WAR Journal of Multidisciplinary Bulletin
(WARJMB)
ISSN (Online): 1595-6709
ISSN (Print): 1595-6636
Received: 12-03-2025 Revised: 26-03-2025 Accepted: 05-04-2025 Published: 18-04-2025
Research Article

ARTIFICIAL INTELLIGENCE AND THE EFFECTIVENESS OF AUDIT QUALITY IN NIGERIA: EXPLORING AUDITORS' PERSPECTIVES

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OPEN ACCESS

Published in
VOl- 1 Issue: 1
DOI:10.5281/zenodo.19514394
PP: 62-78
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Abstract

This study investigates the impact of Artificial Intelligence (AI) on the effectiveness of audit quality in Nigeria from auditors' perspectives. Focusing on three core AI dimensions AI adoption rate, AI maturity and AI reliance the study explores how these constructs shape audit outcomes in terms of objectivity, accuracy, compliance and risk assessment. Using a structured survey distributed to 500 professional auditors across audit firms, regulatory bodies and listed companies, the study analyzed responses from 412 participants in addition to the 15 percent attrition added. Data was subjected to descriptive statistics, factor analysis and multiple regression analysis via SPSS. Results indicates that AI adoption rate significantly enhances audit effectiveness by improving fraud detection and audit precision. AI maturity was found to positively influence the strategic integration of technology in audit workflows, enhancing timeliness and compliance. However, while AI reliance also showed a positive influence, excessive dependence could compromise professional skepticism and ethical judgment. The study emphasizes the importance of balanced AI usage, continuous professional training and regulatory support for optimal AI integration in auditing. Key policy recommendations include developing ethical frameworks, enhancing auditor competence and establishing AI maturity benchmarks. This research contributes to the literature on technology in auditing and provides a strategic guide for audit firms and regulators navigating AI transformation in emerging economies like Nigeria.

Keywords: Artificial Intelligence, Audit Quality, AI Adoption Rate, AI Maturity and AI Reliance

Introduction

Technological advancements have significantly enhanced computer systems' capacity across various domains, enabling increased processing speed, reduced hardware size and enhanced analytical capabilities. The transition from big data (BD) to machine learning (ML) and now to artificial intelligence (AI), in the management and auditing discourse has been swift and transformative (Dwivedi et al., 2021). AI, a subfield of computer science, focuses on creating systems that mimic human intelligence by learning, reasoning, and making informed decisions. These systems can perform tasks such as problem-solving, pattern recognition

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as well as autonomous decision-making, all of which are increasingly relevant in the auditing profession. The evolution of AI and its subcomponents has had a profound impact on how professionals, including auditors perform their duties. With globalization, regulatory reforms and increasing stakeholder expectations, auditors are under pressure to provide higher quality, more timely and accurate insights. AI tools such as natural language processing, predictive analytics and automated anomaly detection are increasingly integrated into audit processes to meet these demands (Issa, Sun, & Vasarhelyi, 2016). As digital technology becomes embedded in every aspect of economic and organizational life, the audit profession is evolving to keep pace. AI tools not only facilitate efficiency through automation but also enable auditors to focus on high-value, judgment-based tasks. The proliferation of audit data and the demand for data-driven insights has led to greater interest in AI adoption in auditing, especially in emerging states such as Nigeria (Olowookere & Akinleye, 2023).

Auditors now have access to vast datasets, and AI offers them the capability to process, interpret and extract valuable insights. In this context, understanding the AI adoption rate among audit firms in Nigeria becomes crucial. It sheds light on how widely AI is being integrated into audit workflows and how such integration influences audit quality. Similarly, the AI maturity of audit firms the extent to which AI tools are strategically and systematically applied affects the depth and reliability of audit procedures (Kokina & Davenport, 2017). Finally, AI reliance refers to the degree to which auditors depend on AI tools in their judgment and decision-making processes, which raises important questions about accountability, bias, and ethical implications (Appelbaum, Kogan, & Vasarhelyi, 2017). The audit landscape in Nigeria is characterized by diverse challenges, ranging from data quality issues to limited access to advanced technologies and regulatory ambiguity. These challenges may hinder effective AI integration. However, the potential benefits enhanced fraud detection, increased assurance quality and reduced audit costs make AI a promising frontier for Nigerian auditors (Uwuigbe et al., 2022).

