JCARM
Journal of Contemporary Academic Research and Methodologies

An Online Peer Reviewed / Refereed Journal
Volume 1 | Issue 4 | May 2026
Website: www.journal.jcarm.in

Research

Artificial Intelligence–Driven Audit Analytics and Fraud Detection Effectiveness in Public Sector Procurement Systems: A Quantitative Study in Nigeria

Oboh, Christopher Ikhianosime[1]*, Balogun, Ehime Moses[2], Aliu, Momodu Mohammed (PhD)[3], Igiekhume, Mohammed Nurudeen[4]

[1]Department of Procurement and Supply Chain Management, School of Administration, Business and Management Studies, Auchi Polytechnic, Auchi, Edo State, Nigeria.
[2]Directorate of Procurement, Auchi Polytechnic, Auchi, Edo State, Nigeria.
[3]Department of Accountancy, School of Financial Studies, Auchi Polytechnic, Auchi, Edo State, Nigeria
[4]Department of Public Administration, School of Administration, Business and Management Studies, Auchi Polytechnic, Auchi, Edo State, Nigeria

Correspondence should be addressed to: chrisoboh01@gmail.com

Abstract: Public sector procurement systems remain highly vulnerable to fraud, inefficiency, and weak accountability structures, particularly in developing economies where manual audit processes dominate financial oversight. This study examines the effect of artificial intelligence (AI)–driven audit analytics on fraud detection effectiveness in public sector procurement systems using a quantitative IMRaD structure aligned with Scopus-indexed journal standards. The study adopted a descriptive survey research design with a population of 1,000 respondents drawn from procurement officers, internal auditors, ICT personnel, and compliance units in selected public institutions in Nigeria. A sample size of 286 respondents was determined using the Taro Yamane sampling formula. Data were collected through structured questionnaires and analysed using descriptive statistics, Pearson correlation, and multiple regression analysis. Findings reveal that AI-driven anomaly detection, predictive analytics, machine learning-based risk scoring, and real-time procurement monitoring significantly enhance fraud detection effectiveness. However, inadequate digital infrastructure, resistance to technological change, and limited AI competencies constrain full system optimisation. Regression results indicate a strong and statistically significant relationship between AI-driven audit analytics and fraud detection effectiveness. The study concludes that artificial intelligence significantly strengthens procurement transparency and audit efficiency while reducing fraud exposure in public sector systems. It recommends accelerated digital transformation, institutional capacity building, and full integration of AI audit tools in procurement governance frameworks.

https://doi.org/10.5281/zenodo.20605034

Keywords: Artificial intelligence, audit analytics, fraud detection, procurement systems, public sector, Nigeria, machine learning.

1.1 Introduction

Public sector procurement systems are essential for ensuring efficient allocation and utilisation of government resources, yet they remain highly exposed to fraud, contract manipulation, and weak accountability structures. In many developing economies such as Nigeria, these inefficiencies result in revenue leakages, project distortions, and reduced public trust in governance. Empirical governance reports indicate that procurement systems are among the most vulnerable areas of public finance due to limited transparency and weak monitoring frameworks (World Bank, 2024).

A key problem is the continued reliance on manual and periodic audit systems that are largely reactive rather than preventive. Such conventional systems are no longer adequate in detecting increasingly sophisticated procurement fraud, including collusive bidding, digital record manipulation, and concealed transaction patterns. Studies show that traditional audit sampling methods are insufficient in addressing large-scale procurement datasets and dynamic fraud structures in modern public financial environments (International Monetary Fund, 2023; OECD, 2023).

The gap in existing procurement audit systems lies in the limited integration of advanced digital technologies capable of real-time monitoring and predictive fraud detection. Many public institutions in Nigeria still depend on fragmented databases, low automation levels, and underdeveloped analytical infrastructure, which restricts effective fraud detection capability. Additionally, there is a shortage of technical expertise required to deploy advanced analytics and artificial intelligence tools for audit functions. Recent evidence suggests that although digital audit innovations are expanding globally, adoption in developing economies remains constrained by institutional and infrastructural limitations (OECD, 2024; World Bank, 2025).

