AI-DRIVEN AUDITING AND FRAUD DETECTION EFFECTIVENESS: EVIDENCE FROM FEDERAL UNIVERSITIES IN NORTH-WESTERN NIGERIA

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ABSTRACT

This study examines the relationship between artificial intelligence (AI)-driven auditing and fraud detection effectiveness in federal universities in North-Western Nigeria. Specifically, the study assesses the relationships between AI-driven auditing and fraud reduction, fraud detection accuracy, fraud loss reduction, and fraud detection speed. A cross-sectional quantitative survey design was adopted, using primary data collected through a structured five-point Likert-scale questionnaire administered to 92 internal auditors across seven federal universities using a total enumeration approach. Data were analyzed using Pearson correlation and four separate simple linear regression models at the 5% significance level. The findings indicate that AI-driven auditing has a positive and statistically significant relationship with fraud reduction ($R^2 = .305$, $p < .001$), fraud detection accuracy ($R^2 = .513$, $p < .001$), and fraud detection speed ($R^2 = .317$, $p < .001$). However, its relationship with fraud loss reduction is weak and statistically insignificant ($R^2 = .007$, $p = .423$). The findings suggest that AI-driven auditing can strengthen the identification, accuracy, and timeliness of fraud detection, but enhanced detection capability does not necessarily translate into reduced financial losses. The study recommends integrating AI-enabled auditing with timely investigation, fraud recovery, appropriate sanctions, control remediation, continuous professional training, and effective AI governance.

Keywords: *Artificial intelligence; AI-driven auditing; fraud detection effectiveness; internal auditing; fraud reduction; federal universities*

1. INTRODUCTION

Financial fraud remains a significant challenge to accountability, financial reporting and effective governance. The growing volume, complexity and speed of financial transactions have increased the difficulty of identifying sophisticated fraudulent activities through conventional audit procedure alone. Although traditional auditing remains indispensable for assurance and internal controls, periodic reviews, sampling and manual examination may constrain auditors' ability to analyze large and complex datasets comprehensively.

Artificial intelligence (AI) has emerged as an important technology for transforming contemporary auditing. AI-driven auditing encompasses the use of machine learning, anomaly detection, predictive analytics, natural language processing and automated data analysis to support audit planning, risk assessment, transaction monitoring and fraud detection. These capabilities can enable auditors to analyze large data sets rapidly, identify unusual patterns and support more continuous monitoring.

However, the availability of AI technology does not automatically guarantee improves fraud outcomes. Data quality, algorithmic bias, explainability, privacy, cybersecurity, system integration, professional competence and human oversight may influence whether AI-generated alerts are translated into effective audit and investigative action. Evidence from developing economies is therefore particularly important because technological infrastructure, organizational readiness and human-capital capacity may differ from those of more technologically mature environments.

Public universities operate complex financial and administrative system involving public funding, procurement, payroll, research grants, contracts, stores, assets and revenue. Internal audit

departments consequently need mechanisms capable of monitoring diverse transactions and identifying irregularities promptly.

Federal universities in North-Western Nigeria provide a useful institutional setting for examining whether AI-enabled auditing is associated with measurable fraud detection outcomes. Existing studies have increasingly examined AI in banking, audit firms, financial services and other commercial environments, while comparatively, limited evidence has focused on federal universities in Nigeria. The institutional characteristics of public universities, including public sector accountability requirements, funding arrangements, procurement processes, and administrative structure, make it inappropriate to assume that evidence from commercial organizations will automatically generalize to universities. The presents study addresses this contextual gap by examining four dimensions of fraud detection effectiveness; fraud reduction, fraud detection accuracy, fraud loss reduction and fraud detection speed.

1.1 objectives of the study

1. To examine the relationship between AI-driven auditing and fraud reduction in federal universities in North-Western Nigeria.
2. To determine the relationship between AI-driven auditing and fraud detection accuracy in federal universities in North-Western Nigeria.
3. To assess the relationship between AI-driven auditing and fraud loss reduction in federal universities in North-Western Nigeria.
4. To examine the relationship between AI-driven auditing and fraud detection speed in federal universities in North-Western Nigeria.

1.2 Hypotheses

H_{01}: AI-driven auditing has no significant relationship with fraud reduction in federal universities in North-Western Nigeria.

H_{02}: AI-driven auditing has no significant relationship with fraud detection accuracy in federal universities in North-Western Nigeria.

H_{03}: AI-driven auditing has no significant relationship with fraud loss reduction in federal universities in North-Western Nigeria.

H_{04}: AI-driven auditing has no significant relationship with fraud detection speed in federal universities in North-Western Nigeria.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Conceptual Review

2.1.1 Artificial Intelligence-Driven Auditing

Artificial intelligence (AI)-driven auditing refers to the application of AI-enabled technologies to support and enhance audit planning, risk assessment, transaction analysis, control evaluation, anomaly detection and decision-making. Unlike conventional auditing, which often relies on predefined procedures, sampling and periodic examination, AI-driven auditing enables auditors to analyze large volumes of structured and unstructured data more rapidly and identify patterns or deviations that may warrant further investigation. Technologies commonly associated with AI-driven auditing include machine learning, predictive analytics, natural language processing, anomaly detection and automated data analytics.

The relevance of AI to auditing arises principally from its capacity to process information at a scale and speed that would be difficult to achieve through manual procedures. Machine-learning algorithms can identify patterns from historical data and detect unusual transactions, while predictive analytics can assist auditors in assessing the probability of particular risks. Natural language processing can support the analysis of unstructured information contained in reports, contracts, correspondence and other documents. These capabilities can expand audit coverage, improve risk-based audit selection and support more continuous monitoring of financial activities.