1.2 STATEMENT OF THE PROBLEM

In recent years, AI-driven tools such as robotic process automation, data analytics and predictive modeling have been reshaping the auditing landscape. Traditional audit techniques are increasingly being replaced or supplemented by AI-powered systems. However, the AI adoption rate in Nigeria remains uneven, with some firms embracing it while others lag behind due to infrastructure, cost or knowledge barriers. Moreover, there is a lack of empirical data assessing the AI maturity of auditing firms in Nigeria. Without a clear understanding of how developed and integrated these technologies are within audit practices, it is difficult to determine their actual contribution to audit quality. This limits stakeholders' ability to trust the outcomes of AI-enabled audits.

Additionally, concerns about AI reliance particularly the risk of over-dependence on automated systems without sufficient human oversight highlight the need for ethical frameworks and professional judgment to guide auditors. If not carefully managed, this reliance could lead to critical errors, reduce professional skepticism and weaken audit assurance (Rashid, Asif, & Yaqub, 2023). The Nigerian audit environment is further complicated by insufficient high-quality, structured datasets and inconsistent reporting standards. These issues affect how AI systems learn and operate, potentially leading to inaccurate predictions or undetected anomalies. The absence of standardized metrics to assess AI effectiveness across audit firms also presents an evaluation gap, making it difficult to benchmark performance or compare across firms or sectors. In light of these challenges, there is a need for a deeper exploration of how AI technologies

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are being used as perceived by auditors in Nigeria, the extent to which they are trusted and embedded into audit practice and what impact they are having on audit effectiveness.

1.3 OBJECTIVES OF THE STUDY

The primary aim of this study is to explore the impact of artificial intelligence on audit quality in Nigeria by analyzing auditors' perspectives. Specifically, the study seeks to:

i. Examine the effect of the AI adoption rate on audit quality in Nigeria.
ii. Assess the effect of AI maturity on audit quality in Nigeria.
iii. Determine the effect of AI reliance on audit quality in Nigeria.

1.4 SCOPE OF THE STUDY

This study focuses on the audit profession in Nigeria, examining how artificial intelligence influences audit quality within both large and mid-tier audit firms. The analysis considers the broader Nigerian socio-economic, regulatory and technological environment, including challenges such as infrastructure deficits, professional development, data integrity and regulatory compliance. The study requires interdisciplinary expertise across AI systems, auditing standards, professional ethics and statistical modeling. It draws upon theories of technological adoption, decision support systems, and audit effectiveness frameworks.

1.5 SIGNIFICANCE OF THE STUDY

The study holds several critical significances:

First, it contributes to the growing body of literature on the application of artificial intelligence (AI) in the audit profession, specifically within the Nigerian context. Examining how auditors perceive and utilize AI technologies, this study provides evidence on how AI adoption rate*,* AI maturity*, and* AI reliance influence audit effectiveness. The research offers valuable insights into the challenges and opportunities surrounding AI deployment in Nigerian audit practices. It sheds light on how these technologies can be harnessed to enhance audit quality through improved fraud detection, error minimization, enhanced analytical capabilities and real-time risk assessment. Additionally, the study investigates the role of AI adoption rate in driving technological integration among audit firms. Understanding how quickly and broadly AI tools are being embraced provides a window into the readiness of the auditing sector for digital transformation. Furthermore, by evaluating AI maturity, the extent to which AI technologies are refined, customized and seamlessly embedded into audit processes, this research identifies the technological capacity and strategic development of AI in professional audit settings. The aspect of AI reliance explores how dependent auditors have become on AI systems in executing core tasks. This helps to clarify the implications for auditor independence, professional judgment, and ethical standards. Practically, the findings will assist audit firms, regulatory bodies, and professional accounting organizations in formulating strategies and guidelines for responsible AI integration. They will also help firms enhance audit quality, reduce operational costs and respond more agilely to dynamic client environments. Lastly, the study lays the foundation for future research into the broader intersection of AI and audit quality in emerging markets. It identifies current gaps in knowledge, such as regulatory readiness, ethical implications and the industry-specific barriers to AI adoption, encouraging further scholarly exploration in these areas.

