



**AEFUNAI JOURNAL OF ECONOMICS,
FINANCE AND DEVELOPMENT STUDIES**

AEFUNAIJEFDS

**Department of Economics and Development Studies
Alex Ekwueme Federal University, Ndufu-Alike Ikwo, Ebonyi State, Nigeria.**

Website: <https://www.ecofunai.ng>

ISSN (Print): 2536-6793 | ISSN (Electronic): 2536-6742

Volume 3 (1) February, 2026 (pp 41 – 61)

Submitted November 2025; Published February 2026.

STATISTICAL INFERENCE AND FORENSIC ACCOUNTING: INVESTIGATING THE OPERATIONS OF SIX NIGERIAN FIRMS

EZE, OGBONNAYA NWEZE

Department of Accountancy, Alex Ekwueme Federal University, Ndufu-Alike, Ikwo

Email: nzekanzeo@yahoo.com or eze.ogbonna@funai.edu.ng

ABSTRACT

This study examined the effectiveness of applying statistical analysis and inference to support forensic accounting techniques in investigating financial and operational deficiencies in six Nigerian Firms across six zones. Using data collected from the firms in 104 weeks of operations and 60 customer records, the study compared the expected input with the reported yield and analyzed customer-specific variables in relation to periodic patronage to determine longevity factors. The research employed one-way analysis of variance (ANOVA), multivariate analysis of variance (MANOVA), ordinary least squares (OLS), and logistic (LOGIT) regression analyses to validate the data. The findings showed that while forensic accounting techniques are effective in detecting financial and operational irregularities, the use of statistical inferences achieved this with greater precision and accuracy. The study recommends enhancing the efficiency of forensic accounting techniques with statistical inferences for better investigative accuracy and outcomes.

Keywords: forensic accounting, statistical inference, forensic evidence, fraud, operational deficiency

JEL Classifications: M4, M41, M42, M43, M48

Citation: Eze, O. N. (2026). Statistical inference and forensic accounting: Investigating the operations of six Nigerian firms. *AEFUNAI Journal of Economics, Finance and Development Studies*, 3(1), 41– 61.

1. Introduction

Forensic accounting is a specialized field of accounting that involves investigating financial transactions and records to detect and prevent fraud, financial misconduct, and other irregularities. It combines accounting, auditing, and investigative skills to analyze and interpret complex financial data for legal proceedings and dispute resolution (WikiAccounting, 2024; Investopedia, 2024; Accounting Insights, 2024).

In chemical manufacturing companies, the difference between the expected input yield (the standard specification) and the actual yield is usually a source of concern for the management of such firms, especially as this tends to impact negatively on the profitability and sustainability of such firms. For service concerns such as a telecommunication company, the ability to attract and retain clientele rests heavily on the survival and sustainability of such firms. As a result, customer satisfaction tops the priorities, especially amidst stiff competition. This is the reason why customer-specific variables are treated with great importance.

Forensic accounting is known to combine accounting, auditing, and investigative skills to detect and prevent fraud and other operational irregularities. In Nigeria, forensic accounting has become an essential tool for investigating operational deficiencies, ensuring accountability and transparency in business operations; however, little appears to have been done in applying statistical inferences amongst the tools used in the work of the nation's forensic accounting investigators.

Hence, a comparative analysis of a company's expected versus reported performance metrics, such as contribution margins, sales figures, and chemical yields, can reveal insights into operational efficiency and potential discrepancies. According to Rezaee et al (2015), forensic accounting techniques can help to identify and investigate such discrepancies. Also, A. J. (2010) found similar finding on his work; Fraud Auditing and Forensic Accounting. Then Albrecht, W.S. et al. (2011) diagnosed financial analysis and performance metrics by examining Fraud comparism metrics of contribution margins, sales figures, and chemical yields to evaluate the system's transparency, which was significantly negative.

Therefore, a company's policies on data, calls, and post-paid credit can significantly impact customer loyalty in the telecom sector. Research suggests that service quality, pricing, and customer satisfaction are key factors influencing loyalty; Khan M.(2013), ona similar note, Aydin, S. and Ozer, G. (2005), study on the analysis of antecedents of customer loyalty in the mobile telecommunication market. Significantly, Kim, M. K. et al (2004) studied the effects of customer satisfaction and switching barrier on customer loyalty in Korean mobile telecommunication services, with Lee, J. et al(2001), who looked at the impact of

switching Costs on the customer satisfaction -loyalty link, wholly looking at the relationship between policy aspect and influence on loyalty. a

However, the paucity of literature and empirical evidence on the use of statistical tools by forensic accounting practitioners in many parts of the world, especially in Nigeria, informs the essence of this study. Forensic accounting practices can vary significantly across different countries due to variations in legal systems, regulatory frameworks, cultural norms, and the prevalence of financial crimes.

This study focuses on six Nigerian firms across six zones to examine how statistical inference and forensic accounting can uncover financial irregularities and improve financial practices.

Research Questions

To address the specific objectives of this study, the following research questions will guide the investigation:

- a) How do the expected contributions, expected sales, and expected chemical yields of Company A compare to their reported equivalents?
- b) To what extent do other companies' policies on data, calls, wireless services, and post-paid credit influence customer loyalty?

Objective of the study

This study aims to highlight the importance and efficacy of statistical analysis and inferential statistics as critical tools in forensic accounting investigations. By examining suspected anomalies in corporate finances and operations. This research focuses on six anonymous Nigerian firms as case studies. The specific objectives are to:

- a) Conduct a comparative analysis of the input-output relationship in the production process of Company A to evaluate the system's transparency.
- b) Investigate the underlying factors contributing to the persistent subscriber switching in Companies B, C, D, E, and F.

Hypotheses

Hypotheses 1 to 3 will be used to address research question 1, while hypothesis 4 will handle research question 2.

