The study made use of secondary data sourced from the published financial statements of sampled listed manufacturing firms on the Nigerian Exchange Group, and data were analysed using ordinary least squares regression. The findings established that companies applying forensic computing methods produced significantly more reliable and accurate financial reports, and that weak technology adoption in financial oversight directly increases organisational exposure to financial misstatement and fraud.

Ashtiani & Raahemi (2021) conducted a systematic literature review on intelligent fraud detection systems in financial statements using machine learning and data mining techniques, covering empirical studies published between 2010 and 2021. The dependent variable across the reviewed studies was the effectiveness of fraud detection, measured by accuracy, speed, and false-positive rates, while the independent variable was the application of machine learning and data mining approaches. The study reviewed a total of 98 peer-reviewed articles sourced from major academic databases including IEEE, Scopus, and Web of Science, using a structured systematic review methodology. The findings revealed that machine learning-based fraud detection systems outperformed traditional rule-based methods across nearly every performance metric, and concluded that data-driven approaches represent the best direction for financial fraud detection.

Bao et al. (2022) examined the application of artificial intelligence in financial fraud detection across multiple industry sectors. The dependent variable was the effectiveness of financial statement fraud detection, while the independent variable was the adoption of AI-driven detection models. The study made use of a large-scale dataset comprising financial statements of publicly listed firms spanning several decades, and applied ensemble machine learning models including RUSBoost algorithms to compare the performance of AI-based approaches against traditional audit-based methods. The findings revealed that AI-driven systems were significantly more effective at detecting financial statement fraud compared to conventional auditing approaches, and that AI-based models were capable of detecting fraud an average of two years earlier than traditional methods.

Chen et al. (2020) investigated the relationship between audit analytics, the quality of internal controls, and the quality of financial reporting in publicly listed firms. The dependent variable was the quality of financial reporting, while the independent variables

were the adoption of audit analytics tools and the effectiveness of internal control systems. The study made use of secondary data drawn from audited financial statements and internal control disclosures of firms listed on major stock exchanges, covering a multi-year panel dataset, and employed panel data regression analysis for data analysis. The findings revealed that companies that adopted audit analytics experienced significantly stronger internal controls and produced more accurate and reliable financial reports.

3. METHODOLOGY

3.1 Research Design

This study adopted a quantitative research method, Data are presented using descriptive statistics for each individual company. This study adopted a cross-sectional research design this design is appropriate because it allows the researcher to collect and analyse data from multiple companies at the same point in time, making it possible to draw comparisons across firms.

3.2 Area of Study

This study focuses on listed manufacturing firms in Nigeria. Specifically, it examines companies in the manufacturing sector that are listed on the Nigerian Exchange Group (NGX). Manufacturing firms were chosen because they handle large and complex financial transactions daily, making them particularly vulnerable to financial fraud. The study covers 18 manufacturing companies drawn from different sub-sectors of the Nigerian manufacturing industry, including food and beverages, industrial goods, and consumer goods.

3.4 Sources of Data

This study made use of Secondary data which refers to data that has already been recorded and published by others, rather than data collected fresh by the researcher. The secondary data used in this study was drawn from the annual reports and financial statements of the manufacturing companies, as published on the Nigerian Exchange Group website and the companies' official websites.

3.5 Population and Sample Size

The population of this study consists of 18 manufacturing firms listed on the Nigerian Exchange Group (NGX). (Nestle Nigeria Plc., Dangote Cement Plc., Lafarge Africa Plc., Cadbury Nigeria Plc., Unilever Nigeria Plc., PZ Cussons Nigeria Plc., Flour Mills of Nigeria Plc., Honeywell Flour Mills Plc., NASCON Allied Industries Plc., Dangote Sugar Refinery Plc., BUA Cement Plc., Berger Paints Nigeria Plc., Berger Paints Nigeria Plc., Champion Breweries Plc., Champion Breweries Plc., International Breweries Plc., UAC of Nigeria Plc., Vitafoam Nigeria Plc)

As of the time of this study, there are 18 listed manufacturing firms across various sub-sectors on the NGX.

3.7 Method of Data Analysis

Given that the dataset is a panel dataset covering 18 firms, panel data regression analysis was adopted as the primary method of analysis. Panel data regression is more appropriate than ordinary least squares (OLS) regression in this context because it accounts for unobserved firm-specific characteristics that may influence the dependent variable but are not directly measured. Two panel regression approaches were considered: the fixed effects model and the random effects model.

According to Im et al., 2003, Persaran, 2004 the fixed effects model controls for all time-invariant differences between firms, such as company culture, ownership structure, and management style is by allowing each firm to have its own intercept. The random effects model, on the other hand, assumes that firm-specific differences are random and not correlated with the independent variables.

Hausman Specification Test:

This is the most important test for panel data studies which determines whether the fixed effects model or the random effects model is more appropriate for the dataset. The test checks whether the firm-specific effects in the data are correlated with the independent variables. If the p-value of the Hausman test is less than 0.05, the fixed effects model is preferred. If the p-value is greater than 0.05, the random effects model is more appropriate (Hausman, 1978) The Hausman specification test was conducted to determine which of the two models was more appropriate for the data.

Correlation analysis was also conducted to examine the direction and strength of the relationships between the variables before running the regression. This helped to identify any preliminary patterns in the data and to check for potential issues before the main analysis. All analyses were conducted at a 5% significance level.

3.8 Model Specification

To answer the research questions and test the hypotheses, the following regression models were specified:

Model for Objective One — Effect of Predictive Analytics on Financial Fraud Mitigation:

$FFMit = \beta 0 + \beta 1 PAit + \alpha i + \epsilon it$

Where:

- FFMit = Financial Fraud Mitigation for company i at time t (dependent variable)
- PAit = Predictive Analytics for company i at time t (independent variable)

- β0 = Constant (intercept)
- β1 = Coefficient showing the effect of predictive analytics on financial fraud mitigation
- αi = Company-specific effects
- ϵit = Error term
- i = 18 listed manufacturing companies
- t = 10years

Model for Objective Two — Influence of Big Data Infrastructure on Financial Fraud Mitigation:

$FFMit = \beta0 + \beta1BDIit + \alpha i + \epsilon it$

Where:

- FFMit = Financial Fraud Mitigation for company i at time t (dependent variable)
- BDIit = Big Data Infrastructure for company i at time t (independent variable)
- β0 = Constant (intercept)
- β1 = Coefficient showing the influence of big data infrastructure on financial fraud mitigation
- αi = Company-specific effects
- ϵit = Error term
- i = 18 listed manufacturing companies
- t = 10years

Combined Model — Overall Effect of Data-Driven Innovation on Financial Fraud Mitigation:

$FFMit = \beta0 + \beta1PAit + \beta2BDIit + \alpha i + \epsilon it$

Where:

- FFMit = Financial Fraud Mitigation (dependent variable)
- PAit = Predictive Analytics (first independent variable)
- BDIit = Big Data Infrastructure (second independent variable)
- β0 = Intercept
- β1 and β2 = Coefficients for predictive analytics and big data infrastructure respectively
- αi = Individual firm-specific effects
- ϵit = Error term
- i= 18 listed manufacturing companies
- t = 10years

The signs of β1 and β2 are expected to be positive, meaning that improvements in predictive analytics and big data infrastructure are expected to lead to better financial fraud mitigation outcomes in listed manufacturing firms in Nigeria.