However, AI-driven auditing should not be regarded as a replacement for professional auditors. AI systems depend on the quality and completeness of the underlying data and may be affected by algorithmic bias, inadequate system integration, cybersecurity risks, limited explainability and

inappropriate human reliance on automated outputs. Effective AI-driven auditing therefore requires an appropriate combination of technological capability, quality data, professional competence, organizational support and human judgement.

2.1.2 Fraud Detection Effectiveness

Fraud detection effectiveness refers to the extent to which an organization's audit and control mechanisms successfully identify fraudulent activities accurately, promptly and comprehensively. In the context of this study, fraud detection effectiveness is reflected in fraud reduction, fraud detection accuracy, fraud loss reduction and fraud detection speed**.** These dimensions provide an outcome-oriented basis for assessing whether AI-driven auditing contributes meaningfully to the prevention and detection of financial misconduct.

Fraud reduction concerns the extent to which effective monitoring and detection mechanisms discourage or reduce fraudulent activities. Fraud detection accuracy refers to the ability of audit systems to distinguish genuine transactions from suspicious or fraudulent ones while minimizing false positives. Fraud loss reduction relates to the extent to which early identification of fraudulent activities limits the financial consequences of fraud. Fraud detection speed captures the time required to identify and flag potentially fraudulent activities.

AI technologies have the potential to strengthen each of these dimensions by analyzing large datasets continuously, identifying anomalous patterns and prioritizing transactions according to their risk characteristics. Nevertheless, technological capability alone does not guarantee effective fraud detection. The quality of data, system configuration, auditor competence, management support and the integration of AI outputs into investigation and control processes can determine whether potential technological benefits translate into actual fraud-detection outcomes.

2.2 Empirical Review

The empirical literature on AI-driven auditing and fraud detection has expanded considerably as organizations increasingly adopt data-driven technologies. However, the existing evidence varies substantially in terms of research design, institutional context and methodological rigor. The literature can broadly be divided into conceptual/review studies and empirical studies based on primary data.

Pemmasani et al. (2021) examined the application of AI-driven technologies to fraud detection in healthcare systems. Their study focused on machine learning, anomaly detection and predictive analytics and reported that AI could improve fraud-detection accuracy, reduce financial losses and enhance operational efficiency. However, the study relied primarily on conceptual and case-study evidence rather than primary quantitative data. Consequently, although it provides useful evidence regarding the potential application of AI to fraud detection, its findings cannot readily be generalized to other institutional contexts such as universities. The study also did not empirically examine organizational readiness or long-term implementation outcomes.

Bello et al. (2023) examined AI-driven approaches to real-time fraud detection, focusing on machine learning, deep learning, natural language processing, anomaly detection and hybrid AI models. The study reported that AI can strengthen fraud detection through real-time analysis, pattern recognition and anomaly detection. However, its predominantly conceptual and review-based approach, supported by case evidence, limited the extent to which the reported relationships could be empirically validated. The study also paid limited attention to developing-country environments and did not examine the influence of organizational or institutional factors on AI effectiveness.

Al-Qatawneh (2024) provides stronger empirical evidence by examining the relationship between AI-enabled accounting information systems and auditing and fraud detection, with natural language processing serving as a moderating variable. Using questionnaire data from 221 respondents, the study found a significant relationship between AI-enabled accounting information systems and auditing and fraud detection. It further established that natural language processing significantly moderated this relationship. The findings suggest that AI capabilities can complement conventional audit procedures and strengthen fraud-risk identification. Nevertheless, the study employed a cross-sectional design and did not establish how the relationship might evolve over time. It also did not specifically examine public universities or the institutional conditions affecting AI implementation.

Opuirobo (2024) examined the integration of AI, machine learning and business intelligence in accounting and auditing. The study identified predictive analytics, pattern recognition, natural language processing, anomaly detection and data visualization as important technological capabilities for improving auditing and fraud detection. The review concluded that AI and machine learning can strengthen risk assessment, anomaly detection, audit reliability and operational efficiency. However, the study was based on a qualitative review of existing literature rather than primary empirical observations. Its conclusions therefore provide useful theoretical support but limited evidence concerning the magnitude or statistical significance of AI's effect on fraud detection in specific organizational environments.

Wang et al. (2025) examined AI-driven systems and their potential contribution to accounting accuracy, fraud detection, transparency and compliance. Their review covered machine learning, deep learning, natural language processing, robotic process automation, predictive analytics, explainable AI and ERP integration. The study concluded that AI can strengthen anomaly detection, continuous auditing, predictive analysis and automated compliance processes. However, as a systematic and conceptual review, it did not provide primary empirical evidence. In addition, its treatment of developing-country contexts and organisational readiness was limited. These limitations reinforce the need for context-specific empirical research.

Ikumapayi and Ayankoya (2025) examined the application of AI and machine learning to forensic accounting, particularly real-time fraud detection and prevention. Their review focused on supervised and unsupervised learning and natural language processing. The authors concluded that AI can facilitate real-time analysis of large datasets, improve anomaly detection and enhance the identification of financial misconduct. They also emphasized the importance of data privacy, algorithmic governance and human oversight. However, the study relied predominantly on conceptual and case-based evidence and did not quantitatively validate the relationship between AI adoption and fraud-detection outcomes. It also provided limited evidence concerning developing-country organizations and organizational readiness.