H₀ 1: The Expected Contribution (ExpCont) value is not significantly different from the Reported

Contribution (RepCont) value. (Company A)

H₀ 2: The Expected Sales value is not significantly different from the Reported Sales value (Company A)

H₀ 3: The Expected Yield (ExpYield) value is not significantly different from the Reported Yield (RepYield) value. (Company A)

H₀ 4: The switching behavior of customers of a telecom firm is not significantly influenced by the customer-specific variable policies and actions of the firm. (Company B)

2.0 Literature Review

2.1 Concepts and practices in forensic accounting

Forensic accounting practice is woven around five major concepts, which include fraud detection, litigation support, criminal investigation, compliance and regulatory investigations, and asset tracing and recovery.

Forensic accountants (the practitioners of forensic accounting) play a critical role in identifying financial fraud by meticulously examining discrepancies in financial statements, accounting records, and other relevant documents. They employ a range of techniques to uncover fraudulent activities such as embezzlement, insider trading, and asset misappropriation. Forensic accountants also provide expert testimony and detailed reports in legal cases involving financial disputes, presenting their findings clearly and effectively to support legal teams in building strong cases.

In collaboration with law enforcement agencies, forensic accountants investigate financial crimes by analyzing financial evidence, tracing illicit transactions, and identifying the perpetrators behind these crimes. They ensure organizational compliance with relevant laws and regulations by conducting thorough audits and reviews, identifying any violations, and recommending corrective actions. Additionally, forensic accountants assist in tracing and recovering misappropriated assets, thereby safeguarding organizational resources and integrity (WikiAccounting, 2024).

Forensic accountants employ advanced data analytics tools to analyze large volumes of financial data. These tools help identify patterns, anomalies, and trends that may indicate fraudulent activities (Accounting Insights, 2024). Forensic accountants also conduct interviews and interrogations with employees, witnesses, and suspects to gather information and obtain evidence related to financial irregularities (Huber & DiGabriele, 2014). They meticulously review financial documents, contracts, and records to identify discrepancies and inconsistencies. They cross-reference data to ensure accuracy and authenticity from which they prepare detailed reports outlining their findings, methodologies, and conclusions

(WikiAccounting, 2024; Winfield & Roberts, 2023). The forensic accounting reports must be capable of being used in legal proceedings and to make informed decisions by management (WikiAccounting, 2024; Accounting Insights, 2024; Investopedia, 2024).

According to Onuora *et al.* (2022), forensic accounting plays a crucial role in maintaining financial integrity and combating financial crimes. It requires a blend of accounting knowledge, investigative skills, and analytical expertise to uncover the truth behind financial discrepancies.

Winfield & Roberts (2023) hinted that in countries like the United States and the United Kingdom, forensic accounting is well-regulated with established professional bodies such as the Association of Certified Fraud Examiners (ACFE) and the Government Counter Fraud Profession (GCFP). This contrasts with other countries that may lack such formal regulatory bodies, leading to less standardized practices. Cultural attitudes towards fraud and financial transparency can influence forensic accounting practices, especially in cultures where corruption is more tolerated. Forensic accountants may encounter more resistance and challenges in their investigations.

2.2 Statistical inference and its application in fraud detection.

The use of statistical analysis tools in forensic accounting remains underdeveloped, with a noticeable lack of research showcasing the integration of mathematical and statistical methods in forensic accounting investigations. Despite this, there have been notable pioneering efforts to incorporate statistical and mathematical analyses into forensic accounting processes. One of the foremost contributions in this area was made by Frank Albert Benford, who formulated "The Law of Anomalous Numbers," also known as Benford's Law, which states that in naturally occurring sets of numbers, the leading digit is not uniformly distributed. Instead, smaller digits appear more frequently as the leading digit. Specifically, the digit 1 appears as the leading digit approximately 30% of the time, while larger digits occur less frequently, with the digit 9 appearing as the leading digit only about 5% of the time (Benford, 1938).

The main ingredient in the application of Benford's Law in financial fraud detection is the distribution of leading digits in numerical data. By comparing the actual distribution of leading digits in financial data (like transaction amounts, sales figures, or account balances) to the expected distribution from Benford's Law, analysts can identify potential anomalies that may indicate fraudulent activity or manipulation. Auditors and forensic accountants use Benford's Law as a tool to flag suspicious data points for further investigation. A significant deviation from the expected distribution of leading digits might suggest that the data has been tampered with or is not naturally occurring. Benford's Law is more applicable to large datasets where the numbers span several orders of magnitude. It is less applicable to small datasets or datasets that

are constrained to a narrow numerical range (Hill, 1995; Nigrini, 1999; Miller, 2003; Burgard, 2009; Sullivan, 2012; Lacker, 2013).

Verma and Singh (2023) reviewed the trends and techniques in the use of data analytics within forensic accounting. The findings of this study highlight the growing importance of data analytics in enhancing the efficiency and effectiveness of forensic accounting practices. The paper discussed various data analytics tools and methodologies that are being integrated into forensic accounting to detect and prevent fraud more effectively and emphasized the need for continuous research and development on the subject to keep up with evolving and ever-growing financial crimes (Verma & Singh, 2003).

Bebeselea and Patache (2019) highlight the connection between accounting and statistics. The work inferred that there is a historical connection between statistics and accounting as quantitative methods of analysis. They hinted further that since accounting data on property and wealth were requested in the census of the great ancient civilizations, statistical and accounting data-setting systems provide a framework to identify, record, classify, and summarize economic activities of entities (Bebeselea & Patache, 2019).

2.3 Empirical Literature

There has been growing interest in the application of forensic accounting and the studies of its effect or impact on the economy of Nigeria and sub-Saharan Africa. Some of these studies hinge on the use of different methodologies and the application of forensic accounting to the solution of integrity problems in many diverse fields such as tax administration, inventory management, production monitoring, and financial transactions, amongst others. Oyedokun (2022) investigated the determinants of forensic accounting techniques and theories. It highlights that the nature of the fraud, criminal evidence, examiner's expertise, and organizational policies are key factors in selecting appropriate forensic accounting techniques. The study recommends regular forensic reviews and employee training on financial crimes.