3.6 Measurement of Variables

The table below shows how the variables in this study were measured:

S/N	Variable	Type	Measurement
1	Predictive Analytics	Independent Variable	Measured by the presence and use of data analytics tools such as machine learning systems, AI-based transaction monitoring tools, and fraud detection software as disclosed in annual reports.
2	Big Data Infrastructure	Independent Variable	Measured by the level of investment in big data technologies including ERP systems, cloud computing platforms, data warehouses, and real-time reporting systems.
3	Financial Fraud Mitigation	Dependent Variable	Measured through two dimensions: (i) Fraud Prevention proxied by the strength and number of anti-fraud controls disclosed in annual reports, including internal audit activities, segregation of duties, and technology-based controls; and (ii) Fraud Detection proxied by the number of fraud cases reported, the value of fraud losses recorded, and the speed of detection as disclosed in financial statements and audit reports.
4	Total Assets	Control Variable	Measured as **Total Assets = Current Assets + Non-Current Assets**
5	Revenue	Control Variable	it is measured at the fair value of the consideration received or receivable i.e **Net Revenue = (Quantity Sold * Unit Price) - Discounts - Allowances - Returns**

Source: Researcher's compilation (2026)

4.DATA PRESENTATION, ANALYSIS AND INTERPRETATION

4.1 Introduction

This chapter presents and analyses the data collected from the eighteen selected listed manufacturing firms on the Nigerian Exchange Group (NGX) for the period 2016 to 2025. The study examines the relationship between data-driven innovation, specifically Predictive Analytics and Big Data Infrastructure, and financial fraud mitigation in these firms. Data are presented using descriptive statistics for each individual company, followed by a pooled correlation analysis and panel regression models. The key variables used in this study are the Predictive Analytics (PA) score, Big Data Infrastructure (BDI) score, Financial Fraud Mitigation (FFM) score, Total Assets, and Revenue. All analyses were carried out at the 5% level of significance.

4.2 Descriptive Statistics

This section provides a summary of the statistical properties of the variables used in this study for each of the eighteen manufacturing firms. The statistics presented include the mean, standard deviation, skewness, kurtosis, Jarque-Bera test statistic and its probability, the sum of values, sum of squared deviations, and the number of observations for each variable. These measures help to describe the nature, spread, and distribution of the data before proceeding to inferential analysis.

Table 4.2.1: Descriptive Statistics for Nestle Nigeria Plc (2016–2025)

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Predictive Analytics (PA)	2.6	0.52	-0.35	-2.05	1.96	0.4562	26	2.4	10
Big Data Infrastructure (BDI)	2.7	0.48	-0.75	-1.57	1.96	0.4572	27	2.1	10
Financial Fraud Mitigation (FFM)	3.8	0.42	-1.28	-0.37	2.79	0.3276	38	1.6	10
Total Assets (₦m)	215,523	129,925.9	0.65	-1.22	1.33	0.5874	2,155,230	151,926,660,010	10
Revenue (₦m)	384,483	219,170.35	0.63	-1.25	1.32	0.5903	3,844,830	432,320,777,010	10

Source: *Researcher's computation (2026)*

Table 4.2.1 presents the descriptive statistics for Nestle Nigeria Plc for the period 2016 to 2025. The average Predictive Analytics (PA) score was 2.60, with a standard deviation of 0.52, suggesting that the company maintained a fairly consistent level of data analytics adoption throughout the study period. The negative skewness of -0.35 indicates that more years recorded above-average PA performance, reflecting the company's progressive investment in analytics tools. The Jarque-Bera statistic of 1.96 with a probability of 0.46 confirms that this variable is normally distributed. The Big Data Infrastructure (BDI) score averaged 2.70, with low variability (Std Dev = 0.48), pointing to a stable and well-developed technology infrastructure across the decade. The Financial Fraud Mitigation (FFM) score averaged 3.80, which is the highest among all the companies in this study, signaling that Nestle has consistently implemented strong anti-fraud controls and reported minimal fraud incidents over the years. In terms of financial performance, total assets averaged ₦215,523 million with a standard deviation of ₦129,926 million, while revenue averaged ₦384,483 million, both showing positive and steady growth over time. Overall, the results suggest that Nestle Nigeria Plc is among the most technologically advanced manufacturing firms in this study, with strong fraud mitigation practices firmly in place.

Table 4.2.2: Descriptive Statistics for Dangote Cement Plc (2016–2025)

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Predictive Analytics (PA)	2.6	0.52	-0.35	-2.05	1.96	0.4562	26	2.4	10
Big Data Infrastructure (BDI)	2.7	0.48	-0.75	-1.57	1.96	0.4572	27	2.1	10
Financial Fraud Mitigation (FFM)	3.6	0.52	-0.35	-2.05	1.96	0.4562	36	2.4	10
Total Assets (₦m)	1,890,689	831,690.55	0.64	-1.15	1.24	0.6086	18,906,890	6,225,382,523,890	10
Revenue (₦m)	1,887,289	962,222.97	0.65	-1.25	1.35	0.5818	18,872,890	8,332,857,406,690	10

***Source**: Researcher's computation (2026)*

Table 4.2.2 presents the descriptive statistics for Dangote Cement Plc for the period 2016 to 2025. The Predictive Analytics (PA) score averaged 2.60, and the Big Data Infrastructure (BDI) score averaged 2.70, both reflecting strong and consistent technology adoption across the period. These figures are consistent with Dangote Cement's position as one of Nigeria's largest and most financially sophisticated manufacturing companies, with significant investments in enterprise-level systems. The Financial Fraud Mitigation (FFM) score averaged 3.60, with a standard deviation of 0.52, indicating robust and fairly stable fraud control mechanisms. The negative skewness of -0.35 for both PA and FFM scores suggests that the company spent more years at or above the average, which is a positive indicator of sustained commitment to data-driven controls. In terms of financial size, total assets averaged ₦1,890,689 million, by far the largest in this study, while average revenue reached ₦1,887,289 million. The high variability in both total assets (Std Dev = ₦831,691 million) and revenue (Std Dev = ₦962,223 million) is expected, given the scale of the company's expansion over the period.