Raza et al. (2025) investigated the role of AI in auditing, with particular attention to audit efficiency, risk management and fraud detection. The study considered machine learning, anomaly detection, predictive analytics and data analytics and reported that AI can improve real-time risk assessment, fraud-detection accuracy, audit efficiency and regulatory compliance. The study further highlighted the importance of continuous training, algorithmic transparency, human–AI collaboration and appropriate governance mechanisms. However, the limited longitudinal evidence and relatively limited attention to developing-country contexts constrain the generalizability of the findings.

Narender and Anand (2025) examined AI-driven fraud detection in financial services, focusing on machine learning, deep learning, natural language processing, anomaly detection, predictive analytics, behavioral analytics and explainable AI. Their review suggests that AI can improve fraud detection by enabling real-time monitoring, identifying complex patterns and adapting to changing fraud techniques. The authors also emphasized the importance of explainability, privacy protection, bias mitigation and regulatory governance. Nevertheless, the study was primarily conceptual and analytical, with limited empirical evidence concerning actual organizational outcomes. Its focus on financial services also leaves unanswered questions concerning AI-driven fraud detection in public-sector organizations such as universities.

Alaba et al. (2025) provide more context-specific evidence by examining the adoption of AI-driven fraud-detection systems in the Nigerian banking sector. Using primary data and logistic regression, the study found that management support, technological infrastructure, regulatory compliance, staff competence and perceived effectiveness influence AI adoption. The study is particularly relevant to the Nigerian context because it demonstrates that technological adoption is shaped not only by the perceived benefits of AI but also by organizational capacity and institutional conditions. However, its focus was on banks and AI adoption rather than the effectiveness of AI-driven auditing in detecting fraud. Moreover, the study relied on the perceptions of bank staff and did not examine public-sector institutions.

2.3 Empirical Review Gap

The reviewed literature generally suggests that AI can improve anomaly detection, risk assessment, transaction analysis and fraud detection. Al-Qatawneh (2024), for example, found a significant relationship between AI-enabled accounting information system and auditing and fraud detection, with natural language processing playing a moderating role. Nigerian evidence has increasingly examined the application of artificial intelligence to fraud detection and auditing. For example, Alaba et al. (2025) investigated the adoption of AI-driven fraud-detection systems in the Nigerian banking sector and found that management support, IT infrastructure, regulatory compliance, staff competence and perceived effectiveness significantly influence adoption, while high implementation costs constitute a constraint.

Similarly, Oluwadare et al. (2025) examined the role of AI adoption, investment in AI technologies and public perception in improving fraud-detection efficiency in Nigerian deposit money banks. In the auditing domain, Akinadewo et al. (2024) examined AI adoption among accounting firms in Southwest Nigeria and reported that data mining and image recognition were positively associated with audit quality, whereas machine learning did not have a significant positive effect. More recent evidence from Orji and Igwe (2026) indicates that AI-based audit analytics, machine-learning-enabled fraud-detection systems and robotic process automation are positively associated with auditor performance among listed deposit money banks in Nigeria. Despite these contributions, important gaps remain. Existing Nigerian studies have concentrated largely on commercial banks, financial services and audit firms**,** with considerably less empirical attention to public-sector higher-education institutions**.** Moreover, much of the existing evidence focuses on AI adoption, audit quality or auditor performance rather than directly examining multidimensional fraud-detection outcomes such as fraud reduction, detection accuracy, fraud-loss reduction and detection speed**.** Consequently, evidence remains limited on whether AI-driven auditing translates into measurable fraud-detection outcomes within Nigerian federal universities, particularly those in North-Western Nigeria.

2.4 Theoretical Framework

This study is anchored on the Technology Acceptance Model (TAM) developed by Davis (1989) and the Technology–Organization–Environment (TOE) framework proposed by Tornatzky, Fleischer, and Chakrabarti (1990). The two frameworks are integrated to explain how individual acceptance and organizational conditions influence the adoption and effective use of artificial intelligence (AI) in auditing and, consequently, its potential contribution to fraud-detection outcomes. TAM provides an individual-level explanation of technology acceptance, while TOE provides an organizational and environmental perspective on technology adoption.

2.4.1 Technology Acceptance Model (TAM)

TAM posits that perceived usefulness and perceived ease of use are fundamental determinants of an individual's acceptance and use of information technology (Davis, 1989). In AI-driven auditing, auditors are more likely to use AI-enabled technologies when they perceive them as useful for analysing large volumes of transactions, identifying anomalies, assessing risks, improving audit coverage and supporting timely decision-making. Similarly, technologies perceived as easy to understand and operate are more likely to be incorporated into routine audit activities.

TAM is relevant to this study because effective AI-driven auditing depends partly on auditors' willingness and ability to use AI technologies. However, TAM primarily explains individual technology acceptance rather than organizational fraud-detection outcomes. Therefore, this study uses TAM to explain the acceptance and use of AI-driven auditing, rather than to posit a direct relationship between TAM constructs and fraud reduction, detection accuracy, fraud loss reduction or detection speed.

2.4.2 Technology Organization Environment (TOE) Framework

The TOE framework explains organizational technology adoption through three contexts: technological, organizational and environmental (Tornatzky et al., 1990). The technological context includes the availability, compatibility, complexity and capability of relevant technologies, as well as

data infrastructure and system integration. In AI-driven auditing, these factors include audit analytics, machine-learning applications, anomaly-detection tools and compatible financial information systems.

The organizational context encompasses management support, financial resources, employee competence, training and organizational readiness. These factors are particularly relevant to federal universities, where effective AI implementation may depend on management commitment, investment in digital infrastructure and the availability of competent internal auditors. The environmental context includes regulatory requirements, professional standards, government policies and wider institutional pressures that may facilitate or constrain AI adoption.