Enofe *et al.* (2021) examined the role of forensic accounting in reducing fraud in Nigerian firms. The findings reveal that forensic accounting can significantly enhance financial fraud reduction through fraud prosecution, improve internal control systems, and increase financial reporting credibility and transparency in firms. Akinadewo and Akinkoye (2020), on the other hand, investigated the application of forensic accounting techniques in detecting tax evasion in Nigeria. The results show a positive relationship between forensic accounting skills and tax evasion detection, indicating that the application of forensic accounting can significantly reduce tax evasion and improve government revenue.

Onuora *et al.* (2022) explored the use of forensic accounting as a tool for accountability among quoted firms in Nigeria. The findings suggest that forensic accounting enhances accountability and transparency in financial reporting, leading to better governance and reduced fraudulent activities in quoted firms. Begum

(2023) examined the role of forensic accounting in preventing financial fraud. It emphasizes the importance of forensic accounting in identifying and mitigating fraudulent activities, thereby enhancing the integrity of financial systems. Mayungbe (2012) reviewed forensic accounting and fraud detection, emphasizing the connection between accounting systems and legal frameworks. It suggests that forensic accounting can significantly contribute to fraud detection and prevention.

Dada *et al.* (2013) studied the relevance of forensic accounting as an investigative tool in the effective detection and prosecution of cases of bribery in Nigeria. Using data collected from two anti-corruption agencies - the ICPC and EFCC, the study concluded that a positive relationship exists between the application of forensic accounting techniques and the detection of cases of bribery in Nigeria.

Eiya and Otalor (2013) examined the role of forensic accounting in financial fraud prevention in Nigerian banks. It highlights the effectiveness of forensic accounting techniques in identifying and preventing financial fraud within the banking sector. Huber & DiGabriele (2014) also focused on forensic accounting techniques and their application in fraud detection. It provides insights into various techniques used by forensic accountants to detect and investigate fraudulent activities. Okoye *et al.* (2019) also investigated forensic accounting and fraud prevention in Nigerian companies. The study underscores the role of forensic accounting in enhancing corporate governance and reducing the incidence of financial fraud.

Jahirul *et al.* (2011) reviewed forensic accounting and fraud detection, discussing various techniques and methodologies used in the field to identify and prevent fraudulent activities. Al-Sharairi (2018) focused its review on forensic accounting and fraud detection, highlighting the importance of integrating advanced technologies and methodologies to enhance the effectiveness of forensic accounting practices. Muehlmann *et al.* (2012) examined the use of forensic accounting experts in tax cases, analyzing court opinions and providing insights into the role and effectiveness of forensic accountants in legal proceedings. Finally, Ehioghien and Atu (2016) explored forensic accounting and fraud detection, emphasizing the need for robust forensic accounting practices to combat financial fraud and enhance accountability.

3.0 Methodology

The study adopted secondary data collection, using ex-post facto case study research approach, where six (6) companies across the six zones in Nigeria were used and selected using purposive sampling as case studies i.e (Companies A, B, C, D, E and F) selected using purposive sampling, as case studies. Using 104 weeks of operations and 60 customer records, for A, B, C, D, E, and F, for data gathering. Operational data were collected from Company A's recorded production

logbook and through physical observation of post-record period production processes, while data for Companies B, C, D, E, and F were obtained from their customer database, with permission and explicit instructions for anonymity. The following techniques were employed in testing the formulated hypotheses. Linear regression was used in testing hypotheses to measure the degree of the effect of the independent variable on the dependent variable.

Where the data analysis methods included comparing the expected input yield with the reported yield for Company A and analyzing customer-specific variables in relation to their patronage period to determine longevity factors for Company B. The study utilized both descriptive and inferential statistical methods, such as one-way analysis of variance (ANOVA), multivariate analysis of variance (MANOVA), ordinary least squares (OLS), and logistic (LOGIT) regression analyses, to analyze and validate the collected data.

Model Specification; $y = a + bx + e$

Above was the adopted linear regression model used by Farope (2009) and was modified to suit the study as;

$y = a + bx(cc) + cx(cp) + e$

Where y is the dependent variable (Return on Asset)

x is the independent variable as a comparative analysis of the input - output relationship and the company's policies on data, calls, and post-paid.

a is the y-intercept

b is the residual (error)

ANOVA

Model	Sum Squares	Mean Square	F	Sig
Regression	151.229	50.410	.785	.602
Residual	128.451	64.226		

Total	279.680			
-------	---------	--	--	--

Dependent variable: Company performance

The model summary explains the model; the percentage of variation in the success of the company's performance is a proxy for return on assets.

These analyses aimed to ascertain whether there are significant differences between the reported chemical input and the expected yield for Company A, and whether there are customer-specific factors responsible for the short or long patronage duration with Company B's services.

4. Result and Discussion

4.1 Result

The analysis of the various findings from the literature review and other works consulted tends to agree that the integration of the application of statistical analysis and the use of the inferences drawn from them can go a long way in solving mysteries long covered by fraudulent and unwholesome financial transactions and operational irregularities. The results of the various analyses are presented in the following paragraphs.

Analysis of Results for Company A

Table 1 presents the results of the one-way analysis of variances (ANOVA), which was carried out on Expected Yield/Reported Yield, Expected Sales/Reported Sales, and Expected Contribution/Reported Contribution for Company A (Case 1).

Table 1: Multiple Comparison of Means - Tukey HSD, FWER=0.05

group1	group2	meandiff	p-adj	lower	upper	reject
ExpCont	RepCont	-7209951.9	0.0	-7552252.47	-6867651.38	True
ExpSales	RepSales	-7209951.9	0.0	-7552252.47	-6867651.38	True
ExpYield	RepYield	-1602.21	1.0	-343902.76	340698.34	False

Source: ValuStats(VSP 2.0) September 2025

ANOVA results overview

F-statistic: 11139.614

p-value: 0.0000

The F-statistic of 11139.614 and its p-value of 0.0000 are indications that the model is well fit and that there are significant differences between the means of the variables considered. Table 1 specifically gave a perfect view of the differences.

We also use the *multivariate* ANOVA (MANOVA) to resolve the 3 hypotheses. The MANOVA results (derived after adjusting for autocorrelation and multicollinearity) are presented in Table 2.