2.0 LITERATURE REVIEW

2.1 CONCEPTUAL REVIEW

2.1.1 CONCEPT OF ARTIFICIAL INTELLIGENCE

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Artificial Intelligence (AI) refers to the ability of machines and software systems to mimic, learn from and even surpass human cognitive functions in performing complex tasks. According to Abid et al. (2022), AI enables systems to interpret and respond to human behavior and speech, making it instrumental in automating decision processes. AI tools like speech recognition systems (Siri and Alexa), facial recognition on platforms like Facebook and intelligent search engines like Google exemplify how AI is already deeply embedded in various industries (Prakash, 2023). Arvind and Prithwiraj (2022) describe AI as a transformative technology that empowers organizations to process real-time data and respond proactively to operational needs. AI's ability to adapt through learning from past data makes it particularly valuable in dynamic environments like auditing. Gartner (2023) emphasizes that different AI technologies such as natural language processing (NLP), machine learning algorithms and neural networks have varied impacts on business functions. Deep learning models have proven especially effective in identifying financial anomalies, predicting business risks and assessing patterns within large volumes of transactional data.

2.1.2 CONCEPT OF AI ADOPTION RATE

AI adoption rate is the extent and pace at which audit firms or individual auditors integrate AI tools into their audit processes. It captures the willingness and readiness of audit institutions to embrace AI-driven technologies for tasks such as risk assessment, fraud detection, data analysis and predictive modeling. The rate of adoption is influenced by organizational culture, perceived benefits, cost, regulatory readiness and auditor competence (Dwivedi et al., 2023). In the Nigerian audit context, the adoption rate is emerging gradually, driven by global trends and pressure to increase audit efficiency and reliability (Eze et al., 2023).

2.1.3 CONCEPT OF AI MATURITY

AI maturity as the level of sophistication and integration of AI systems within an auditing organization. It assesses how well-developed, scalable and embedded AI technologies are in the audit life cycle, from planning and execution to reporting and review (Bughin et al., 2022). Higher AI maturity is characterized by the ability to harness complex algorithms for predictive analytics, deep learning and real-time data processing, enabling more informed audit decisions. In Nigeria, AI maturity among audit firms varies significantly, often constrained by infrastructure, training, and regulatory challenges (Okoye & Egbunike, 2022).

2.1.4. CONCEPT OF AI RELIANCE

AI reliance refers to the extent to which auditors depend on AI-generated outputs in their decision-making processes. It reflects the trust and dependence placed on AI systems to carry out or support critical audit judgments. High reliance suggests confidence in the accuracy, consistency and interpretability of AI tools, while low reliance may indicate skepticism or lack of transparency in AI systems (Ransbotham et al., 2023). In audit quality discussions, AI reliance must be balanced with professional skepticism and ethical standards to avoid overdependence on automated outcomes.

2.2 EMPIRICAL REVIEW

2.2.1 AI ADOPTION RATE AND THE EFFECTIVENESS OF AUDIT QUALITY

Recent studies have emphasized the pivotal role of Artificial Intelligence (AI) adoption in reshaping auditing practices, especially in developing economies such as Nigeria. According to Musa and Adebayo (2024), AI adoption in audit processes significantly enhances risk detection and real-time decision-making, thereby increasing audit precision and efficiency. Their study, conducted across 35 auditing firms in Lagos, utilized regression-based analytics to examine how early adoption of AI tools such as automated data extraction and predictive analytics impacts audit outcomes. The results indicated that firms with higher AI

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adoption rates reported fewer post-audit adjustments and stronger client confidence. Similarly, Ibrahim and Danjuma (2023) analyzed the extent to which the introduction of AI into statutory audit procedures influenced compliance and audit reporting quality in Nigerian-listed firms. Using panel data covering the period 2018 to 2022, they found a positive relationship between AI adoption and reduced audit failure rates. These findings affirm that the speed and scope at which auditing firms embrace AI technologies play a foundational role in strengthening audit reliability and regulatory adherence.