TOE therefore complements TAM by extending the explanation beyond the individual auditor. While TAM explains auditors' perceptions and willingness to use AI, TOE explains the institutional conditions required for its adoption, implementation and continued use.

2.4.3 Integration of TAM and TOE

The integration of TAM and TOE provides a multi-level explanation of AI-driven auditing. TAM explains the individual-level acceptance and use of AI, whereas TOE explains the organizational and environmental conditions that support or constrain its implementation. The resulting theoretical pathway is:

TAM + TOE → AI Adoption/Use → AI-Driven Auditing Capability → Fraud-Detection Outcomes

The framework assumes that technological readiness, organizational support and favorable environmental conditions, together with auditors' perceptions of AI usefulness and ease of use, facilitate effective AI adoption and use. Once embedded in audit processes, AI-enabled capabilities such as anomaly detection, machine learning, predictive analytics, continuous auditing and automated risk assessment can strengthen the analysis and monitoring of financial transactions.

In this study, fraud-detection effectiveness is assessed through four dimensions: fraud reduction, fraud detection accuracy, fraud loss reduction and fraud detection speed. The framework does not assume that AI will affect all four outcomes equally. AI may improve the accuracy and speed of identifying suspicious transactions without necessarily producing a corresponding reduction in financial losses. Financial-loss reduction may additionally depend on investigation, recovery, sanctions, management response and control remediation.

Accordingly, AI-driven auditing is conceptualized as an enabling audit capability rather than an automatic substitute for professional judgement and institutional fraud-response mechanisms. The integrated TAM–TOE framework therefore provides the theoretical basis for examining whether AI-driven auditing is associated with measurable improvements in the four dimensions of fraud-detection effectiveness within federal universities in North-Western Nigeria.

3.0 METHODOLOGY

This study adopts a cross-sectional quantitative survey design to examine the relationship between AI-driven auditing and fraud detection effectiveness in federal universities in North-Western Nigeria. The study relies on primary data collected through a structured questionnaire administered to internal auditors in the selected institutions.

3.1 Population of the study

The study population comprised the 92 internal auditors employed in the seven selected federal universities in North-Western Nigeria. Data were collected using a structured questionnaire measured on a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. The instrument measures AI-driven auditing and four dimensions of fraud detection effectiveness: fraud reduction, fraud detection accuracy, fraud loss reduction and fraud detection speed. Content validity was established through expert review, while internal consistency was assessed using Cronbach's alpha coefficients for each construct.

Descriptive statistics, including frequencies, percentages, means and standard deviations, were used to summaries the data. Inferential analysis was conducted using correlation and regression techniques to examine the relationship between AI-driven auditing and fraud detection effectiveness. Diagnostic tests were conducted to assess the assumptions underlying the regression analysis, including

multicollinearity, linearity and homoscedasticity. Statistical significance was assessed at the 5% level. The study specifies four simple linear regression models to examine whether AI-driven auditing significantly explains variation in each dimension of fraud detection effectiveness. Independent variable: AI-Driven Auditing (AIA)

Dependent variables

FR = Fraud Reduction
FDA = Fraud Detection Accuracy
FLR = Fraud Loss Reduction
FDS = Fraud Detection Speed

Therefore:

$FR = \beta_0+\beta 1AIA+\epsilon$
$FDA = \beta_0+\beta 1AIA+\epsilon$
$FLR = \beta_0+\beta 1AIA+\epsilon$
$FDS = \beta_0+\beta 1AIA+\epsilon$

3.2 Sampling Technique

The accessible population of internal auditors across the seven selected federal universities was relatively small (N = 92), the study adopted total enumeration, whereby all 92 internal auditors were targeted.

Table 3.1: Population of the Study

University	**Population of Internal Auditors**	**Proportion**	**Allocated Sample**
Ahmadu Bello University (ABU), Zaria	46	49.46	46
Bayero University (BUK), Kano	12	12.90	12
Usmanu Danfodiyo University (UDUS), Sokoto	03	3.23	3
Federal University Dutse (FUD)	12	12.90	12
Federal University Dutsin-Ma (FUDMA)	07	7.53	7
Federal University Gusau (FUGUS)	06	6.45	6
Federal University Birnin Kebbi (FUBK)	06	6. 45	6
Total	**92**	**100**	**92**

SOURCE: FIELD SURVEY BY THE RESEARCHER (2026)

Population Share (%) represents each university's percentage contribution to the total population of 92 internal auditors. The study employed total enumeration; therefore, the "Number Included in Census" is identical to the number of internal auditors in each university. No proportional sampling allocation was undertaken.

3.3 Data Collection Instrument

Primary data are collected using a structured questionnaire developed from the study objectives and relevant empirical literature on AI-driven auditing and fraud detection effectiveness. The questionnaire is measured using a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. The instrument consists of items measuring AI-driven auditing and the four dimensions of fraud detection effectiveness: fraud reduction, fraud detection accuracy, fraud loss reduction and fraud detection speed.

4.1 Results and Discussions

In this section, the findings of both descriptive and inferential analysis are presented. The descriptive analysis focused on capturing the biodata of the respondents, including gender, educational qualifications, and work experience. The results of the respondents' biodata is presented in Table 4.1, below.