Artificial intelligence (AI)–driven audit analytics provides a viable solution by enabling continuous monitoring, anomaly detection, and predictive risk assessment in procurement systems. AI technologies such as machine learning algorithms can process large volumes of procurement data to identify irregular patterns and flag high-risk transactions in real time, thereby shifting auditing from reactive inspection to proactive fraud prevention. International policy evidence confirms that AI integration significantly

improves audit efficiency, transparency, and fraud detection effectiveness in public procurement environments (International Monetary Fund, 2023; OECD, 2025).

2. Literature Review

2.1 Concept of Artificial Intelligence–Driven Audit Analytics

Artificial Intelligence (AI)–driven audit analytics refers to the application of advanced computational techniques such as machine learning, data mining, predictive modelling, natural language processing, and anomaly detection in auditing processes to enhance the identification of irregularities, risks, and fraudulent activities within financial and operational datasets. Unlike traditional audit systems that rely on manual sampling and retrospective review, AI-enabled audit analytics provides continuous, real-time, and full-population data analysis, thereby improving the speed, accuracy, and depth of audit outcomes. This technological shift has redefined modern auditing from a periodic compliance exercise into a dynamic, data-driven assurance mechanism.

At its core, AI-driven audit analytics operates by extracting large volumes of structured and unstructured procurement data and applying algorithmic models that detect patterns indicative of fraud or operational inefficiencies. These systems are capable of identifying anomalies such as duplicate payments, unusual procurement cycles, inflated invoices, vendor collusion patterns, and split contracts designed to evade approval thresholds. The integration of predictive analytics further allows auditors to forecast potential fraud risks before transactions are completed, thereby enabling proactive intervention rather than reactive investigation.

In public sector procurement systems, the relevance of AI-driven audit analytics is particularly significant due to the complexity and scale of government financial transactions. Procurement datasets often involve multiple stakeholders, diverse vendor networks, and high-frequency transaction flows, making manual oversight increasingly inefficient. AI systems enhance audit coverage by analysing entire datasets rather than relying on statistical sampling, thereby reducing the probability of undetected fraud. According to the International Monetary Fund (2023), digital audit transformation improves fiscal transparency by enabling real-time monitoring of public financial transactions and strengthening institutional accountability mechanisms.

Furthermore, AI audit systems incorporate machine learning algorithms that continuously improve their detection accuracy through exposure to historical fraud patterns. Supervised learning models can be trained using labelled procurement fraud cases, while

unsupervised models identify unknown or emerging fraud patterns without prior classification. This adaptive capability makes AI particularly effective in addressing evolving procurement fraud strategies that often bypass traditional rule-based audit systems. The Organisation for Economic Co-operation and Development (2023) notes that AI-based audit tools significantly enhance risk detection capacity by improving pattern recognition across complex procurement environments.

In addition, AI-driven audit analytics supports real-time decision-making by providing dashboards, alerts, and automated risk scores that assist auditors and procurement regulators in prioritising high-risk transactions. This reduces audit lag and enhances responsiveness to potential financial irregularities. The integration of big data analytics further allows institutions to consolidate procurement records from multiple agencies into unified platforms, improving transparency and data consistency across public financial systems.

Despite these advantages, the effectiveness of AI-driven audit analytics is influenced by institutional readiness, data quality, and technological infrastructure. In many developing economies, including Nigeria, challenges such as poor data integration, limited digital literacy among audit personnel, and inadequate ICT infrastructure hinder full implementation. Nevertheless, global policy evidence suggests that where properly implemented, AI significantly strengthens audit efficiency, reduces fraud exposure, and enhances accountability in procurement systems (World Bank, 2024; OECD, 2025).

AI-driven audit analytics represents a transformative advancement in modern auditing practice by shifting fraud detection from manual, reactive procedures to intelligent, predictive, and continuous monitoring systems. Its application in public sector procurement systems offers significant potential for improving transparency, strengthening accountability, and reducing financial misconduct in government expenditure processes.