H1: *AI adoption rate positively influences the effectiveness of audit quality.*

2.2.3 AI MATURITY AND THE EFFECTIVENESS OF AUDIT QUALITY

Beyond adoption, the maturity level of AI infrastructure significantly determines its effectiveness in audit processes. Olatunji and Onuoha (2024) explored the concept of AI maturity defined as the depth of integration, system adaptability, and internal competence in AI utilization across medium- and large-sized audit firms in Nigeria. Using a mixed-methods approach combining survey data and in-depth interviews, their research revealed that mature AI systems facilitate continuous audit engagements, automated anomaly detection and better compliance with International Standards on Auditing (ISA). In a related study, Thompson and Udo (2024) examined audit departments within multinational subsidiaries in Nigeria and highlighted that advanced AI maturity correlates with improved audit timeliness and fraud detection accuracy. The study applied structural equation modeling (SEM) to validate the interaction between AI system maturity and the reliability of audit conclusions, showing that firms with well-established AI infrastructures significantly outperform others in audit documentation and risk assessment.

H2: *AI maturity positively impacts the effectiveness of audit quality.*

2.2.4 AI RELIANCE AND THE EFFECTIVENESS OF AUDIT QUALITY

AI reliance refers to the extent to which auditors depend on AI tools for planning, evidence gathering, and audit judgment. Eze and Balogun (2024) investigated how over-reliance or under-reliance on AI affects professional skepticism and audit judgment. Their findings suggest that while strategic reliance on AI can streamline repetitive tasks and enhance audit trail accuracy, excessive dependence may dilute auditor critical thinking and increase the risk of overlooking anomalies not captured by AI algorithms. Furthermore, Usman and Adeyemi (2023) employed a longitudinal study on Big 4 audit firms operating in Nigeria to assess how AI reliance influences audit effectiveness over time. The study revealed that balanced AI reliance improves audit scope and enhances the reliability of auditor conclusions, particularly in industries with high data complexity, such as financial services and oil & gas. These findings suggest that AI reliance, when properly aligned with professional expertise and ethical guidelines, can significantly contribute to audit effectiveness.

H3: *AI reliance positively influences the effectiveness of audit quality.*

2.2.5 AI FUNCTIONS AND AUDIT QUALITY

The application of AI in auditing can be understood through three functional dimensions: *AI adoption rate*, *AI maturity* and *AI reliance*. **AI Adoption Rate** refers to how quickly audit firms are implementing AI technologies across their workflows. A higher adoption rate often indicates greater openness to innovation and a willingness to invest in digital transformation (PwC, 2022).

AI Maturity reflects the degree to which AI systems are refined and fully integrated into audit practices. Mature AI systems support complex tasks such as real-time fraud detection, audit evidence gathering and judgment support (Kokina & Davenport, 2017). Audit firms with higher AI maturity levels demonstrate more consistency and reliability in AI-aided decision-making. **AI Reliance** highlights how

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dependent auditors are on AI tools for key processes. While increased reliance can boost efficiency and accuracy, it also raises concerns about overdependence, reduced professional skepticism and the erosion of human judgment (IAASB, 2022). Studies also point to ethical challenges associated with AI integration. These include data privacy concerns, algorithmic bias, transparency and accountability (Turel & Cavarretta, 2020). For instance, Li et al. (2019) observed that successful AI deployment in professional services requires clear policies around transparency and data protection, as these factors directly influence stakeholder trust. In auditing specifically, Wirtz et al. (2020) found that AI-enhanced systems such as predictive analytics and real-time dashboards improve audit quality and client confidence but require thoughtful design to mitigate ethical concerns. Wu et al. (2021) echoed these findings, noting the importance of responsible AI usage in maintaining credibility and regulatory compliance. Therefore, for Nigerian audit firms, understanding and managing *AI adoption rate*, *AI maturity* and *AI reliance* is essential not only for improving audit effectiveness but also for sustaining professional integrity and stakeholder trust in a technology-driven future.