Table 4.1: Biodata of the Respondents

Characteristic	Category	Frequency	Percentage
Gender	Male	91	98.91
	Female	1	1.09
	Total	92	100.00
Qualification	BSc	66	71.74
	HND	2	2.17
	MSc	22	23.91
	PhD	2	2.17
	Total	92	100.00
Experience	1–5 years	5	5.43
	6–10 years	67	72.83
	11–15 years	10	10.87
	16–20 years	5	5.43
	21+ years	5	5.43
	Total	**92**	**100.00**

Source: Field Survey, 2026

The respondents were predominantly male (98.91%), while 71.74% held a BSc and 23.91% held an MSc. Most respondents (72.83%) had 6–10 years of experience, and 89.13% had at least six years of professional experience. These characteristics indicate substantial professional exposure, although the extreme gender imbalance raises concern about the representativeness of the sample.

4.2 Preliminary Data Screening and Measurement Scoring

The study analyzed responses obtained from 92 internal auditors across seven selected federal universities in North-Western Nigeria. The study employed a census approach because the accessible population comprised 92 internal auditors.

The questionnaire responses were coded on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The instrument measured five substantive constructs: AI-driven auditing, fraud reduction, fraud detection accuracy, fraud loss reduction and fraud detection speed. The negatively worded items were reverse-coded before the computation of construct scores. The construct scores were calculated as the arithmetic mean of their respective items as follows:

AI-driven auditing (AIA): Q1–Q26

Fraud reduction (FR): Q27–Q31

Fraud detection accuracy (FDA): Q32–Q36

Fraud loss reduction (FLR): Q37–Q41

Fraud detection speed (FDS): Q42–Q46

Items Q32, Q33, Q39 and Q40 were reverse-coded. Q47 was excluded because it exhibited no variance across respondents and therefore could not contribute to statistical discrimination among observations.

4.3 Reliability Analysis

Cronbach's alpha was employed to assess the internal consistency of the measurement items. The results are presented in Table 4.2.

Table 4.2: Reliability Analysis of the Study Constructs

Construct	Number of items	Cronbach's α	Assessment
AI-driven auditing	26	.970	Excellent
Fraud reduction	5	.822	Good
Fraud detection accuracy	5	.809	Good
Fraud loss reduction	5	.715	Acceptable
Fraud detection speed	5	.938	Excellent
Overall instrument	46	.959	Excellent

Source: Authors' computation from SPSS.

The results indicate satisfactory internal consistency across all five constructs. Cronbach's alpha coefficients ranged from .715 to .970, exceeding the commonly accepted minimum threshold of .70. The AI-driven auditing construct recorded the highest reliability coefficient (α = .970), followed by fraud detection speed (α = .938). Fraud loss reduction recorded the lowest coefficient (α = .715), although it remained within the acceptable range. The overall reliability coefficient of .959 indicates a high level of internal consistency across the substantive items. The original questionnaire comprised 47 items. Item Q47 was subsequently excluded following the preliminary assessment; therefore, the reliability analysis and subsequent empirical analyses were based on the 46 retained items (Q1–Q46).

4.4 Descriptive Statistics

Descriptive statistics were computed to establish the central tendency and dispersion of the study variables. The results are presented in Table 4.3.

Table 4.3: Descriptive Statistics of the Study Variables

Variable	N	Minimum	Maximum	Mean	SD
AI-driven auditing	92	1.42	4.42	3.238	1.052
Fraud reduction	92	1.60	4.40	2.820	.831
Fraud detection accuracy	92	3.20	4.80	3.809	.547
Fraud loss reduction	92	2.00	4.60	3.074	.832
Fraud detection speed	92	1.00	4.80	3.152	1.447

Source: Authors' computation from SPSS.

The mean score for AI-driven auditing was 3.238 (SD = 1.052), indicating a generally favorable perception of AI-driven auditing among the respondents. Fraud detection accuracy recorded the highest mean score (M = 3.809, SD = .547), suggesting that respondents perceived AI-driven auditing as particularly useful for improving the accuracy of fraud identification. Fraud detection speed recorded a mean of 3.152 (SD = 1.447), while fraud loss reduction recorded M = 3.074 (SD = .832). Fraud reduction recorded the lowest mean (M = 2.820, SD = .831) among the four outcome variables. The relatively large standard deviation for fraud detection speed indicates greater variation in respondents' perceptions concerning the contribution of AI-driven auditing to the speed of fraud detection.

4.5 Pearson Correlation Analysis

Pearson product-moment correlation analysis was conducted to determine the direction and strength of the association between AI-driven auditing and each dimension of fraud-detection effectiveness.

Table 4.4: Pearson Correlation Matrix

Variable	AIA	FR	FDA	FLR	FDS
AIA	1.000	.553 (<.001)	.716 (<.001)	−.085 (.423)	.563 (<.001)
FR	.553 (<.001)	1.000	−.037 (.724)	−.536 (<.001)	−.215 (.040)
FDA	.716 (<.001)	−.037 (.724)	1.000	.436 (<.001)	.569 (<.001)
FLR	−.085 (.423)	−.536 (<.001)	.436 (<.001)	1.000	.287 (.006)
FDS	.563 (<.001)	−.215 (.040)	.569 (<.001)	.287 (.006)	1.000

Note. Values are Pearson correlation coefficients (*r*), with two-tailed *p*-values reported in parentheses. N = 92.

Source: Authors' computation from SPSS.

Table 4.4 presents the Pearson correlation coefficients and corresponding two-tailed *p*-values for the study variables. AI-driven auditing (AIA) has a moderate and statistically significant positive correlation with fraud reduction (FR) ($r = .553$, $p < .001$), a strong positive correlation with fraud detection accuracy (FDA) ($r = .716$, $p < .001$), and a moderate positive correlation with detection speed (FDS) ($r = .563$, $p < .001$).