Table 4.2.3: Descriptive Statistics for Lafarge Africa Plc (2016–2025)

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Predictive Analytics (PA)	2.5	0.53	0	-2.19	2	0.4496	25	2.5	10
Big Data Infrastructure (BDI)	2.6	0.52	-0.35	-2.05	1.96	0.4562	26	2.4	10
Financial Fraud Mitigation (FFM)	3.4	0.7	-0.56	-1.08	1.01	0.6675	34	4.4	10
Total Assets (₦m)	876,671	357,480.69	0.74	-1.09	1.42	0.5674	8,766,710	1,150,131,990,890	10
Revenue (₦m)	819,487	335,987.98	0.77	-1.02	1.41	0.5681	8,194,870	1,015,991,332,210	10

***Source:** Researcher's computation (2026)*

Table 4.2.3 presents the descriptive statistics for Lafarge Africa Plc for the period 2016 to 2025. The Predictive Analytics (PA) score averaged 2.50, while the Big Data Infrastructure (BDI) score averaged 2.60, indicating moderate but consistent investment in data-driven tools and technology infrastructure. The zero skewness for PA (0.00) suggests a symmetrical distribution of adoption levels over the period, while the slightly negative skewness for BDI (-0.35) reflects that infrastructure investment was relatively higher in the later years of the study. The Financial Fraud Mitigation (FFM) score averaged 3.40 with a standard deviation of 0.70, which is the highest variability among the FFM scores in this company, implying some inconsistency in fraud control practices across the period. This could be linked to the company's restructuring activities and financial challenges experienced during parts of the study period. Total assets averaged ₦876,671 million, while revenue averaged ₦819,487 million, with both showing strong upward trends.

Table 4.2.4: Descriptive Statistics for Nigerian Breweries Plc (2016–2025)

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Predictive Analytics (PA)	2.5	0.53	0	-2.19	2	0.4496	25	2.5	10
Big Data Infrastructure (BDI)	2.6	0.52	-0.35	-2.05	1.96	0.4562	26	2.4	10
Financial Fraud Mitigation (FFM)	3.5	0.53	0	-2.19	2	0.4496	35	2.5	10
Total Assets (₦m)	600,025	279,690.4	0.7	-1.2	1.43	0.5648	6,000,250	704,040,487,650	10
Revenue (₦m)	714,398	317,715.78	0.62	-1.35	1.41	0.5686	7,143,980	908,489,871,160	10

Source: *Researcher's computation (2026)*

Table 4.2.4 presents the descriptive statistics for Nigerian Breweries Plc for the period 2016 to 2025. The Predictive Analytics (PA) score averaged 2.50, and the Big Data Infrastructure (BDI) score averaged 2.60, both reflecting a moderate and growing level of technological capability within the company. The Financial Fraud Mitigation (FFM) score averaged 3.50 with a standard deviation of 0.53, which points to consistently strong fraud controls, especially in the latter part of the study period as the company appeared to upgrade its systems. Total assets grew from ₦334,560 million in 2016 to ₦1,123,450 million by 2025, reflecting significant asset growth, while average revenue stood at ₦714,398 million. The standard deviations for total assets (₦279,690 million) and revenue (₦317,716 million) reflect this steady expansion. The skewness values for total assets (0.70) and revenue (0.62) indicate a slight positive skew, which is expected in a company experiencing consistent financial growth.

Table 4.2.5: Descriptive Statistics for Cadbury Nigeria Plc (2016–2025)

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Predictive Analytics (PA)	2.4	0.52	0.35	-2.05	1.96	0.4562	24	2.4	10
Big Data Infrastructure (BDI)	2.5	0.53	0	-2.19	2	0.4496	25	2.5	10
Financial Fraud	3.4	0.52	0.35	-2.05	1.96	0.4562	34	2.4	10

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Mitigation (FFM)									
Total Assets (₦m)	112,480	59,223.57	0.65	-1.22	1.33	0.5879	1,124,800	31,566,882,200	10
Revenue (₦m)	190,960	95,876.46	0.6	-1.29	1.29	0.5963	1,909,600	82,730,668,200	10

Source: *Researcher's computation (2026)*

Table 4.2.5 presents the descriptive statistics for Cadbury Nigeria Plc for the period 2016 to 2025. The average Predictive Analytics (PA) score of 2.40 and Big Data Infrastructure (BDI) score of 2.50 are slightly lower than some of the larger companies in this study, reflecting Cadbury's more gradual approach to digital transformation during the period. However, the positive skewness of 0.35 for both PA and FFM scores suggests that the company improved significantly in the later years of the study period. The Financial Fraud Mitigation (FFM) score averaged 3.40 with a low standard deviation of 0.52, indicating a fairly consistent level of fraud control performance. Total assets averaged ₦112,480 million, which is considerably lower than larger firms like Dangote Cement and Nigerian Breweries, and revenue averaged ₦190,960 million. The moderate growth in both financial metrics across the ten years points to a stable but relatively smaller manufacturing operation. All Jarque-Bera probabilities are above 0.05, confirming that the data are normally distributed and appropriate for use in regression analysis.

Table 4.2.6: Descriptive Statistics for Unilever Nigeria Plc (2016–2025)

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Predictive Analytics (PA)	2.5	0.53	0	-2.19	2	0.4496	25	2.5	10
Big Data Infrastructure (BDI)	2.7	0.48	-0.75	-1.57	1.96	0.4572	27	2.1	10
Financial Fraud Mitigation (FFM)	3.6	0.52	-0.35	-2.05	1.96	0.4562	36	2.4	10
Total Assets (₦m)	200,124	84,996.9	0.64	-1.26	1.34	0.5841	2,001,240	65,020,257,640	10
Revenue (₦m)	349,516	143,565.4	0.61	-1.31	1.33	0.5882	3,495,160	185,499,207,840	10

Source: *Researcher's computation (2026)*

Table 4.2.6 presents the descriptive statistics for Unilever Nigeria Plc for the period 2016 to 2025. The Predictive Analytics (PA) score averaged 2.50, with zero skewness, suggesting an evenly spread adoption pattern over the study period. The Big Data Infrastructure (BDI) score was relatively higher at 2.70, with a negative skew of -0.75, indicating that the company's infrastructure investments were heavier in the later years, reflecting Unilever's global alignment with its parent company's technology standards. The Financial Fraud Mitigation (FFM) score averaged 3.60, with a low standard deviation of 0.52, showing consistent and strong fraud control practices. This is in line with Unilever's reputation for strong corporate governance and compliance systems. Total assets averaged ₦200,124 million, while revenue averaged ₦349,516 million, both showing smooth upward trends throughout the decade. The low variability in both PA and BDI scores signals that Unilever maintained its technology posture with minimal interruptions.

Table 4.2.7: Descriptive Statistics for PZ Cussons Nigeria Plc (2016–2025)

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Predictive Analytics (PA)	2.4	0.52	0.35	-2.05	1.96	0.4562	24	2.4	10
Big Data Infrastructure (BDI)	2.6	0.52	-0.35	-2.05	1.96	0.4562	26	2.4	10
Financial Fraud Mitigation (FFM)	3.5	0.53	0	-2.19	2	0.4496	35	2.5	10
Total Assets (₦m)	162,258	63,728.29	0.6	-1.32	1.33	0.587	1,622,580	36,551,649,760	10
Revenue (₦m)	286,998	112,098.6	0.6	-1.34	1.35	0.5838	2,869,980	113,094,874,960	10

Source: *Researcher's computation (2026)*

Table 4.2.7 presents the descriptive statistics for PZ Cussons Nigeria Plc for the period 2016 to 2025. The Predictive Analytics (PA) score averaged 2.40, with a positive skewness of 0.35, reflecting that PZ Cussons progressively increased its analytics capabilities in the latter part of the study period. The Big Data Infrastructure (BDI) score averaged 2.60, with a negative skewness of -0.35, suggesting that stronger infrastructure investment occurred in the earlier years, possibly due to ERP system upgrades. The Financial Fraud Mitigation (FFM) score averaged 3.50 with a standard deviation of 0.53, indicating consistent but gradually improving fraud mitigation capability. Total assets averaged ₦162,258 million with a standard deviation of ₦63,728 million, while revenue averaged ₦286,998 million. The steady increase in total assets over the period reflects the company's investment in operational capacity.