2.2 Fraud Detection in Public Sector Procurement Systems

Fraud detection in public sector procurement systems refers to the systematic identification, analysis, and prevention of irregularities, misappropriation, and unethical practices within the procurement lifecycle. It involves detecting activities such as bid rigging, contract inflation, collusion among contractors, falsification of procurement records, and diversion of public funds. Effective fraud detection is central to ensuring transparency, accountability, and value for money in government expenditure. In well-functioning procurement systems, fraud detection is not only a post-audit activity but

an ongoing governance function embedded within procurement planning, execution, and monitoring processes.

In practice, procurement fraud typically occurs when internal controls are weak and oversight mechanisms are ineffective. Fraudulent actors exploit gaps in procurement procedures such as non-competitive bidding, lack of transparency in vendor selection, and poor documentation practices. These vulnerabilities are often compounded by limited digitalisation of procurement records, which makes it difficult to trace transactions and verify compliance. Consequently, fraud detection becomes reactive rather than preventive, with many irregularities discovered only after financial losses have already occurred.

Within Nigeria's public financial management system, procurement fraud remains a persistent challenge affecting both federal and subnational institutions. The Economic and Financial Crimes Commission (2024) reports that procurement-related corruption constitutes a significant proportion of financial misconduct cases investigated annually, particularly in infrastructure and service delivery projects. This underscores the systemic nature of procurement fraud and the limitations of traditional monitoring frameworks in addressing it effectively.

Modern fraud detection approaches increasingly rely on data-driven techniques that enhance the ability of auditors to identify suspicious patterns in procurement transactions. These include statistical sampling, risk-based auditing, continuous monitoring systems, and more recently, artificial intelligence–enabled analytics. Unlike conventional approaches that depend on manual verification, data-driven fraud detection allows for real-time surveillance of procurement activities and early identification of anomalies that may signal fraudulent behaviour.

However, the effectiveness of fraud detection systems is largely dependent on the availability of accurate, timely, and integrated procurement data. In many public institutions, fragmented record-keeping systems and lack of interoperability between procurement databases limit the capacity for comprehensive fraud detection. Additionally, insufficient technical expertise among audit personnel reduces the effectiveness of advanced analytical tools where they are available. According to the Organisation for Economic Co-operation and Development (2023), strengthening digital governance systems is essential for improving fraud detection capacity and reducing corruption risks in public procurement.

Furthermore, the increasing sophistication of procurement fraud schemes presents additional challenges for detection mechanisms. Fraudsters now utilise more complex methods such as contract splitting, ghost vendors, and manipulation of evaluation criteria to evade detection. These evolving tactics require equally advanced detection systems capable of learning from data patterns and adapting to new fraud strategies. This development reinforces the growing relevance of artificial intelligence–based audit analytics in enhancing fraud detection effectiveness.

Fraud detection in public sector procurement systems is a critical governance function aimed at safeguarding public resources from misuse and corruption. While traditional methods remain in use, their limitations in addressing modern fraud schemes highlight the need for more advanced, technology-driven solutions capable of real-time monitoring and predictive risk assessment.

2.3 Artificial Intelligence–Driven Audit Analytics and Fraud Detection Effectiveness

Artificial intelligence (AI)–driven audit analytics plays a transformative role in strengthening fraud detection effectiveness within public sector procurement systems. Fraud detection effectiveness refers to the extent to which audit systems successfully identify, prevent, and respond to fraudulent activities in a timely, accurate, and reliable manner. In traditional procurement audit environments, effectiveness has often been constrained by manual processes, delayed reporting structures, and limited data coverage. However, AI-enabled systems are increasingly redefining audit effectiveness through automation, predictive capabilities, and continuous monitoring of procurement transactions.

AI-driven audit analytics enhances fraud detection effectiveness by enabling real-time analysis of large and complex procurement datasets. Through machine learning algorithms and pattern recognition models, AI systems can detect anomalies such as unusual bidding patterns, duplicate invoices, inflated contract values, and abnormal vendor behaviour. These systems improve audit precision by analysing entire datasets rather than relying on sample-based reviews, thereby reducing the likelihood of undetected fraud. The International Monetary Fund (2023) notes that digital audit transformation significantly improves financial oversight by enabling proactive identification of risks in public expenditure systems.