2.3 THEORETICAL FRAMEWORK

This study is anchored on the Theory of Innovation Diffusion, specifically focusing on the Rate of Adoption, which posits that the adoption of innovations typically follows an S-curve trajectory (Rogers, 2003; Singh et al., 2023). The theory illustrates that the early stages of innovation adoption, such as AI adoption rate, occur gradually due to limited awareness and skepticism. However, as knowledge and perceived value increase, adoption accelerates sharply before eventually stabilizing as the innovation matures and reaches saturation. In the context of auditing, AI adoption rate represents the initial awareness, interest and trial usage of artificial intelligence tools among audit professionals and firms. This phase is often characterized by caution and experimentation. As the use of AI advances, AI maturity sets in signifying the development of structured processes, improved competence, and integration of AI systems into the audit workflow (Alsharif et al., 2022). Eventually, AI reliance emerges, where AI technologies become critical in ensuring audit quality, supporting complex decision-making, and enhancing assurance functions (Appelbaum, 2023). The temporal aspect of innovation diffusion is also crucial. Firstly, the adoption process is cognitive and unfolds over time, beginning with awareness and understanding, progressing to attitude formation, and culminating in the decision to adopt or reject (Rogers, 2003). Secondly, adoption occurs at different rates across social segments early adopters, majority users, and laggards each influencing others within the audit ecosystem. Lastly, the rate of adoption or the relative speed at which auditors embrace AI technologies is measurable over a specified period and significantly shapes overall audit effectiveness (Siddiqui & Younas, 2024). This framework provides a comprehensive basis for examining how Nigerian auditors perceive and implement AI across different dimensions and how these dynamics ultimately affect the quality of audit outcomes.

2.4 METHODOLOGY

This study adopts a **survey research design**, as it involves the administration of a structured questionnaire aimed at examining the effect of **Artificial Intelligence (AI)** on the **effectiveness of audit quality** in Nigeria from the perspectives of professional auditors. The **population** for this study comprises **Professional Auditors** in Nigeria, including practitioners from audit firms (Big Four and indigenous), internal auditors in listed companies and audit regulators or oversight bodies. The sampling frame is drawn from members of professional accounting bodies, ICAN, ANAN, CITN and audit professionals in regulatory agencies like the Financial Reporting Council of Nigeria (FRCN) and the Office of the Auditor-General of

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the Federation and the States. The **Yamane (1967)** formula was employed to determine a **sample size of 359 respondents**. However, to compensate for potential non-responses, an additional **15%** was included, increasing the final target sample to **approximately 412 respondents**. Data was gathered through a **self-administered structured questionnaire**, selected for its ability to efficiently collect standardized responses from a wide population within a short timeframe. This method ensures consistency, generalizability and objectivity in the analysis. The questionnaire was designed as a **composite measurement instrument** to assess the relationship between **Artificial Intelligence constructs** and **Audit Quality**. The AI constructs (independent variables) were broken down into:

AI Adoption Rate (AAR) – measured using 5 items labeled AAR1 to AAR5
AI Maturity (AIM) – measured using 5 items labeled AIM1 to AIM5
AI Reliance (AIR) – measured using 5 items labeled AIR1 to AIR5

The dependent variable, **Audit Quality (AQ)**, was measured across dimensions such as objectivity, accuracy, independence, compliance with auditing standards and risk assessment quality using 6 items labeled AQ1 to AQ6. A **multiple regression analysis** was conducted to examine the effect of the AI constructs on audit quality. This statistical technique enables the assessment of the degree to which each independent variable contributes to the prediction of audit quality outcomes.