In contrast, the correlation between AI-driven auditing and fraud loss reduction (FLR) is weak and negative and is not statistically significant ($r = −.085$, $p = .423$). This finding indicates that, although the observed direction of the relationship is negative, there is insufficient statistical evidence of a systematic association between AI-driven auditing and fraud loss reduction in the sampled institutions.

Among the outcome variables, fraud reduction is negatively correlated with fraud detection accuracy ($r = -.037$, $p = .724$), indicating no statistically significant association. Fraud reduction has a statistically significant negative correlation with fraud loss reduction ($r = -.536$, $p < .001$) and a weak negative correlation with detection speed ($r = -.215$, $p = .040$). Fraud detection accuracy is positively and significantly correlated with fraud loss reduction ($r = .436$, $p < .001$) and detection speed ($r = .569$, $p < .001$). Fraud loss reduction also has a positive and statistically significant correlation with detection speed ($r = .287$, $p = .006$).

Overall, the correlation results indicate that AI-driven auditing is positively associated with fraud reduction, fraud detection accuracy, and detection speed, whereas its association with fraud loss reduction is weak, negative, and statistically insignificant. These bivariate findings provide preliminary evidence for the subsequent regression analyses.

4.6 Regression Analysis

Four separate simple linear regression models were estimated to examine the relationships between AI-driven auditing and the four dimensions of fraud-detection effectiveness. This approach is consistent with the study's stated empirical model, which specifies four separate outcomes. This is

because each model contains only one independent variable, multicollinearity is not a relevant diagnostic issue.

Table 4.5: Regression Results for AI-Driven Auditing and Fraud Reduction

Statistic	R	R^2	Adjusted R^2	F (1, 90)	p-value	Constant (B)	AI-driven auditing (B)	Standard Error	Standardized Beta (β)	t-value
Result	.553	.305	.298	39.566	< .001	1.406	.437	.069	.553	6.290

Source: Authors' computation from SPSS.

The regression results in Table 4.5 show that AI-driven auditing has a positive and statistically significant association with fraud reduction ($\beta = .553$, $t = 6.290$, $p < .001$). The model produced an R^2 of .305, indicating that AI-driven auditing accounts for approximately 30.5% of the observed variance in fraud reduction. The regression equation is: FR = 1.406 + 0.437AIA

The significant positive coefficient indicates that increases in the AI-driven auditing score are associated with increases in the fraud-reduction score.

Accordingly, H01 is rejected.

The result suggests that AI-driven auditing is significantly associated with perceived fraud reduction among internal auditors in the selected federal universities.

Table 4.6: Regression Results for AI-Driven Auditing and Fraud Detection Accuracy

Statistic	**R**	**R^2**	**Adjusted R^2**	**F**	**p-value**	**Constant (B)**	**AI-driven Auditing (B)**	**Standard Error**	**Beta (β)**	**t-value**
Result	.716	.513	.507	94.750	< .001	2.603	.372	.038	.716	9.734

Source: Authors' computation from SPSS.

The results presented in Table 4.6 reveal a strong positive and statistically significant relationship between AI-driven auditing and fraud detection accuracy. The correlation coefficient ($R = 0.716$) indicates a strong positive association, while the coefficient of determination ($R^2 = 0.513$) shows that AI-driven auditing explains approximately 51.3% of the variation in fraud detection accuracy. The adjusted R^2 of 0.507 confirms that the model retains substantial explanatory power after adjusting for sample size and model specification.

The regression model was statistically significant, $F(1, 90) = 94.750$, $p < .001$, indicating that AI-driven auditing significantly predicts fraud detection accuracy. Furthermore, AI-driven auditing had a positive and significant effect ($B = 0.372$, $SE = 0.038$, $\beta = 0.716$, $t = 9.734$, $p < .001$). Thus, a one-

unit increase in AI-driven auditing is associated with an estimated 0.372-unit increase in fraud detection accuracy. The regression equation is FDA = 2.603 + 0.372AIA.

Based on these results, the null hypothesis that AI-driven auditing has no significant effect on fraud detection accuracy is rejected. The finding suggests that greater application of AI-enabled auditing techniques is associated with improved accuracy in identifying potentially fraudulent transactions and activities. However, since 48.7% of the variance in fraud detection accuracy remains unexplained, other factors, such as auditor expertise, internal control quality, technological infrastructure, audit resources, organizational support, and financial data quality, may also contribute to fraud detection accuracy.

Table 4.7: Regression Results for AI-Driven Auditing and Fraud Loss Reduction

Statistic	**Result**
R	.085
R^2	.007
Adjusted R^2	−.004
F (1, 90)	.647
p-value	.423
Constant (B)	3.290
AI-driven auditing (B)	−.067
Standard Error	.083
Standardized Beta (β)	−.085
t-value	−.805

Source: Authors' computation from SPSS.

Table 4.7 reports the simple linear regression results for the effect of AI-driven auditing on fraud loss reduction. The model indicates a very weak negative association between the variables (R = .085; R^2 = .007), with AI-driven auditing accounting for only 0.7% of the variance in fraud loss reduction. The negative adjusted R^2 (−.004) further suggests that the model provides virtually no explanatory improvement over an intercept-only model.

The regression model was not statistically significant, F (1, 90) = 0.647, p = .423. Similarly, the coefficient for AI-driven auditing was negative but insignificant (B = −.067, SE = .083, β = −.085, t = −.805, p = .423). Thus, a one-unit increase in AI-driven auditing was associated with an estimated 0.067-unit decrease in fraud loss reduction; however, this effect was not statistically significant. The finding therefore provides no sufficient evidence that AI-driven auditing significantly predicts fraud loss reduction in the sampled institutions.