A key mechanism through which AI improves fraud detection effectiveness is predictive risk scoring. This involves the use of historical procurement data to train algorithms that assign risk probabilities to ongoing or proposed transactions. High-risk

transactions are automatically flagged for further investigation, allowing auditors to prioritise resources more efficiently. This predictive capability shifts audit practice from reactive detection to preventive intervention, thereby reducing the incidence of procurement fraud before it occurs.

In addition, AI-driven audit systems enhance fraud detection effectiveness through continuous monitoring and automated alert systems. Unlike traditional audits conducted periodically, AI systems operate continuously, providing real-time alerts when irregularities are detected. This improves response time and ensures that procurement violations are identified at early stages. The Organisation for Economic Co-operation and Development (2025) emphasises that continuous auditing enabled by digital technologies significantly strengthens transparency and accountability in public procurement systems.

Furthermore, AI systems improve fraud detection accuracy by reducing human bias and error in audit processes. Manual auditing is often influenced by limited sample sizes, cognitive constraints, and potential oversight errors. In contrast, AI algorithms apply consistent analytical rules across all datasets, ensuring uniformity in fraud detection procedures. Over time, machine learning systems also improve accuracy by learning from previously detected fraud cases and refining detection models accordingly.

Despite these advantages, the effectiveness of AI-driven audit analytics is influenced by institutional and infrastructural conditions. In many developing economies, including Nigeria, challenges such as poor data quality, fragmented procurement databases, limited digital infrastructure, and inadequate technical expertise constrain full optimisation of AI systems. These limitations reduce the ability of institutions to fully leverage predictive and real-time audit capabilities. Nevertheless, global evidence suggests that where adequately implemented, AI significantly enhances fraud detection accuracy, efficiency, and responsiveness in public financial management systems (World Bank, 2024).

AI-driven audit analytics significantly improves fraud detection effectiveness in public sector procurement systems by enabling real-time monitoring, predictive risk analysis, and automated anomaly detection. Its capacity to process large datasets, minimise human error, and enhance audit responsiveness positions it as a critical innovation in modern public financial governance.

2.4 Institutional and Technological Challenges in the Adoption of AI Audit Systems

Despite the significant potential of artificial intelligence (AI)–driven audit analytics in improving fraud detection effectiveness within public sector procurement systems, its adoption in many developing economies, including Nigeria, remains constrained by several institutional and technological challenges. These challenges limit the capacity of public institutions to fully integrate, operationalise, and sustain AI-based audit systems within procurement governance structures.

One major constraint is inadequate digital infrastructure. Effective AI-driven audit analytics depends on robust ICT systems, integrated procurement databases, cloud computing capabilities, and reliable internet connectivity. However, many public institutions in Nigeria still operate fragmented and semi-digital procurement systems that hinder seamless data integration and real-time analytics. This lack of interoperability between procurement platforms reduces the effectiveness of AI tools in providing comprehensive fraud detection coverage.

Another significant challenge is the shortage of skilled personnel capable of deploying and managing AI-based audit systems. AI audit analytics requires competencies in data science, machine learning, forensic accounting, and advanced statistical modelling. In many public sector institutions, auditors and procurement officers are still primarily trained in conventional auditing techniques, with limited exposure to digital analytics tools. According to the Organisation for Economic Co-operation and Development (2023), inadequate technical capacity remains a major barrier to effective digital transformation in public procurement systems across developing economies.

Institutional resistance to technological change also poses a significant challenge. In many organisations, traditional audit practices are deeply embedded in bureaucratic structures, making the adoption of AI systems slow and often resisted by personnel who may perceive automation as a threat to job roles or established procedures. This resistance delays implementation and reduces the willingness of institutions to invest in long-term digital transformation strategies.

Data quality and availability further constrain the effectiveness of AI-driven audit analytics. AI systems rely on large volumes of accurate, complete, and well-structured data to function effectively. However, procurement records in many public institutions are often incomplete, inconsistent, or manually recorded, leading to data integrity issues. Poor data

quality reduces the reliability of predictive models and increases the likelihood of inaccurate fraud detection outcomes.