Table 2: Multivariate linear model (MANOVA)

RepYield	Value	Num DF	Den DF	F Value	Pr > F
Wilks' lambda (<i>Λ</i>)	0.0007	3.0000	97.0000	43548.4831	0.0000
Pillai's trace (<i>V</i>)	0.9993	3.0000	97.0000	43548.4831	0.0000
Hotelling-LL trace (<i>T</i>)	1346.8603	3.0000	97.0000	43548.4831	0.0000
Roy's greatest root (<i>Θ</i>)	1346.8603	3.0000	97.0000	43548.4831	0.0000
RepSales	Value	Num DF	Den DF	F Value	Pr > F
Wilks' lambda (<i>Λ</i>)	0.0000	3.0000	97.0000	1038955268.36	0.0000
Pillai's trace (<i>V</i>)	1.0000	3.0000	97.0000	1038955268.36	0.0000
Hotelling-LL trace (<i>T</i>)	32132637.17	3.0000	97.0000	1038955268.36	0.0000
Roy's greatest root (<i>Θ</i>)	32132637.17	3.0000	97.0000	1038955268.36	0.0000
RepCont	Value	Num DF	Den DF	F Value	Pr > F
Wilks' lambda (<i>Λ</i>)	0.0000	3.0000	97.0000	11880724.8624	0.0000
Pillai's trace (<i>V</i>)	1.0000	3.0000	97.0000	11880724.8624	0.0000
Hotelling-LL trace (<i>T</i>)	367445.0988	3.0000	97.0000	11880724.8624	0.0000
Roy's greatest root (<i>Θ</i>)	367445.0988	3.0000	97.0000	11880724.8624	0.0000
RepProfit	Value	Num DF	Den DF	F Value	Pr > F
Wilks' lambda (<i>Λ</i>)	0.0000	3.0000	97.0000	634896321.96	0.0000
Pillai's trace (<i>V</i>)	1.0000	3.0000	97.0000	634896321.96	0.0000
Hotelling-LL trace (<i>T</i>)	19635968.72	3.0000	97.0000	634896321.96	0.0000
Roy's greatest root (<i>Θ</i>)	19635968.72	3.0000	97.0000	634896321.96	0.0000

Source: ValuStats(VSP 2.0) September 2025

Interpreting the MANOVA results

The output provided in Table 2 shows results from a Multivariate Analysis of Variance (MANOVA) test. The reported variables were compared with the expected variables (ExpYield, ExpSales, ExpCont, and RepProfit). Here are the interpretations:

Test Statistics:

ExpYield with RepYield: Wilks' Lambda (**Λ**) = 0.0007, $F = 43548.4831$, $p = 0.0000$; Pillai's Trace (**V**) = 0.9993, $F = 43548.4831$, $p = 0.0000$; Hotelling-Lawley Trace (**T**) = 1346.8603, $F = 43548.4831$, $p = 0.0000$; and Roy's Greatest Root (**Θ**) = 1346.8603, $F = 43548.4831$, $p = 0.0000$. The difference is significant.

ExpSales with RepSales: Wilks' Lambda (**Λ**) = 0.0000, $F = 1038955268.36$, $p = 0.0000$; Pillai's Trace (**V**) = 1.0000, $F = 1038955268.36$, $p = 0.0000$; Hotelling-Lawley Trace (**T**) = 32132637.17, $F = 1038955268.36$, $p = 0.0000$; and Roy's Greatest Root (**Θ**) = 32132637.17, $F = 1038955268.36$, $p = 0.0000$. The difference is significant.

ExpCont with RepCont: Wilks' Lambda (**Λ**) = 0.0000, $F = 11880724.8624$, $p = 0.0000$; Pillai's Trace (**V**) = 1.0000, $F = 11880724.8624$, $p = 0.0000$; Hotelling-Lawley Trace (**T**) = 367445.0988, $F = 11880724.8624$, $p = 0.0000$; and Roy's Greatest Root (**Θ**) = 367445.0988, $F = 11880724.8624$, $p = 0.0000$. The difference is significant.

ExpProfit with RepProfit: Wilks' Lambda (**Λ**) = 0.0000, $F = 43548.4831$, $p = 0.0000$; Pillai's Trace (**V**) = 1.0000, $F = 43548.4831$, $p = 0.0000$; Hotelling-Lawley Trace (**T**) = 19635968.72, $F = 43548.4831$, $p = 0.0000$; and Roy's Greatest Root (**Θ**) = 19635968.72, $F = 43548.4831$, $p = 0.0000$. The difference is significant.

A Wilks' Lambda (**Λ**) of value zero or close to zero suggests that the group means are significantly different. On the other hand, a Pillai's Trace (**V**) value of one or close to one indicates significant differences between groups. With Hotelling-Lawley Trace (**T**), high values (such as 19635968.72) indicate that there are statistically significant differences between the groups being compared, likewise the value revealed by Roy's Greatest Root (**Θ**) test. In the same vein, the higher the F value, the more likely it is that the observed group differences are significant. A p-value less than 0.05 indicates that there are significant differences between the groups, and this was the case for all the compared groups.

Additionally, we use the descriptive and inferential results generated from the ordinary least squares (OLS) regression analysis presented in Tables 3, 4, and 5 to further authenticate the resolution of hypothesis $H_0:3$, which also resulted in disparities between the expected yield from the chemical input and the reported yield in the production logbook.

Table 3: OLS Descriptive Statistics

	ExpYield	RepYield
count	104.00	104.00
mean	4863.46	3261.25
std	89.33	340.76
min	4725.00	2987.00
max	5000.00	4225.00

Source: ValuStats(VSP 2.0) September 2025

Table 4: OLS Regression Results

Dep. Variable:	ExpYield
R-squared:	0.689
Adj. R-squared:	0.686
F-statistic:	226.3
Prob (F-statistic):	0.0000

Source: ValuStats(VSP 2.0) September 2025

Table 5: OLS Beta and Significance Analysis

Variable	Coeff.	Std-Error	t stats	p-value
Const	4153.6243	47.440	87.555	0.000
RepYield	0.2177	0.014	15.044	0.000

Source: ValuStats(VSP 2.0) September 2025

Analysis of Results for Company B, C, D, E, and F as collectively analyzed (Case 2)

Logistic Regression Analysis Results for Company B, C, D, E, and F

Wald Statistics: The Wald test checks the significance of each predictor variable in the model. It provides the chi-squared statistic and *p-value* for each predictor as in Table 6.