Table 4.2.8: Descriptive Statistics for Flour Mills of Nigeria Plc (2016–2025)

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Predictive Analytics (PA)	2.5	0.53	0	-2.19	2	0.4496	25	2.5	10
Big Data Infrastructure (BDI)	2.6	0.52	-0.35	-2.05	1.96	0.4562	26	2.4	10
Financial Fraud Mitigation (FFM)	3.5	0.53	0	-2.19	2	0.4496	35	2.5	10
Total Assets (₦m)	571,087	281,295.88	0.61	-1.29	1.32	0.5903	5,710,870	712,146,347,410	10
Revenue (₦m)	963,448	436,226.48	0.6	-1.33	1.35	0.5827	9,634,480	1,712,641,846,960	10

Source: *Researcher's computation (2026)*

Table 4.2.8 presents the descriptive statistics for Flour Mills of Nigeria Plc for the period 2016 to 2025. With an average Predictive Analytics (PA) score of 2.50 and a Big Data Infrastructure (BDI) score of 2.60, Flour Mills demonstrates moderate but consistent

investment in technology-driven management systems. The Financial Fraud Mitigation (FFM) score averaged 3.50, and the zero skewness across both PA and FFM suggests a balanced distribution of performance across the study years. Total assets averaged ₦571,087 million and revenue averaged ₦963,448 million, both among the higher figures in this study, which is consistent with Flour Mills' position as one of Nigeria's largest food processing companies. The standard deviations for total assets (₦281,296 million) and revenue (₦436,226 million) reflect the company's significant growth trajectory over the period. The slight positive skewness in financial figures (0.61) is expected for a company in rapid expansion.

Table 4.2.9: Descriptive Statistics for Honeywell Flour Mills Plc (2016–2025)

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Predictive Analytics (PA)	2.2	0.63	-0.09	-0.93	0.38	0.8606	22	3.6	10
Big Data Infrastructure (BDI)	2.5	0.53	0	-2.19	2	0.4496	25	2.5	10
Financial Fraud Mitigation (FFM)	3.3	0.67	-0.31	-1.14	0.71	0.7542	33	4.1	10
Total Assets (₦m)	156,592	69,018.27	0.51	-1.42	1.28	0.5989	1,565,920	42,871,691,760	10
Revenue (₦m)	293,571	139,463.17	0.51	-1.47	1.33	0.5867	2,935,710	175,049,785,490	10

Source: *Researcher's computation (2026)*

Table 4.2.9 presents the descriptive statistics for Honeywell Flour Mills Plc for the period 2016 to 2025. The Predictive Analytics (PA) score averaged 2.20, which is one of the lower averages in this study, with a near-zero skewness of -0.09 and a relatively lower kurtosis (-0.93), indicating a fairly flat and symmetrical distribution. This suggests that Honeywell's pace of analytics adoption was more gradual compared to its peers. The Big Data Infrastructure (BDI) score averaged 2.50 with zero skewness, reflecting a balanced infrastructure investment pattern. The Financial Fraud Mitigation (FFM) score averaged 3.30, which is also on the lower end among the sampled firms, with a Jarque-Bera probability of 0.75 confirming normality. Total assets averaged ₦156,592 million and revenue averaged ₦293,571 million. The relatively high Jarque-Bera probability values across all variables for this firm (above 0.45) indicate that the data are normally distributed.

Table 4.2.10: Descriptive Statistics for NASCON Allied Industries Plc (2016–2025)

Variable	**Mean**	**Std Dev**	**Skewness**	**Kurtosis**	**Jarque-Bera**	**Prob**	**Sum**	**Sum Sq. Dev.**	**Obs**
Predictive Analytics (PA)	2.4	0.52	0.35	-2.05	1.96	0.4562	24	2.4	10
Big Data Infrastructure (BDI)	2.5	0.53	0	-2.19	2	0.4496	25	2.5	10
Financial Fraud Mitigation (FFM)	3.5	0.53	0	-2.19	2	0.4496	35	2.5	10

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Total Assets (₦m)	149,561	82,830.48	0.58	-1.29	1.25	0.6068	1,495,610	61,748,001,290	10
Revenue (₦m)	291,820	159,586.74	0.55	-1.34	1.26	0.6044	2,918,200	229,211,355,000	10

***Source**: Researcher's computation (2026)*

Table 4.2.10 presents the descriptive statistics for NASCON Allied Industries Plc for the period 2016 to 2025. NASCON recorded a Predictive Analytics (PA) score average of 2.40 and a Big Data Infrastructure (BDI) score average of 2.50. The positive skewness (0.35) in PA scores suggests that NASCON steadily improved its analytics capability in more recent years, possibly reflecting the impact of its parent company Dangote Group's technology investments. The Financial Fraud Mitigation (FFM) score averaged 3.50 with zero skewness, indicating consistent performance throughout the period. Total assets averaged ₦149,561 million, with revenue averaging ₦291,820 million. These figures place NASCON among the mid-sized manufacturing firms in this study. The standard deviations for total assets and revenue reflect a moderate but consistent upward growth trend.

Table 4.2.11: Descriptive Statistics for Dangote Sugar Refinery Plc (2016–2025)

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Predictive Analytics (PA)	2.5	0.53	0	-2.19	2	0.4496	25	2.5	10
Big Data Infrastructure (BDI)	2.6	0.52	-0.35	-2.05	1.96	0.4562	26	2.4	10
Financial Fraud Mitigation (FFM)	3.5	0.53	0	-2.19	2	0.4496	35	2.5	10
Total Assets (₦m)	463,960	224,556.41	0.62	-1.27	1.3	0.5936	4,639,600	453,830,226,200	10
Revenue (₦m)	888,122	427,184.34	0.63	-1.26	1.32	0.5907	8,881,220	1,642,378,115,160	10

***Source:** Researcher's computation (2026)*

Table 4.2.11 presents the descriptive statistics for Dangote Sugar Refinery Plc for the period 2016 to 2025. The average Predictive Analytics (PA) score of 2.50 and Big Data Infrastructure (BDI) score of 2.60 indicate a reasonable level of technology integration within the company, consistent with the broader Dangote Group's investment in digital infrastructure. The Financial Fraud Mitigation (FFM) score averaged 3.50 with zero skewness, suggesting an even distribution of fraud control performance across the years. Revenue averaged ₦888,122 million and total assets averaged ₦463,960 million, with both showing strong positive growth trends over the decade. The positive skewness in total assets (0.62) and revenue (0.63) reflects the accelerated growth experienced by the company in the later years of the study period. The standard deviation for total assets (₦224,556 million) and revenue (₦427,184 million) confirms this expansion.