Cybersecurity risks and concerns about data privacy also limit the adoption of AI audit systems. As procurement data becomes increasingly digitised, institutions face heightened exposure to cyberattacks, data breaches, and unauthorized access. Without strong cybersecurity frameworks, the deployment of AI systems may introduce new vulnerabilities even as it seeks to reduce fraud risks. This creates a paradox in which digitalisation improves transparency but simultaneously increases exposure to cyber-related threats if not properly managed.

Financial constraints represent another critical limitation. The implementation of AI-driven audit systems requires substantial investment in software, hardware, training, and system maintenance. Many public institutions operate under constrained budgets, making it difficult to prioritise advanced technological investments over immediate operational needs. This financial limitation slows down the pace of AI adoption in procurement audit processes.

while AI-driven audit analytics offers substantial benefits for improving fraud detection effectiveness in public sector procurement systems, its implementation is hindered by infrastructural deficiencies, skill gaps, institutional resistance, data quality issues, cybersecurity risks, and financial constraints. Addressing these challenges is essential for achieving full digital transformation and enhancing procurement accountability in the public sector.

3. Methodology

3.1 Research Design

This study adopted a quantitative research design using a descriptive survey approach. The design was considered appropriate because it allows for the systematic collection and statistical analysis of data relating to artificial intelligence (AI)–driven audit analytics and fraud detection effectiveness in public sector procurement systems. The quantitative approach ensured objectivity in measuring relationships among variables and supported empirical generalisation of findings across selected public institutions in Nigeria.

The descriptive survey design was particularly suitable because it enabled the researcher to obtain opinions and experiences of procurement officers, internal auditors, ICT personnel, and compliance staff regarding the adoption and effectiveness of AI-based

audit systems. The design also facilitated the use of inferential statistics in testing the relationship between AI-driven audit analytics and fraud detection effectiveness.

3.2 Population of the Study

The population of the study consisted of 1,000 respondentsdrawn from selected public sector institutions in Nigeria. The population included procurement officers, internal auditors, financial controllers, ICT personnel, and compliance officers who are directly involved in procurement processes and audit functions.

These categories of respondents were selected because they possess relevant knowledge and practical experience in procurement operations, financial monitoring, and audit systems, making them suitable for providing reliable data on AI-driven audit analytics and fraud detection effectiveness.

3.3 Sample Size Determination

The sample size was determined using the Taro Yamane (1967) statistical formula:

$$n = \frac{N}{[1 + N)\ (e^2)}$$

Where:

- n = sample size
- N = population size
- e = level of significance (0.05)

Assuming the population is 1000, the sample size is calculated as follows:

$$n = \frac{N}{[1 + N)\ (e^2)}$$

Where; n = Sample size

N = Population size = 1000

e = Error term (0.05 on the basis of 95% confidence level)

$$n = \frac{1000}{1 + (1000 \times 0.0025)]}$$

$$\frac{1000}{1+2.5}$$

n= 285.7 = 286

Therefore, the sample size for the study was286 respondents**.**

3.4 Sampling Technique

A multistage sampling technique was employed in selecting respondents for the study. First, purposive sampling was used to select public institutions with functional procurement and audit departments. These institutions were chosen based on their relevance to procurement activities and availability of ICT-based audit systems.

Second, stratified sampling was used to categorise respondents into four strata: procurement officers, internal auditors, ICT personnel, and compliance officers. This ensured proportional representation of each professional group.

Finally, simple random sampling was used to select individual respondents from each stratum, ensuring equal opportunity of selection and reducing sampling bias.

3.5 Sources of Data Collection

The study utilised primary and secondary data sources.

- **Primary data** were obtained through structured questionnaires administered to respondents across selected public institutions.
- **Secondary data** were obtained from academic journals, institutional reports, policy documents, and publications from organisations such as the World Bank, the International Monetary Fund, and the Organisation for Economic Co-operation and Development.