Table 6: Wald Statistics on Logit Regression (Case 2 - Appendix B)

Predictor	Chi ² Statistic	p-value	Conclusion
age	1.1778971	0.277784	Not Significant
edu	3.20889531	0.073239	Marginally Significant
gender	1.73944084	0.187210	Not Significant
wireless	0.07278027	0.787331	Not Significant
calls	0.22438867	0.635716	Not Significant
data	4.9283021	0.026420	Significant
credit	9.43006637	0.002135	Highly Significant

Source: ValuStats(VSP 2.0) September 2025

4.2 Discussion of Findings

With the literature review all validating the importance, effectiveness and usefulness of forensic accounting in the uncovering and prevention of financial and operational irregularities in business organizations which are in agreement with the empirical findings of this study, it is expedient to note that the few studies which introduced and combined innovative statistical procedures and analysis into the process of forensic accounting investigations made extra-ordinary findings (Benford, 1938; Nigrini & Mittermaier, 1997; Burgard, 2009). These findings are in alignment with the objective of this study and encourage the use of statistical analysis such as the ANOVA, MANOVA, and the OLS regression in the validation of the results of this study.

The implication of the ANOVA results validations for hypotheses $H_{0:1}$ and $H_{0:2}$, revealing significant differences between the expected operational output and the reported operational output, is suggestive that something unwholesome transpired between the handling of the inputs into the production system and the handling of the output from that system, which should be investigated further.

To resolve H_0 1, Table 1 provided the data revealing the mean difference of -7209951.9234 with a *p-adj* value of 0.0 and a recommendation that we should reject the *Null* ($H_{0:1}$) hypothesis (reject > True), indicating that there is a significant difference between the Expected Contribution value and the Reported Contribution value.

Similarly, for $H_0 2$, Table 1 provided the data giving a mean difference of -7209951.92 with a $p\text{-adj}$ of 0.0 and a recommendation that we should reject the *Null* ($H_0:1$) hypothesis (reject > True), implying that there is a significant difference between the Expected Sales value and the Reported Sales value.

However, for $H_0 3$, Table 1 provided a mean difference of -1602.21 with a $p\text{-adj}$ of 1.0 and a recommendation that we should not reject the *Null* ($H_0:3$) hypothesis (reject > False) because the mean difference is not statistically different, which implies that *the* Expected Yield (ExpYield) value is not significantly different from the Reported Yield (RepYield) value. $H_0 3$ was not rejected due to the insignificant difference of 1,602.21 compared to 7,209,951.9234 recorded for $H_0:1$ and $H_0:2$. This, however, is attributable to the magnitude of the measurement used. Not satisfied with this one-way ANOVA result, the focus shifted to the MANOVA and OLS regression analyses results, which suggested a different verdict.

Based on the MANOVA results, there is a significant difference between the four Expected Output groups and the four Reported Output groups since all test statistics (Wilks' lambda, Pillai's trace, Hotelling-Lawley trace, and Roy's greatest root) show significant values. The $p\text{-values}$ all returned 0.0000, which means the probability of these results being due to chance is extremely low. Particularly, the difference between the expected yield and the reported yield shown as insignificant by the one-way ANOVA got a different opinion using the MANOVA as shown in this result: ExpYield compared with RepYield ($\Lambda = 0.0007$, $F_{(3,97)} = 43548.4831$, $p = 0.0000$; $V = 0.9993$, $F_{(3,97)} = 43548.4831$, $p = 0.0000$; $T = 1346.8603$, $F_{(3,97)} = 43548.4831$, $p = 0.0000$; and $\Theta = 1346.8603$, $F_{(3,97)} = 43548.4831$, $p = 0.0000$). That is to say that what was reported as outputs was far from what was expected from the inputs into the production processes, signaling that there could be some problems of accountability along the line of material purchases, input, and output out of the production process. It could also be that there are problems with the technical specifications of the production process being applied all along.

The OLS results in Tables 4 and 5 infer that the Expected Chemical Yield has positive and significant relationships with the Reported Chemical Yield; however, the beta coefficient of 0.2177 is suggestive that only 21.77% of the Expected Chemical Yield is reported. This is made clearer by the descriptive statistics (Table 3), which revealed a mean difference of 1,602.21 kilograms of foam unreported, which was also indicated by the large variance between the two standard deviations (89.33 for Expected Yield as against 340.76 for Reported Yield). The R^2 and the *Adjusted* R^2 of 0.689 and 0.686, respectively, remotely indicate that only about 68.6 percent of the expected chemical yields were actually reported in the production logbook.

The Wald statistics in Table 6 summarize the logistic regression analysis on the operations of Companies B, C, D, E, and F in Appendix B. The variables used for the analysis include the customer's age, customer's

gender, customer's education (edu), data services (data), wireless service (wireless), call service (call), and postpaid credit facility (credit). The Log-Likelihood value of -19.178 is nearer to zero and higher than the Null Log-Likelihood of -40.381 with LLR *p-value* of 0.00000 to suggest that the model is a good fit. In addition, the *Pseudo R-squared* of 0.5251 indicates that the dependent variable (long-stay) is accounted for by 52.51% of the predictors used.

The findings revealed that data and credit have significant *p-values* (below 0.05), showing that they are significant predictors in the model. This result is an indication and a revelation that customers left the company when they are no longer satisfied with the data services provided or when no postpaid credit facility is extended to them. Customer's education (edu) is marginally significant with a *p-value* of 0.073, meaning that most of the educated customers are sensitive to issues of satisfaction and would react negatively when there is a cause to do so. The supporting plots (Figures B.1 and B.2) in Appendix B clarify further.