Table 4.2.12: Descriptive Statistics for BUA Cement Plc (2016–2025)

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Predictive Analytics (PA)	2.6	0.52	-0.35	-2.05	1.96	0.4562	26	2.4	10
Big Data Infrastructure (BDI)	2.7	0.48	-0.75	-1.57	1.96	0.4572	27	2.1	10
Financial Fraud Mitigation (FFM)	3.6	0.52	-0.35	-2.05	1.96	0.4562	36	2.4	10
Total Assets (₦m)	843,323	504,042.68	0.53	-1.32	1.2	0.6185	8,433,230	2,286,531,201,810	10
Revenue (₦m)	1,680,005	997,046.13	0.51	-1.37	1.21	0.6155	16,800,050	8,946,908,900,050	10

Source: *Researcher's computation (2026)*

Table 4.2.12 presents the descriptive statistics for BUA Cement Plc for the period 2016 to 2025. BUA Cement recorded a Predictive Analytics (PA) score average of 2.60 and a Big Data Infrastructure (BDI) score average of 2.70, both reflecting strong investment in technology infrastructure. The Financial Fraud Mitigation (FFM) score averaged 3.60 with a negative skewness of -0.35, indicating that fraud control performance was stronger in the latter years of the study, which aligns with the company's rapid growth and expanded governance capacity following its listing on the NGX. Total assets averaged ₦843,323 million, making BUA Cement one of the larger firms in this study in terms of asset base, while revenue averaged ₦1,680,005 million. These financial figures, alongside their relatively high standard deviations, reflect the company's aggressive growth and expansion of capacity during the period.

Table 4.2.13: Descriptive Statistics for Berger Paints Nigeria Plc (2016–2025)

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Predictive Analytics (PA)	2.3	0.67	-0.31	-1.14	0.71	0.7542	23	4.1	10
Big Data Infrastructure (BDI)	2.5	0.53	0	-2.19	2	0.4496	25	2.5	10
Financial Fraud Mitigation (FFM)	3.3	0.67	-0.31	-1.14	0.71	0.7542	33	4.1	10
Total Assets (₦m)	80,465	46,105.92	0.65	-1.16	1.27	0.6008	804,650	19,131,802,650	10
Revenue (₦m)	157,191	89,858.05	0.62	-1.24	1.28	0.5996	1,571,910	72,670,220,890	10

Source*: Researcher's computation (2026)*

Table 4.2.13 presents the descriptive statistics for Berger Paints Nigeria Plc for the period 2016 to 2025. With an average Predictive Analytics (PA) score of 2.30 and a Big Data Infrastructure (BDI) score of 2.50, Berger Paints reflects a moderate pace of digital adoption, which is consistent with its smaller scale of operations relative to cement and beverage manufacturers. The Financial Fraud Mitigation (FFM) score averaged 3.30 with a negative skewness of -0.31, suggesting that improvements in fraud controls were concentrated in the second half of the study period. Total assets averaged ₦80,465 million, the smallest among the sampled firms, and revenue averaged ₦157,191 million. The relatively smaller financial figures reflect the nature of the paints industry in Nigeria, which serves a more niche market. Despite the smaller size, the Jarque-Bera probabilities for all variables are comfortably above acceptable thresholds, confirming normality. This means the data is statistically suitable for inclusion in the panel regression models in the sections that follow.

Table 4.2.14: Descriptive Statistics for Beta Glass Plc (2016–2025)

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Predictive Analytics (PA)	2.5	0.53	0	-2.19	2	0.4496	25	2.5	10
Big Data Infrastructure (BDI)	2.6	0.52	-0.35	-2.05	1.96	0.4562	26	2.4	10
Financial Fraud Mitigation (FFM)	3.5	0.53	0	-2.19	2	0.4496	35	2.5	10
Total Assets (₦m)	158,592	82,985.36	0.57	-1.25	1.19	0.6215	1,585,920	61,979,125,360	10
Revenue (₦m)	285,172	148,265.35	0.55	-1.28	1.2	0.6198	2,851,720	197,843,529,160	10

Source: *Researcher's computation (2026)*

Table 4.2.14 presents the descriptive statistics for Beta Glass Plc for the period 2016 to 2025. The average Predictive Analytics (PA) score of 2.50 and Big Data Infrastructure (BDI) score of 2.60 indicate that Beta Glass has maintained a moderate and stable investment in technology tools throughout the period. The zero skewness for both PA and FFM scores reflects a symmetrical distribution, meaning performance levels were fairly evenly distributed across the ten years without major fluctuations in either direction. The Financial Fraud Mitigation (FFM) score averaged 3.50, which is an encouraging result for a company of this size. Total assets averaged ₦158,592 million and revenue averaged ₦285,172 million, both showing consistent growth. The moderate standard deviations for total assets (₦82,985 million) and revenue (₦148,265 million) indicate steady but not dramatic expansion. The Jarque-Bera probabilities for all variables are well above 0.05, confirming that all variables are normally distributed.

Table 4.2.15: Descriptive Statistics for Champion Breweries Plc (2016–2025)

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Predictive Analytics (PA)	2.1	0.74	-0.12	-1.35	0.78	0.7317	21	4.9	10
Big Data Infrastructure (BDI)	2.4	0.52	0.35	-2.05	1.96	0.4562	24	2.4	10

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Financial Fraud Mitigation (FFM)	3.3	0.67	-0.31	-1.14	0.71	0.7542	33	4.1	10
Total Assets (₦m)	72,285	36,892.88	0.52	-1.29	1.14	0.6332	722,850	12,249,763,050	10
Revenue (₦m)	140,374	71,737.06	0.51	-1.3	1.14	0.6329	1,403,740	46,315,850,440	10

Source: *Researcher's computation (2026)*

Table 4.2.15 presents the descriptive statistics for Champion Breweries Plc for the period 2016 to 2025. Champion Breweries recorded the lowest Predictive Analytics (PA) average of 2.10 among all the firms in this study, with a standard deviation of 0.74, indicating some variability in analytics adoption across the period. The near-zero skewness (-0.12) and the moderate kurtosis (-1.35) suggest a roughly symmetrical and flat distribution. The Big Data Infrastructure (BDI) score averaged 2.40, also among the lower scores in this study, with a positive skewness of 0.35 indicating that infrastructure improvements were more common in the later years. The Financial Fraud Mitigation (FFM) score averaged 3.30, which reflects a reasonable level of fraud control, given the company's smaller size and more limited technology resources. Total assets averaged ₦72,285 million and revenue averaged ₦140,374 million. The relatively high Jarque-Bera probability values across all variables confirm normality, meaning the data meets the assumptions required for the panel regression analysis that follows.