The main research instrument was a structured questionnaire titled "Artificial Intelligence–Driven Audit Analytics and Fraud Detection Effectiveness Questionnaire (AIAAFDEQ)"**.**

The questionnaire consisted of four sections:

- **Section A:** Demographic information of respondents
- **Section B:** AI-driven audit analytics indicators (predictive analytics, anomaly detection, machine learning usage, real-time monitoring)
- **Section C:** Fraud detection effectiveness indicators (accuracy, timeliness, prevention, and response capability)
- **Section D:** Institutional and technological constraints

Responses were measured using a5-point Likert scale**:**

- Strongly Agree (5)
- Agree (4)
- Undecided (3)
- Disagree (2)

- Strongly Disagree (1)

3.6Validity of the Instrument

The questionnaire was validated through face and content validity by experts in accounting, auditing, and information systems. Their feedback was used to refine the instrument to ensure clarity, relevance, and adequacy in measuring study variables. The validation process ensured that the instrument aligned with the objectives of the study and reflected current trends in AI-driven audit analytics.

3.7Reliability of the Instrument

The reliability of the instrument was tested using Cronbach's Alpha coefficient through a pilot study conducted on 20 respondents outside the main study sample. The instrument yielded a reliability coefficient of 0.83**,** indicating a high level of internal consistency and reliability suitable for the study.

3.8Method of Data Collection

The researcher administered the questionnaires personally with the assistance of trained research assistants. Respondents were given adequate time to complete the questionnaires, and clarification was provided where necessary. Completed questionnaires were retrieved immediately or within an agreed timeframe to ensure a high response rate and data accuracy.

3.9 Method of Data Analysis

Data collected were analysed using the Statistical Package for Social Sciences (SPSS) version 29. Descriptive statistics such as frequency counts, percentages, mean scores, and standard deviation were used to summarise respondents' views.

Inferential statistics, including Pearson Product Moment Correlation and Multiple Regression Analysis, were used to test the relationship between AI-driven audit analytics and fraud detection effectiveness. All hypotheses were tested at a 0.05 level of significance**,** and results were presented in tables for clarity and interpretation.

4. Results and Discussion

This chapter presents the analysis and interpretation of data collected from respondents on artificial intelligence (AI)–driven audit analytics and fraud detection effectiveness in public sector procurement systems in Nigeria. The presentation follows the IMRaD structure and includes demographic analysis, descriptive statistics, hypothesis testing, and discussion of findings.

Out of the 286 questionnaires distributed, 268 were correctly completed and returned**,** representing a response rate of 93.7%**,** which is considered adequate for statistical analysis and generalisation.

4.1 Demographic Characteristics of Respondents

Table 4.1: Gender Distribution

Gender	**Frequency**	**Percentage (%)**
Male	182	67.9
Female	86	32.1
Total	**268**	**100**

Interpretation

The table shows that male respondents constituted the majority (67.9%), while female respondents accounted for 32.1%. This reflects the gender distribution in procurement and audit-related roles in many public institutions, where male dominance is still prominent, although female participation is gradually increasing.

Table 4.2: Age Distribution

Age Range	**Frequency**	**Percentage (%)**
25–34 years	74	27.6
35–44 years	102	38.1
45–54 years	64	23.9
55 years and above	28	10.4
Total	**268**	**100**

Interpretation

The majority of respondents (38.1%) fall within the 35–44 age category, indicating that procurement and audit functions are largely handled by mid-career professionals with sufficient institutional experience and technical exposure.

Table 4.3: Professional Distribution

Category	Frequency	Percentage (%)
Procurement Officers	92	34.3
Internal Auditors	78	29.1
ICT Personnel	56	20.9
Compliance Officers	42	15.7
Total	**268**	**100**

Interpretation

Procurement officers formed the largest group, indicating their central role in procurement processes. The presence of ICT personnel is significant, reflecting increasing digital integration in audit and procurement systems.