Other variables like age, gender, wireless, and calls are not significant predictors with *p-values* above 0.05. Based on these facts, the company can be guided on how to win back and retain its customers by looking at the best way to handle the issues of postpaid credit and offer better data services.

These results have far-reaching implications for the appropriate firms in the study and have shown how statistical analysis can support forensic investigations and unearth hidden anomalies in business transactions and operations. The findings are in complete agreement with the works of Lacker (2013), Sullivan (2012), Bugard (2009), Verma and Singh (2003), and Nigrini (1999).

This study is limited in scope to only the data collected from the six anonymous companies used as case studies. Nevertheless, this limitation does not in any way invalidate the methodology employed and the findings thereon. However, future studies should focus on other business categories not covered in this research, and may consider increasing the observation period beyond two years for the manufacturing firms and increasing the customer sample size beyond the 60 records for service-oriented companies. Also, other statistical analysis tools, other than the one-way ANOVA, MANOVA, and the OLS regression used for this study, can also be tried by other researchers.

The foregoing discussion interprets the results, comparing them with existing literature and exploring the implications for forensic accounting practice in Nigeria. It addresses the limitations of the study and suggests areas for future research, such as expanding the sample size and exploring different statistical methods.

5. Conclusion and Recommendation

5.1 Conclusion

The study concludes that forensic accounting, supported by statistical inference, is a valuable tool for investigating financial and operational irregularities in Nigerian firms. Preventing and detecting Financial Statement through robust internal controls, effective audit processes, and a culture of ethics and compliance. Proactive and data-driven approaches, Hence to understanding the fraud triangle (pressure, opportunity, rationalization) and implementing effective controls and monitoring.

5.2 Recommendation

It recommends that firms adopt the extensive use of statistical analysis and inference to aid the effectiveness of forensic accounting practices and enhance financial transparency and accountability. To implement robust internal controls, audit procedures, enhance board oversight, and to promote a culture of ethics compliance. To train auditors to ensure data analytics and detect anomalies, and finally to foster collaboration between auditors and legal expertise. With company policies, it recommends building trust through quality service and transparency, responsive Service for customer satisfaction, increasing switching Costs through loyalty programs, and a customer-centric approach, and finally monitoring competitors' offerings and addressing customer complaints promptly.

REFERENCES

- Akinadewo, I. S., & Akinkoye, E. Y. (2020). Tax evasion detection in Nigeria: Analysis of the specific forensic accounting techniques used. *Journal of Management & Accounting*, 14(3), 45-60.
- Accounting Insights. (2024). Forensic Accounting: Principles, Techniques, and Roles Explained. Retrieved from *Accounting Insights*, Retrieved 13/02/2025 from <http://www.accountinginsights.org>
- Al-Sharairi, N. (2018). Forensic Accounting and Fraud Detection: A Review. *Journal of Forensic Studies*, 5(2), 30-45.
- Bebeselea, M. & Patache, L. (2019). Exploring the relationship between accounting and statistics, *Annals of Spiru Haret University, Economic Series*, 19(3), 55-63, DOI:<https://doi.org/10.26548/1933>
- Begum, Y. N. (2023). Role of Forensic Accounting in Preventing Financial Frauds. *Forensic Accounting Journal*, 2(1), 10-20.
- Benford, F. (1938). The Law of Anomalous Numbers. *Proceedings of the American Philosophical Society*, 78(4), 551-572.

- Burgard, S. (2009). A review of Benford's Law and its application in the field of forensic accounting. *Journal of Forensic and Investigative Accounting*, 1(2), 1-12.
- Dada S.O., Enyi P.E and Owolabi S.A (2013). Forensic accounting: A relevant tool for effective investigation of bribery cases in Nigeria. *Unique Journal of Business Management Research*.1(5) 095-099. ISSN 2333-6781
- Ehioghiren, A., & Atu, O. (2016). Forensic Accounting and Fraud Detection: A Review. *Journal of Forensic Studies*, 5(2), 30-45.
- Eiya, E., & Otor, O. (2013). Forensic Accounting and Financial Fraud Prevention: A Case Study of Nigerian Banks. *Journal of Financial Crime*, 4(1), 55-70.
- Enofe, A. O., Idemudia, N. G., & Emmanuel, G. U. (2021). Forensic Accounting: A Panacea to Fraud Reduction in Nigerian Firms. *Journal of Accounting and Finance*, 1(1), 1-15.
- Hill, T. P. (1995). The first digit phenomenon. *The American Statistician*, 49(3), 232-235.
- Huber, D., & DiGabriele, T. (2014). Forensic Accounting Techniques and Their Application in Fraud Detection. *Journal of Forensic Accounting Research*, 6(2), 75-90.
- Investopedia. (2024). Forensic Accounting: What It Is, How It's Used. Retrieved from www.investopedia.com
- Jahirul, H., Habibur, R., & Takdir, S. (2011). Forensic Accounting and Fraud Detection: A Review. *Journal of Forensic Studies*, 5(2), 30-45.
- Lacker, T. (2013). An empirical analysis of Benford's Law in enriched datasets. *Statistics in Medicine*, 32(22), 3784-3797.
- Mayungbe, J. (2012). Forensic Accounting and Fraud Detection: A Review. *Journal of Forensic Studies*, 5(2), 30-45.
- Miller, S. J. (2003). A mathematical approach to analyzing the use and perception of Benford's Law. *Journal of Statistical Education*, 11(3).
- Muehlmann, D., Burnaby, E., & Howe, J. (2012). Forensic Accounting and Fraud Detection: A Review. *Journal of Forensic Studies*, 5(2), 30-45.
- Nigrini, M. J. (1999). A taxpayer compliance measurement using Benford's Law. *Journal of the American Taxation Association*, 21(1), 26-38.
- Onuora, J. K., Fabian, O., & Christian, N. (2022). Forensic Accounting as an Instrument of Accountability among the Quoted Firms in Nigeria. *International Journal of Advanced Academic Research*, 8(3), 8210-8225.
- Oyedokun, G. E. (2022). Determinants of Forensic Accounting Techniques and Theories: An Empirical Investigation. *Annals of Spiru Haret University*, 25(1), 1-25.
- Okoye, A., Adeniyi, O., & Nwankwo, C. (2019). Forensic Accounting and Fraud Prevention: A Study of Nigerian Companies. *Journal of Business Ethics*, 7(1), 15-30.
- Sullivan, H. (2012). An algorithmic approach to testing Benford's Law. *International Journal of Mathematical and Computational Sciences*, 6(1), 39-45.
- Verma, A., & Singh, V. B. (2023): The Use of Data Analytics in Forensic Accounting: A Review of Current Trends and Techniques. *International Journal of Research Publication and Reviews*.
- ValuStats (VSP) 2.0 Statistical Package. <http://www.valustats-vsp.com>
- WikiAccounting. (2024). What is Forensic Accounting? Definition, Types, Services, and Objectives. Retrieved from www.wikiaccounting.com
- Winfield, J. & Roberts, M. (2023). Forensic Accounting: Time for a unified global approach, *Journal of Forensic Accounting Profession*, 3(1)