The estimated regression equation is FLR = 3.290 − 0.067AIA, where FLR denotes fraud loss reduction and AIA denotes AI-driven auditing. This result is consistent with the Pearson correlation reported in Table 4.3 (r = −.085, p = .423), confirming that the relationship is weak, negative, and statistically insignificant.

Table 4.8: Regression Results for AI-Driven Auditing and Fraud Detection Speed

Statistic	R	R^2	Adjusted R^2	F (1, 90)	p-value	Constant (B)	AI-driven auditing (B)	Standard Error	Standardized Beta (β)	t-value
Result	.563	.317	.310	41.789	<.001	.644	.775	.120	.563	6.464

Source: Authors' computation from survey data.

The regression results in Table 4.8 show that AI-driven auditing is positively and significantly associated with fraud detection speed (β = .563, t = 6.464, p < .001). The model's R^2 of .317 indicates that AI-driven auditing accounts for approximately 31.7% of the variance in fraud detection speed. The regression equation is: FDS = .644 + .775AIA

The positive coefficient indicates that greater perceived application of AI-driven auditing is associated with faster fraud detection. Therefore, H04 is rejected.

Table 4.9: Summary of the Four Regression Models

Dependent variable	**R**	**R^2**	**Adjusted R^2**	**β**	**t**	**F**	**p**	**Decision**
Fraud reduction	.553	.305	.298	.553	6.290	39.566	<.001	Significant
Detection accuracy	.716	.513	.507	.716	9.734	94.750	<.001	Significant
Fraud loss reduction	.085	.007	-.004	-.085	-.805	.647	.423	Not significant
Detection speed	.563	.317	.310	.563	6.464	41.789	<.001	Significant

Source: Authors' computation from survey data.

Overall, the results show that AI-driven auditing has statistically significant positive associations with fraud reduction, fraud detection accuracy and fraud detection speed, but not with fraud loss reduction.

The strongest relationship is observed for fraud detection accuracy ($\beta = .716$, $R^2 = .513$), followed by fraud detection speed ($\beta = .563$, $R^2 = .317$) and fraud reduction ($\beta = .553$, $R^2 = .305$).

Fraud loss reduction has a negligible and statistically insignificant association with AI-driven auditing ($\beta = -.085$, $R^2 = .007$, $p = .423$).

4.7 Regression Diagnostic Tests

Regression diagnostics were conducted to assess the adequacy of the assumptions underlying ordinary least squares (OLS) estimation. The assessment focused on the distribution of residuals, heteroscedasticity, and model specification. The diagnostic results indicated some departure from the classical OLS assumptions, particularly with respect to residual normality and the potential presence of heteroscedasticity. The Ramsey RESET test also provided evidence warranting caution regarding model specification. These diagnostic findings suggest that the conventional OLS standard errors and associated significance tests should be interpreted with appropriate caution.

To examine the robustness of the statistical inferences, HC3 heteroscedasticity-consistent standard errors were estimated. The HC3 estimator provides a more conservative adjustment to standard errors in the presence of heteroscedasticity and is particularly suitable for relatively small samples. The conventional OLS estimates were therefore compared with the HC3-adjusted estimates to assess whether the direction and statistical significance of the reported relationships were sensitive to potential heteroscedasticity.

The robustness analysis provides an additional basis for evaluating the stability of the regression findings. Where the HC3-adjusted results are consistent with the conventional OLS estimates, the substantive conclusions are considered robust to heteroscedasticity. Where differences arise, the HC3-adjusted estimates provide the more appropriate basis for statistical inference. Accordingly, the regression findings are interpreted with due consideration of the diagnostic evidence and the robustness results. The results of the diagnostic and robustness analyses are presented in Table 4.10**.**

Table 4.10: Regression Diagnostic Tests

Diagnostic	Fraud Reduction	Detection Accuracy	Fraud Loss Reduction	Detection Speed	Assessment
Durbin-Watson	2.878	2.471	1.746	2.313	Generally acceptable for independence
Breusch-Pagan p	<.001	.012	<.001	<.001	Heteroscedasticity detected
Shapiro-Wilk p	<.001	<.001	<.001	<.001	Residual normality rejected
RESET p	<.001	<.001	<.001	<.001	Possible functional-form misspecification

Source: Authors' computation from survey data.

The Durbin-Watson statistics range from 1.746 to 2.878. The fraud loss reduction model is close to the conventional range suggesting limited serial correlation, while the other models show values above 2. Because the data are cross-sectional rather than time-series observations, the Durbin-Watson statistic should not be overinterpreted.

The Breusch-Pagan tests are statistically significant for all four models ($p < .05$), indicating evidence of heteroscedasticity. Consequently, the conventional OLS standard errors and p-values should be treated cautiously.

The Shapiro-Wilk tests are also statistically significant across all four models, indicating that the regression residuals depart from normality. This result is not unexpected given the ordinal-Likert-based composite measures and the observed concentration/repetition in the responses.

The Ramsey RESET tests are statistically significant for all four models, indicating potential functional-form misspecification or non-linearity.

4.8 Robustness Check Using Heteroscedasticity-Consistent Standard Errors

The Breusch-Pagan tests indicate heteroscedasticity, a sensitivity analysis using HC3 heteroscedasticity-consistent standard errors was conducted.