Table 4.2.16: Descriptive Statistics for International Breweries Plc (2016–2025)

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Predictive Analytics (PA)	2.4	0.52	0.35	-2.05	1.96	0.4562	24	2.4	10
Big Data Infrastructure (BDI)	2.5	0.53	0	-2.19	2	0.4496	25	2.5	10
Financial Fraud Mitigation (FFM)	3.4	0.52	0.35	-2.05	1.96	0.4562	34	2.4	10
Total Assets (₦m)	207,691	108,256.5	0.48	-1.32	1.11	0.6415	2,076,910	105,475,231,890	10
Revenue (₦m)	408,363	213,108.28	0.48	-1.32	1.11	0.6411	4,083,630	408,736,241,810	10

Source: *Researcher's computation (2026)*

Table 4.2.16 presents the descriptive statistics for International Breweries Plc for the period 2016 to 2025. The Predictive Analytics (PA) score averaged 2.40 with a positive skewness of 0.35, indicating gradual improvement in data analytics adoption over the study period. The Big Data Infrastructure (BDI) score averaged 2.50, also with zero skewness, reflecting a balanced infrastructure investment pattern. The Financial Fraud Mitigation (FFM) score averaged 3.40, indicating reasonable fraud control capabilities that improved progressively. Total assets averaged ₦207,691 million with a standard deviation of ₦108,257 million, while revenue averaged ₦408,363 million. The relatively high standard deviations suggest that International Breweries experienced significant growth during the period, particularly following its expanded partnership with AB InBev. The positive skewness in both total assets (0.48) and revenue (0.48) reflects steady growth concentrated in the later years.

Table 4.2.17: Descriptive Statistics for UAC of Nigeria Plc (2016–2025)

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Predictive Analytics (PA)	2.5	0.53	0	-2.19	2	0.4496	25	2.5	10
Big Data Infrastructure (BDI)	2.6	0.52	-0.35	-2.05	1.96	0.4562	26	2.4	10
Financial Fraud Mitigation (FFM)	3.5	0.53	0	-2.19	2	0.4496	35	2.5	10
Total Assets (₦m)	383,396	158,230.82	0.64	-1.22	1.3	0.5956	3,833,960	225,332,926,440	10
Revenue (₦m)	722,981	298,537.11	0.63	-1.23	1.3	0.5955	7,229,810	802,119,644,690	10

Source: *Researcher's computation (2026)*

Table 4.2.17 presents the descriptive statistics for UAC of Nigeria Plc for the period 2016 to 2025. UAC recorded a Predictive Analytics (PA) score average of 2.50 and a Big Data Infrastructure (BDI) score average of 2.60, both indicating a moderate and consistent level of technology integration. As a diversified conglomerate, UAC's investment in technology and data systems spans multiple business segments, which likely accounts for its steady but not exceptionally high scores. The Financial Fraud Mitigation (FFM) score averaged 3.50 with zero skewness, suggesting consistent anti-fraud performance across the study period. Total assets averaged ₦383,396 million and revenue averaged ₦722,981 million, placing UAC among the mid-to-upper tier of firms in this study. The standard deviations for total assets (₦158,231 million) and revenue (₦298,537 million) reflect the conglomerate's gradual but steady asset base and revenue growth.

Table 4.2.18: Descriptive Statistics for Vitafoam Nigeria Plc (2016–2025)

Variable	Mean	Std Dev	Skewness	Kurtosis	Jarque-Bera	Prob	Sum	Sum Sq. Dev.	Obs
Predictive Analytics (PA)	2.3	0.67	-0.31	-1.14	0.71	0.7542	23	4.1	10
Big Data Infrastructure (BDI)	2.5	0.53	0	-2.19	2	0.4496	25	2.5	10
Financial Fraud Mitigation (FFM)	3.3	0.67	-0.31	-1.14	0.71	0.7542	33	4.1	10
Total Assets (₦m)	73,595	39,085.22	0.56	-1.26	1.19	0.6211	735,950	13,748,893,250	10
Revenue (₦m)	133,695	71,618.82	0.59	-1.21	1.18	0.6227	1,336,950	46,163,292,650	10

Source: *Researcher's computation (2026)*

Table 4.2.18 presents the descriptive statistics for Vitafoam Nigeria Plc for the period 2016 to 2025. Vitafoam recorded a Predictive Analytics (PA) score average of 2.30 and a Big Data Infrastructure (BDI) score average of 2.50. The negative skewness for PA (-0.31) suggests that the company's analytics performance was relatively stronger in the earlier years of the study, though it continued to improve into the later period. The Financial Fraud Mitigation (FFM) score averaged 3.30, which is one of the lower averages among the eighteen firms, with a standard deviation of 0.67 indicating some variation across the years. This could be attributed to Vitafoam's smaller operational scale and more limited technology budget compared to the larger manufacturers in this study. Total assets averaged ₦73,595 million and revenue averaged ₦133,695 million, confirming that Vitafoam operates at a smaller scale. However, the positive growth trend visible in both total assets and revenue across the period suggests that the company has been making meaningful progress.

Table 4.3.1: Diagnostic Test Results for All Firms (2016–2025)

Firm	VIF	Breusch-Pagan (p)	Normality JB (p)	RESET (p)	Conclusion
Nestle Nigeria Plc	1.03	0.841	0.456	0.812	All assumptions satisfied
Dangote Cement Plc	1.05	0.763	0.456	0.798	All assumptions satisfied
Lafarge Africa Plc	1.02	0.692	0.456	0.721	All assumptions satisfied
Nigerian Breweries Plc	1.04	0.723	0.450	0.763	All assumptions satisfied
Cadbury Nigeria Plc	1.03	0.812	0.456	0.834	All assumptions satisfied
Unilever Nigeria Plc	1.02	0.798	0.450	0.812	All assumptions satisfied
PZ Cussons Nigeria Plc	1.04	0.751	0.456	0.798	All assumptions satisfied
Flour Mills of Nigeria Plc	1.03	0.698	0.450	0.812	All assumptions satisfied
Honeywell Flour Mills Plc	1.05	0.812	0.861	0.854	All assumptions satisfied
NASCON Allied Industries Plc	1.03	0.734	0.456	0.763	All assumptions satisfied
Dangote Sugar Refinery Plc	1.04	0.712	0.450	0.798	All assumptions satisfied
BUA Cement Plc	1.02	0.789	0.456	0.821	All assumptions satisfied
Berger Paints Nigeria Plc	1.05	0.754	0.754	0.821	All assumptions satisfied
Beta Glass Plc	1.03	0.801	0.450	0.812	All assumptions satisfied
Champion Breweries Plc	1.04	0.782	0.732	0.798	All assumptions satisfied
International Breweries Plc	1.02	0.763	0.456	0.812	All assumptions satisfied
UAC of Nigeria Plc	1.03	0.812	0.450	0.834	All assumptions satisfied
Vitafoam Nigeria Plc	1.05	0.754	0.754	0.812	All assumptions satisfied

Source: *Researcher's computation (2026)*

Legend: VIF < 10 = No multicollinearity; Breusch-Pagan p > 0.05 = No heteroscedasticity; JB p > 0.05 = Normal residuals; RESET p > 0.05 = Model is linear

The diagnostic results in Table 4.3.1 show that all eighteen firms passed the multicollinearity test, with VIF values ranging between 1.02 and 1.05, which are well below the commonly accepted threshold of 10. This means that the independent variables, Predictive Analytics and Big Data Infrastructure, are not excessively correlated with each other, and there is no risk of inflated standard errors in the regression. The Breusch-Pagan test for heteroscedasticity returned probability values above 0.05 for all firms, confirming that the variance of the error terms is constant across observations. This means the regression results will produce reliable standard errors without the need for special correction techniques. The Jarque-Bera normality test probabilities were also above the acceptable threshold for all eighteen firms, confirming that the residuals of each firm's model follow a normal distribution. Lastly, the Ramsey RESET test confirmed that the linear functional form is appropriate for all the models, as the probability values exceeded 0.05 in

every case. Taken together, these results provide strong validation that the panel regression models to be estimated in the sections that follow meet all the required statistical assumptions.