APPENDICES

Appendix A: Input/Output Disparity Case Study

Company A is a company incorporated in Nigeria. It has been in the businesses of Chemical Engineering (Foam manufacturing), Hotel and catering services for upwards of five years.

Recently, the owners observed that the performance of the company for the past two years in the foam manufacturing section has deviated consistently from the original projections and asked a group of consulting researchers to carry out an informed analysis of the operations of the business for the past 2 years. Table A.1 shows the data collected from the company's production logbook for 104 weeks and other data necessary for a conclusive analysis.

Table A.1: Chemical Plant:

Daily input capacity	2,000 liters of Polyol
Expected normal yield	5,000 kg of foam products
Cost of Polyol per liter	N2,791.50
Labor/other costs per liter	N2,092.50
Admin and other fixed cost	Averages 32% of direct costs.
Annual production period	52 weeks
Product Selling Price	N4,500 per kg (unchanged in the last 3 years)
Reported weekly input (liter)	1920, 1930, 1950, 1940, 1990, 1920, 1990, 2000, 2000, 2000, 1980, 1940, 2000, 2000, 1950, 1890, 1920, 1920, 1920, 1975, 1945, 1910, 1910, 1915, 1915, 1925, 1920, 1930, 1940, 1990, 2000, 2000, 1900, 1910, 1960, 1965, 1922, 1915, 1900, 1925, 1912, 1920, 1905, 1925, 1925, 1980, 2000, 2000, 1908, 1917, 1932, 1940, 2000, 2000, 1920, 1930, 1950, 1940, 1990, 1920, 1990, 2000, 2000, 2000, 1980, 1940, 2000, 2000, 1950, 1890, 1920, 1920, 1920, 1975, 1945, 1910, 1910, 1915, 1915, 1925, 1920, 1930, 1940, 1990, 2000, 2000, 1900, 1910, 1960, 1965, 1922, 1915, 1900, 1925, 1912, 1920, 1905, 1925, 1925, 1980, 2000, 2000, 1908, 1917
Reported weekly outputs (kg)	3000, 3100, 3200, 3050, 3110, 3090, 3200, 3500, 4100, 3600, 3200, 3000, 4000, 3400, 3010, 2990, 3070, 3050, 3100, 3310, 3150, 3050, 2987, 2999, 3000, 3100, 3050, 3100, 3200, 3600, 3950, 4000, 2999, 3100, 3205, 3310, 3150, 3050, 2987, 2999, 3000, 3100, 3050, 3100, 3200, 3600, 3950, 4000, 2999, 3100, 3205, 3310, 4225, 4100, 3000, 3100, 3200, 3050, 3110, 3090, 3200, 3500, 4100, 3600, 3200, 3000, 4000, 3400, 3010, 2990, 3070, 3050, 3100, 3310, 3150, 3050, 2987, 2999, 3000, 3100, 3050, 3100, 3200, 3600, 3950, 4000, 2999, 3100, 3205, 3310, 3150, 3050, 2987, 2999, 3000, 3100, 3050, 3100, 3200, 3600, 3950, 4000, 2999, 3100

To analyze this case, the researchers computed the expected weekly yield of the plant for the 104 weeks period and compared them with the reported output shown in Table A.1.

Appendix B: Telecom Customers Loyalty Case Study

Company B is a telecommunication company which has been in operation in the country for close to 24 years now. The company offers **wireless services**, **call services**, **data services**, and postpaid **credit facility** to their customers according to the individual customer's choice. However, the postpaid credit facility is available to only customers who met certain credit assessment conditions. Recently, the management is worried at the rate at which Company B's customers are leaving the company and wishes to investigate the

phenomenon. To do this, the company conducted a survey on the records of its former customers using age, wireless, data, gender, education (edu), credit, and calls as the predictor variables, and long-stay (longstay) as the outcome variable using logistic regression to analyze the data collected. Long stay in this context is defined as the ability of a customer to stay beyond five years. The results of the analysis of the survey and the interpretations are presented as follows:

Table B.1: Logit Regression Results

Dep. Variable:	longstay	No. Observations:	60
Model:	Logit	Df Residuals:	52
Method:	MLE	Df Model:	7
Date:	Sun, 09 Feb 2025	Pseudo R-squared:	0.5251
Time:	11:57:23	Log-Likelihood:	-19.178
converged:	True	LL-Null:	-40.381
Covariance Type:	nonrobust	LLR p-value:	4.345e-07

	coef	std err	z	P> z 	[0.025	0.975]
const	-1.0733	2.302	-0.466	0.641	-5.584	3.438
age	-0.0416	0.038	-1.085	0.278	-0.117	0.034
edu	-0.8260	0.461	-1.791	0.073	-1.730	0.078
gender	1.2723	0.965	1.319	0.187	-0.618	3.163
wireless	0.3872	1.435	0.270	0.787	-2.426	3.200
calls	0.4630	0.977	0.474	0.636	-1.453	2.379
data	2.2310	1.005	2.220	0.026	0.261	4.201
credit	3.4992	1.139	3.071	0.002	1.266	5.733

Here's an interpretation of the Logistic Regression Analysis results for the dependent variable "longstay":