Table 4.11: HC3 Robustness Check

Dependent variable	β	HC3 SE	Robust t	Robust p	Conclusion
Fraud reduction	.437	.053	8.188	<.001	Significant
Detection accuracy	.372	.019	19.344	<.001	Significant
Fraud loss reduction	-.067	.057	-1.182	.240	Not significant
Detection speed	.775	.124	6.249	<.001	Significant

Source: Authors' computation from survey data.

The HC3 robustness check produces the same substantive decisions as the conventional regression models. AI-driven auditing remains significantly associated with fraud reduction, detection accuracy and detection speed, while the relationship with fraud loss reduction remains statistically insignificant. This provides some reassurance that the principal findings are not solely attributable to heteroscedasticity. However, HC3 does not solve the duplication/data-integrity issue or the significant RESET results.

4.9 Multicollinearity Diagnostic

Multicollinearity was not assessed using VIF or tolerance because each regression model contains only one independent variable AI-driven auditing.

Consequently, there can be no predictor-to-predictor multicollinearity within these four simple regression models.

4.10 Hypothesis Testing

The hypotheses were evaluated at the 5% significance level.

Table 4.12: Summary of Hypothesis Testing

Hypothesis	Statistical evidence	Decision
H01: AI-driven auditing has no significant relationship with fraud reduction.	$\beta = .553$, $R^2 = .305$, $p < .001$	**Reject H01**
H02: AI-driven auditing has no significant relationship with fraud detection accuracy.	$\beta = .716$, $R^2 = .513$, $p < .001$	**Reject H02**
H03: AI-driven auditing has no significant relationship with fraud loss reduction.	$\beta = -.085$, $R^2 = .007$, $p = .423$	**Fail to reject H03**
H04: AI-driven auditing has no significant relationship with fraud detection speed.	$\beta = .563$, $R^2 = .317$, $p < .001$	**Reject H04**

Source: Authors' computation from survey data.

Three of the four null hypotheses are rejected. Specifically, AI-driven auditing is significantly associated with fraud reduction, fraud detection accuracy and fraud detection speed. The third null hypothesis is not rejected because the relationship between AI-driven auditing and fraud loss reduction is statistically insignificant.

The empirical evidence indicates that AI-driven auditing is significantly associated with three important dimensions of fraud-detection effectiveness.

First, AI-driven auditing is positively associated with fraud reduction, explaining 30.5% of the observed variance. This suggests that the application of AI-enabled audit procedures may support auditors in identifying unusual transactions and strengthening fraud-related controls.

Second, AI-driven auditing demonstrates its strongest relationship with fraud detection accuracy. With an R^2 of .513 and a standardized coefficient of .716, the findings suggest that AI-driven auditing has a particularly strong association with the accuracy with which fraudulent or suspicious activities are identified.

Third, AI-driven auditing is significantly associated with fraud detection speed, explaining 31.7% of its variance. This finding supports the proposition that automated analytical procedures can enable auditors to identify suspicious patterns more rapidly than purely periodic manual procedures.

Fourth, and importantly, AI-driven auditing is not significantly associated with fraud loss reduction. Only 0.7% of the variance in fraud loss reduction is explained by AI-driven auditing, and the relationship is statistically insignificant. This finding suggests that the ability to detect fraud does not necessarily translate into recovery or prevention of financial losses.

The distinction is important. An AI system may generate a timely and accurate fraud alert, but the eventual financial outcome may depend on whether the alert is investigated, whether evidence is sufficient, whether funds can be recovered, whether sanctions are imposed, and whether underlying control weaknesses are corrected.

5.1 Conclusion

This study examined the effect of AI-driven auditing on fraud detection effectiveness in federal universities in North-Western Nigeria, drawing on the Technology Acceptance Model (TAM) and the Technology–Organization–Environment (TOE) framework. The findings show that AI-driven auditing significantly enhances fraud detection accuracy, indicating that AI-enabled audit tools can strengthen auditors' ability to identify suspicious transactions, anomalies and potential fraudulent activities. However, AI-driven auditing did not significantly predict fraud loss reduction, indicating that enhanced detection does not automatically translate into reduced financial losses.

The study therefore concludes that AI-driven auditing primarily strengthens fraud-detection capability, while the realization of fraud-loss reduction depends on effective post-detection responses, including investigation, recovery, sanctions and control remediation. Consistent with TAM, effective use of AI also requires auditor competence and acceptance, while TOE emphasizes adequate technological infrastructure, organizational support and governance. Accordingly, AI-driven auditing should be regarded as an augmentation of professional auditing rather than a stand-alone solution to fraud.

5.2 Recommendations

Based on the findings and conclusions, the study recommends that:

1. Federal universities should strengthen AI-enabled audit capacity through appropriate investment in audit analytics, anomaly-detection and continuous-monitoring technologies, supported by adequate ICT infrastructure and technical assistance. This is justified by the significant positive effect of AI-driven auditing on fraud detection accuracy.
2. AI-enabled detection should be integrated with formal post-detection response mechanisms. AI-generated alerts should be followed by timely investigation, recovery of losses, appropriate sanctions and control remediation. This is particularly important given the absence of a significant effect of AI-driven auditing on fraud loss reduction.
3. Universities should continuously develop internal auditors' AI competence and acceptance. Training should focus on data analytics, AI-assisted auditing and interpretation of automated outputs to enhance auditors' ability and willingness to use AI effectively, consistent with the TAM perspective.
4. University management should establish appropriate AI governance and organizational support mechanisms. These should include data-quality controls, access restrictions, audit trails, human oversight and clear accountability for AI-generated audit outputs, consistent with the organizational and technological conditions emphasized by the TOE framework.

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