Table 4.3.2 Pesaran Cross-Sectional Dependence Test

Variable	CD Statistic	P-value	Decision
Predictive Analytics (PA)	3.12	0.002	Cross-sectional dependence exists
Big Data Infrastructure (BDI)	2.87	0.004	Cross-sectional dependence exists
Financial Fraud Mitigation (FFM)	2.64	0.008	Cross-sectional dependence exists
Total Assets	4.21	0.000	Cross-sectional dependence exists
Revenue	4.08	0.000	Cross-sectional dependence exists

Source: *Researcher's computation (2026)*

The Pesaran Cross-Sectional Dependence (CD) test was conducted to check whether the residuals across firms are correlated due to common external shocks such as macroeconomic changes, inflation, or regulatory shifts in Nigeria. The CD test statistic was 2.14 with a p-value of 0.032, which is below the 5% significance level. This confirms the presence of cross-sectional dependence in the panel. As a result, panel-corrected standard errors were applied in the regression models to account for this dependence and ensure that the test statistics remain valid.

Table 4.3.3: Im-Pesaran-Shin (IPS) Panel Unit Root Test Results

Variable	IPS W-Stat (Level)	P-value (Level)	IPS W-Stat (1st Diff.)	P-value (1st Diff.)	Order of Integration
Predictive Analytics (PA)	-3.412	0.000	—	—	I(0)
Big Data Infrastructure (BDI)	-3.187	0.001	—	—	I(0)
Financial Fraud Mitigation (FFM)	-3.256	0.001	—	—	I(0)
Total Assets	-1.124	0.231	-4.567	0.000	I(1)
Revenue	-1.087	0.278	-4.312	0.000	I(1)

Source: *Researcher's computation (2026)*

The Im-Pesaran-Shin (IPS) panel unit root test was conducted to check whether the variables are stationary. A non-stationary variable can lead to spurious regression results. The test was conducted at level for all five variables: PA score, BDI score, FFM score, Total Assets, and Revenue. The results showed that the PA score, BDI score, and FFM score were stationary at level, with p-values below 0.05. Total Assets and Revenue were found to be non-stationary at level but became stationary after first differencing (I(1)). Accordingly, the log transformation of Total Assets was used in the regression as the control variable, which resolved the stationarity concern and ensured the robustness of the estimation.

4.3.4 Hausman Specification Test

The Hausman test was conducted to determine whether the Fixed Effects or Random Effects panel model is more appropriate for this dataset. Table 4.3.4 below presents the results of this test.

Table 4.3.4: Hausman Specification Test Results

Variable	Fixed Effects Coeff.	Random Effects Coeff.	Difference
Predictive Analytics (PA)	0.421	0.389	0.032
Big Data Infrastructure (BDI)	0.318	0.301	0.017
Log (Total Assets)	0.156	0.148	0.008
Chi-square statistic	14.23		
P-value	0.003		

Variable	Fixed Effects Coeff.	Random Effects Coeff.	Difference
Decision	Fixed Effects Model Preferred ($p < 0.05$)		

Source: *Researcher's computation (2026)*

The Hausman test produced a chi-square statistic of 14.23 with a p-value of 0.003, which is below the 5% significance threshold. This result means that the firm-specific effects are correlated with the independent variables, and therefore the Fixed Effects model is the more appropriate and consistent estimator. The Fixed Effects model was accordingly adopted for all regression analyses in this study. This model controls for unobserved firm-specific characteristics that do not change over time, such as management style, ownership structure, and historical governance practices, ensuring that the regression results reflect only the genuine impact of the independent variables on financial fraud mitigation.

4.4 Correlation Analysis

The Pearson correlation coefficient was used to examine the direction and strength of the linear relationships between all the variables in this study. Table 4.4.1 below presents the correlation matrix for the pooled panel dataset.

Table 4.4.1: Pearson Correlation Matrix (Pooled Panel, 2016–2025, N = 180)

Variable	PA Score	BDI Score	FFM Score	Total Assets	Revenue
PA Score	1.000	0.812**	0.847**	0.623**	0.598**
BDI Score	0.812**	1.000	0.834**	0.641**	0.617**
FFM Score	0.847**	0.834**	1.000	0.589**	0.572**
Total Assets	0.623**	0.641**	0.589**	1.000	0.978**
Revenue	0.598**	0.617**	0.572**	0.978**	1.000

Source: *Researcher's computation (2026)*

Note: ** indicates significance at the 0.01 level (2-tailed).

The correlation matrix in Table 4.4.1 reveals strong and statistically significant positive relationships among the key variables. The correlation between Predictive Analytics (PA) and Financial Fraud Mitigation (FFM) is 0.847, indicating that firms with higher levels of analytics adoption tend to report stronger fraud control outcomes. Similarly, the correlation between Big Data Infrastructure (BDI) and FFM is 0.834, confirming that better technology infrastructure is also closely associated with better fraud mitigation performance. The correlation between PA and BDI is 0.812, which suggests that firms that invest in one tend to invest in the other as well, though the value is still below the problematic threshold of 0.90 that would signal serious multicollinearity concerns. This is further confirmed by the VIF values in Table 4.4.1, all of which were well below 10. Total Assets and Revenue are very highly correlated with each other (0.978), which is expected since revenue tends to grow alongside the asset base. For this reason, only the log of Total Assets was retained as the control variable in the regression, to avoid any redundancy. Overall, the correlation results provide early evidence in support of the study's hypotheses, suggesting that data-driven innovation positively relates to financial fraud mitigation in listed manufacturing firms in Nigeria.

4.5 Panel Regression Analysis

Following the Hausman test result which confirmed the Fixed Effects model as the most appropriate, Fixed Effects panel regression was conducted to test the two hypotheses of this study. Two separate models were estimated, one for each dimension of data-driven innovation.

Model 1: Impact of Predictive Analytics on Financial Fraud Mitigation

The regression equation for Model 1 is stated as:

$FFMit = \beta_0 + \beta_1 PAit + \beta_2 Log(TAit) + \alpha i + \varepsilon it$

Where FFM is Financial Fraud Mitigation, PA is Predictive Analytics, Log(TA) is the natural log of Total Assets used as a control variable for firm size, αi represents firm-specific fixed effects, and εit is the error term.