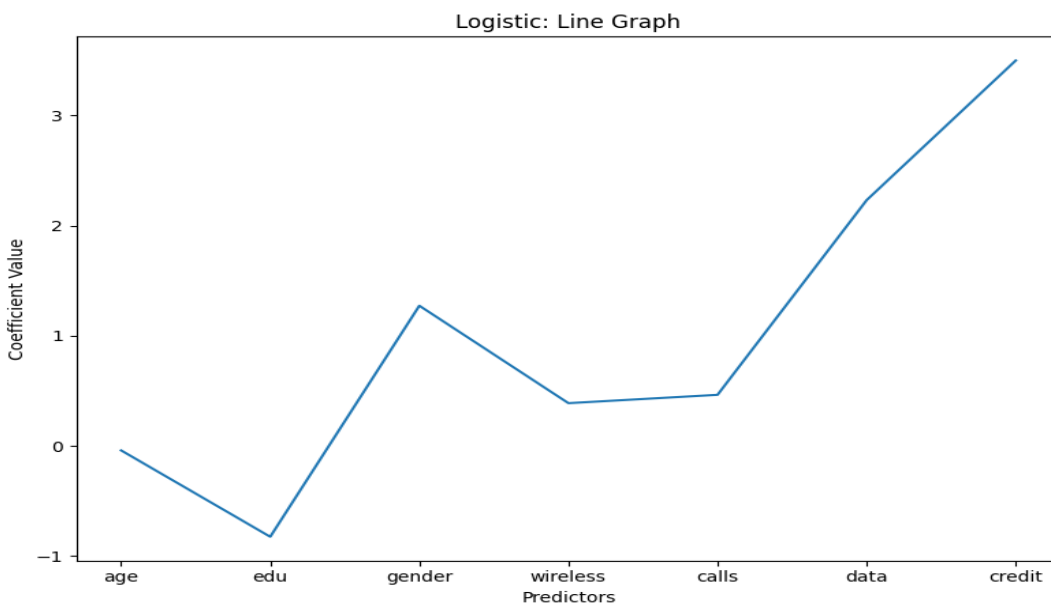
General Model Information:

- **Number of Observations:** 60
- **Degrees of Freedom (Residual):** 52
- **Degrees of Freedom (Model):** 7
- **Method:** Maximum Likelihood Estimation (MLE)
- **Log-Likelihood:** -19.178
- **Pseudo R-squared:** 0.5251
- **LL-Null:** -40.381
- **Covariance Type:** Nonrobust
- **LLR p-value:** 4.345e-07 (indicating the model is highly significant)

Detailed Results for Each Predictor:

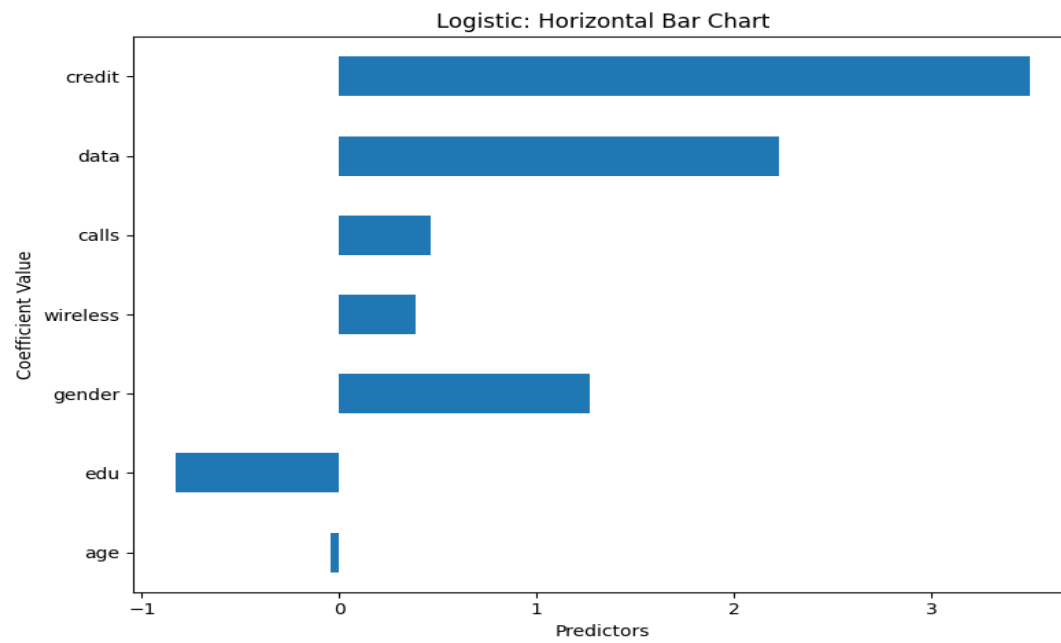
- **const (Intercept):** Coefficient = -1.0733, Standard Error = 2.302, $z = -0.466$, p-value = 0.641
- **age:** Coefficient = -0.0416, Standard Error = 0.038, $z = -1.085$, p-value = 0.278
- **edu (Education):** Coefficient = -0.8260, Standard Error = 0.461, $z = -1.791$, p-value = 0.073
- **gender:** Coefficient = 1.2723, Standard Error = 0.965, $z = 1.319$, p-value = 0.187
- **wireless:** Coefficient = 0.3872, Standard Error = 1.435, $z = 0.270$, p-value = 0.787
- **calls:** Coefficient = 0.4630, Standard Error = 0.977, $z = 0.474$, p-value = 0.636
- **data:** Coefficient = 2.2310, Standard Error = 1.005, $z = 2.220$, p-value = 0.026
- **credit:** Coefficient = 3.4992, Standard Error = 1.139, $z = 3.071$, p-value = 0.002

Figure B.1: Logit Line Graph for Customer-Specific Variable Coefficients – Company B.



Source: ValuStats(VSP 2.0) February 2025

Figure B.2: Logit Bar Chart for Customer-Specific Variable Coefficients – Company B.



Source: ValuStats(VSP 2.0) February 2025