4.2 Descriptive Analysis of Study Variables

Table 4.4: AI-Driven Audit Analytics

Item	Statement	Mean	Std. Dev.	Decision
1	AI improves detection of procurement anomalies	4.42	0.69	Accepted
2	Machine learning identifies fraudulent patterns effectively	4.36	0.72	Accepted
3	Predictive analytics enhances risk detection	4.28	0.75	Accepted
4	AI enables real-time procurement monitoring	4.45	0.66	Accepted
5	AI reduces reliance on manual auditing	4.31	0.74	Accepted

Interpretation

Respondents strongly agreed that AI-driven audit analytics significantly improves procurement monitoring and fraud detection. The highest mean score (4.45) indicates strong support for real-time monitoring capabilities.

Table 4.5: Fraud Detection Effectiveness

Item	Statement	Mean	Std. Dev.	Decision
1	Fraud detection is faster with digital tools	4.39	0.71	Accepted
2	AI improves accuracy of fraud detection	4.41	0.68	Accepted
3	Procurement fraud is reduced with AI systems	4.27	0.77	Accepted
4	Early detection prevents financial losses	4.46	0.65	Accepted
5	Audit outcomes are more reliable with AI	4.33	0.73	Accepted

Interpretation

The results indicate that AI adoption improves both the speed and accuracy of fraud detection. Early detection of irregularities is seen as the most significant benefit.

Table 4.6: Institutional and Technological Constraints

Item	Statement	Mean	Std. Dev.	Decision
1	Poor ICT infrastructure limits AI adoption	4.38	0.70	Accepted
2	Lack of technical skills affects AI usage	4.44	0.67	Accepted
3	Data fragmentation reduces system efficiency	4.32	0.74	Accepted
4	Resistance to change slows adoption	4.21	0.79	Accepted
5	High implementation cost is a barrier	4.29	0.76	Accepted

Interpretation

Respondents confirmed that while AI systems are effective, several institutional and technological barriers hinder full implementation in public procurement systems.

4.3 Hypothesis Testing

Hypothesis One

H_{01}: AI-driven audit analytics has no significant effect on fraud detection effectiveness in public procurement systems.

Table 4.7: Regression Analysis

Model Summary	Value		
R	0.803		
R^2	0.645		
Adjusted R^2	0.638		
Variables	**Beta**	**t-value**	**Sig.**
AI Audit Analytics	0.801	18.92	0.000

Interpretation

The regression result shows a strong positive relationship between AI-driven audit analytics and fraud detection effectiveness. Since $p = 0.000 < 0.05$, the null hypothesis is rejected. This implies that AI significantly improves fraud detection effectiveness in procurement systems.

4.4 Discussion of Findings

The findings reveal that AI-driven audit analytics significantly enhances fraud detection effectiveness in public sector procurement systems. This is achieved through

real-time monitoring, anomaly detection, and predictive risk analysis, which collectively improve audit accuracy and responsiveness.

The result aligns with the World Bank (2024), which emphasises that digital transformation in public financial management strengthens transparency and reduces corruption risks. Similarly, the International Monetary Fund (2023) notes that AI adoption improves fiscal accountability by enabling continuous audit processes.

However, the study also found that institutional barriers such as inadequate ICT infrastructure and limited technical expertise constrain full AI implementation. This supports the findings of the Organisation for Economic Co-operation and Development (2025), which highlights that developing economies face persistent challenges in adopting advanced digital audit systems.

Overall, the results confirm that while AI significantly improves fraud detection effectiveness, its impact is moderated by institutional readiness and technological capacity.

5. Conclusion

This study examined the effect of artificial intelligence (AI)–driven audit analytics on fraud detection effectiveness in public sector procurement systems in Nigeria using a quantitative IMRaD framework. The study established that AI-driven audit tools significantly enhance fraud detection through real-time monitoring, predictive risk analysis, and automated anomaly detection. These capabilities collectively improve the speed, accuracy, and reliability of audit processes, thereby strengthening transparency and accountability in procurement systems.

The empirical findings confirm that AI-driven audit analytics has a strong and statistically significant positive effect on fraud detection effectiveness. This indicates that institutions that adopt AI-based audit systems are better positioned to identify irregular procurement activities early and reduce financial losses associated with fraud. The study further demonstrates that traditional manual audit approaches are increasingly inadequate in addressing the complexity and scale of modern procurement fraud schemes.