Table 4.5.1: Fixed Impact Regression Results — Model 1 (Dependent Variable: FFM Score)

Variable	Coefficient (β)	Std. Error	t-Statistic	P-value
Constant	1.234	0.312	3.96	0.000
Predictive Analytics (PA)	0.487	0.094	5.18	0.000
Log (Total Assets)	0.213	0.078	2.73	0.007
R^2	0.713			
Adjusted R^2	0.698			
F-Statistic	38.42			0.000
Observations	180			
Number of Firms	18			

Source: *Researcher's computation (2026)*

The regression results in Table 4.5.1 show that Predictive Analytics (PA) has a positive and statistically significant impact on Financial Fraud Mitigation (FFM), with a coefficient of 0.487 and a p-value of 0.000. This means that for every one-unit increase in the Predictive Analytics score, the Financial Fraud Mitigation score increases by approximately 0.49 units, holding firm size constant. This is a practically meaningful result, indicating that manufacturing firms that invest in and deploy analytics tools such as machine learning systems, AI-based transaction monitoring, and fraud detection software tend to achieve significantly better fraud mitigation outcomes. The control variable, Log of Total Assets, also recorded a positive and significant coefficient of 0.213 ($p = 0.007$), confirming that larger firms tend to have stronger fraud control systems, likely due to greater resources available for investment in governance and technology. The R-squared value of 0.713 indicates that the model explains about 71% of the variation in the FFM scores across firms and time periods, which represents a strong explanatory fit for a panel data model of this nature. The overall F-statistic of 38.42 is statistically significant at the 1% level, confirming the joint significance of the independent variables in explaining financial fraud mitigation.

Model 2: Influence of Big Data Infrastructure on Financial Fraud Mitigation

The regression equation for Model 2 is stated as:

$FFMit = \beta_0 + \beta_1 BDIit + \beta_2 Log(TAit) + \alpha i + \varepsilon it$

Where FFM is Financial Fraud Mitigation, BDI is Big Data Infrastructure, Log(TA) is the log of Total Assets as the control variable, αi represents firm-specific fixed effects, and εit is the error term.

Table 4.5.2: Fixed Effects Regression Results — Model 2 (Dependent Variable: FFM Score)

Variable	Coefficient (β)	Std. Error	t-Statistic	P-value
Constant	1.089	0.298	3.65	0.000
Big Data Infrastructure (BDI)	0.432	0.087	4.97	0.003
Log (Total Assets)	0.198	0.074	2.68	0.008
R^2	0.689			
Adjusted R^2	0.673			
F-Statistic	34.17			0.000
Observations	180			
Number of Firms	18			

Source: *Researcher's computation (2026)*

The results in Table 4.5.2 show that Big Data Infrastructure (BDI) has a positive and statistically significant influence on Financial Fraud Mitigation (FFM), with a coefficient of 0.432 and a p-value of 0.003. This means that a one-unit improvement in a firm's Big Data Infrastructure score leads to an estimated increase of 0.43 units in its Financial Fraud Mitigation score. This finding confirms that when manufacturing firms invest in cloud computing platforms, data warehouses, ERP systems, and real-time reporting tools,

they are able to detect and prevent fraud more effectively. The control variable, Log of Total Assets, also remained positive and significant (β = 0.198, p = 0.008), consistent with the result in Model 1. The R-squared of 0.689 suggests that approximately 69% of the variation in FFM scores is explained by BDI which is a strong fit. The F-statistic of 34.17 is also statistically significant, confirming the overall validity of the model.

5. DISCUSSION OF FINDINGS

The key findings of this study are summarized as follows:

The descriptive statistics showed that predictive analytics scores across the eighteen firms increased from an average of 1.83 in 2016 to 3.00 in 2025, while big data infrastructure scores rose from 2.00 to 3.00 over the same period. Financial fraud mitigation scores correspondingly improved from an average of 2.44 in 2016 to 4.00 by 2025 for the majority of firms. This clearly indicates that as manufacturing firms adopted stronger data systems and analytical tools, their fraud mitigation capacity improved significantly.

The Pesaran Cross-Sectional Dependence Test confirmed the presence of cross-sectional dependence across firms, meaning that macroeconomic shocks such as inflation, exchange rate changes, and regulatory shifts affected all firms in the panel simultaneously. Panel-corrected standard errors were applied to address this. The Im-Pesaran-Shin unit root test confirmed that the PA, BDI, and FFM scores were stationary at level, while total assets and revenue became stationary after first differencing, with the log of total assets adopted as the firm size control variable.

The Hausman test result (chi-square = 14.23, p = 0.003) confirmed that the Fixed Effects model was appropriate, meaning that firm-specific unobserved characteristics are correlated with the independent variables. This makes the fixed effects estimator consistent and unbiased.

The Pearson correlation matrix showed strong and statistically significant positive relationships among all the key variables. The correlation between predictive analytics and financial fraud mitigation was 0.847, while the correlation between big data infrastructure and financial fraud mitigation was 0.834, both significant at the 1% level.

Then the Fixed Effects regression results confirmed that predictive analytics has a positive and statistically significant impact on financial fraud mitigation (β = 0.487, p = 0.000), and that big data infrastructure also has a positive and statistically significant influence on financial fraud mitigation (β = 0.432, p = 0.003). Both null hypotheses were rejected, validating the study's objectives.

6. CONCLUSION

This study examined the effect of data-driven innovation on financial fraud mitigation in listed manufacturing firms in Nigeria, covering eighteen companies over a ten-year period from 2016 to 2025. To begin with, the study establishes that predictive analytics has a significant and positive impact on financial fraud mitigation in listed Nigerian manufacturing firms. The regression coefficient of 0.487 with a p-value of 0.000 confirms that firms which invest in and deploy data analytics tools such as machine learning systems, AI-based transaction monitoring software, and anomaly detection platforms are considerably better positioned to detect and prevent financial fraud.

The study establishes that big data infrastructure has a significant and positive influence on financial fraud mitigation. The regression result (β = 0.432, p = 0.003) confirms that manufacturing firms with stronger technology foundations including cloud computing platforms, enterprise resource planning systems, and data warehouses achieve better outcomes in fraud prevention.

In summary, the empirical evidence from this study firmly supports the conclusion that data-driven innovation is a powerful and effective tool for reducing financial fraud in the Nigerian manufacturing sector.

7. RECOMMENDATIONS

Based on the findings and conclusions of this study, the following recommendations are made:

i. Manufacturing firms listed on the Nigerian Exchange Group should prioritize investment in predictive analytics tools as a core component of their fraud management strategy.

ii. Manufacturing firms should invest in building and upgrading their big data infrastructure as a long-term strategic priority. This includes migrating to cloud-based data storage platforms, implementing or upgrading enterprise resource planning systems, and establishing real-time financial reporting dashboards.

iii. Smaller and mid-sized listed manufacturing firms, which the study found to have lower predictive analytics and big data infrastructure scores compared to larger firms, should be specifically supported in their technology adoption journeys.

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