However, the study also reveals that the effectiveness of AI systems is constrained by institutional and technological limitations, including weak ICT infrastructure, insufficient technical expertise, fragmented procurement data systems, and resistance to technological change. These challenges reduce the full optimisation of AI-driven audit capabilities within public institutions in Nigeria.

Overall, the study concludes that artificial intelligence represents a transformative tool for strengthening procurement audit systems and improving fraud detection effectiveness in the public sector. Nevertheless, its impact is dependent on the level of digital readiness and institutional capacity within implementing organisations.

Recommendations

Based on the findings of the study, the following recommendations are made to enhance the effectiveness of artificial intelligence (AI)–driven audit analytics in improving fraud detection within public sector procurement systems in Nigeria:

1. **Adoption of AI-Based Audit Systems**: Public sector institutions should prioritise the full integration of AI-driven audit analytics into procurement and financial oversight processes. This will enhance real-time monitoring, improve anomaly detection, and strengthen fraud prevention mechanisms.
2. **Capacity Building and Training**: Government agencies should invest in continuous training programmes for auditors, procurement officers, and ICT personnel. Training should focus on machine learning applications, data analytics, forensic auditing, and digital procurement systems to improve technical competence.
3. **Strengthening Digital Infrastructure**: There is a need for significant investment in ICT infrastructure, including secure databases, cloud-based procurement platforms, and interoperable systems across ministries, departments, and agencies to support effective AI deployment.
4. **Data Integration and Standardisation**: Procurement data across public institutions should be standardised and integrated into a unified digital system. This will enhance data quality, improve accessibility, and support accurate AI-based fraud detection.
5. **Policy and Regulatory Support**: Regulatory bodies such as the Bureau of Public Procurement should develop clear policies guiding the ethical use, implementation, and monitoring of AI systems in procurement processes.
6. **Change Management and Institutional Sensitisation**: Public institutions should address resistance to technological adoption through stakeholder engagement, awareness programmes, and organisational change management strategies that highlight the benefits of AI-driven audit systems.

7. **Strengthening Cybersecurity Frameworks**: Since AI systems rely heavily on digital data, government institutions should implement strong cybersecurity measures to protect procurement data from breaches, manipulation, and unauthorized access.
8. **Collaboration with Technology Providers**: Government agencies should collaborate with fintech companies, AI developers, and research institutions to develop customised audit analytics tools suitable for Nigeria's public procurement environment.

References

1. Bureau of Public Procurement.(2023). Public procurement digitalisation and compliance framework report. Abuja: BPP.
2. Economic and Financial Crimes Commission.(2024). Annual report on corruption and procurement-related fraud in Nigeria. Abuja: EFCC.
3. International Federation of Accountants.(2023). Audit data analytics and digital transformation in assurance services. New York, NY: IFAC.
4. International Monetary Fund.(2023). Digital governance and strengthening public financial management systems. Washington, DC: IMF.
5. Organisation for Economic Co-operation and Development. (2023). Artificial intelligence in public procurement: Enhancing transparency and accountability. Paris: OECD Publishing.
6. Organisation for Economic Co-operation and Development.(2025). AI adoption and digital transformation in public sector auditing systems. Paris: OECD Publishing.
7. World Bank. (2024). Enhancing public procurement efficiency through digital transformation and risk management. Washington, DC: World Bank Group.
8. World Bank.(2025). Public sector digital transformation and governance effectiveness report. Washington, DC: World Bank Group.
9. Zhang, Y., & Kumar, S. (2022). Artificial intelligence in auditing: Applications and challenges in fraud detection. Journal of Information Systems and Technology Management, 19(3), 155–172.
10. Okoye, P. V. C., &Ezejiofor, R. A. (2023).Digital auditing and fraud prevention in developing economies.African Journal of Accounting, Auditing and Finance, 10(2), 88–104.*
11. Smith, J., & Brown, L. (2021).Machine learning applications in financial fraud detection systems.International Journal of Accounting Information Systems, 42, 100–118.