The model is specified as follows:

$AQi=\beta 0+\beta 1AARi+\beta 2AIMi+\beta 3AIRi+$

Where:
AQ= Audit Quality
AAR= AI Adoption Rate
AIM = AI Maturity
AIR= AI Reliance
ε = Error term
β = Coefficients of the predictors

The data collected was coded and entered into the **Statistical Package for Social Sciences (SPSS), version 25**, for analysis. The formulated hypotheses were tested using **multiple regression analysis**, providing insights into the influence of artificial intelligence dimensions on the effectiveness of audit quality in Nigeria.

3.0 RESULTS AND DISCUSSION

Table 1: Demographic Statistics

Variable	Category	Frequency	Percentage (%)
Gender	Male	240	60.00
	Female	160	40.00
Age	18–29	122	30.50
	30–44	148	37.00
	45–59	110	27.50
	60 >	20	5.00
Years of Experience	1–5	130	32.50

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	6–10	165	41.25
	> 10	105	26.25
Specialisation	Accountant	210	52.50
	Internal Auditor	65	16.25
	Finance Manager	125	31.25
Education	Diploma	92	23.00
	First Degree	210	52.50
	Masters	76	19.00
	Ph.D	22	5.50
Professional Qualification	ANAN	135	33.75
	ICAN	50	12.50
	CITN	160	40.00
	ACCA	14	3.50
	None	91	10.25

Source: SPSS Output (2025)

The demographic data from the study reveal key characteristics of the respondents (N = 400), offering insights into the composition of professionals involved in audit-related functions in Nigeria. The sample consists of 60% male and 40% female respondents, reflecting a male-dominated profession. This aligns with prior studies (e.g., Adediran & Okoye, 2023) which found that male professionals still largely dominate the Nigerian financial sector, potentially influencing decision-making styles and audit approaches. Most respondents fall within the 30–44 age bracket (37%), followed by 18–29 (30.5%) and 45–59 (27.5%), with only 5% aged 60 and above. This suggests a relatively young and active workforce, consistent with Onuoha and Eze (2022), who found that younger professionals tend to adopt innovative audit tools like AI faster, affecting audit effectiveness. The majority (41.25%) have 6–10 years of experience, indicating a moderately experienced workforce, which may suggest balanced perspectives in audit quality, as also observed in Musa and Salihu (2023). Accountants form the majority (52.5%), followed by finance managers (31.25%) and internal auditors (16.25%). This indicates a broader accounting influence, potentially shaping how audit practices are perceived and implemented in line with the findings of Adegoke et al. (2024). Over half of the respondents (52.5%) hold a first degree, with 19% holding master's degrees. This educational distribution suggests a fairly knowledgeable workforce, which has been linked to enhanced audit quality in studies like Udo and Bassey (2022). CITN members (40%) and ANAN (33.75%) dominate, while ICAN and ACCA are less represented. This may influence the methodological approach to audits, as professional background often shapes audit style and standards compliance, corroborated by research from Okonjo and Ibrahim (2023). The demographic profile supports the relevance of targeting audit quality enhancement through continuous professional education and technology integration, especially given the high representation of young, degree-holding professionals. With such a background, initiatives focusing on AI integration and audit policy reforms are likely to receive active engagement and faster adoption.

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Table 2. Factor Analysis (Descriptive Summary Table)

Variable	Number of Items	KMO Value	Eigenvalues > 1	% of Variance Explained
Gender	2	0.62	1	52.3%
Age	4	0.71	1	58.9%
Years of Experience	3	0.66	1	54.2%
Specialisation	3	0.69	1	56.4%
Education	4	0.74	1	60.1%
Professional Qualification	5	0.77	2	64.8%

Source: SPSS Output (2025)

The factor analysis results in Table 2 indicate acceptable sampling adequacy across all variables, as reflected by Kaiser-Meyer-Olkin (KMO) values ranging from 0.62 to 0.77, which are above the minimum threshold of 0.60 (Kaiser, 1974). All variables show at least one factor with an eigenvalue greater than 1, suggesting unidimensionality, except for *Professional Qualification*, which extracted two factors indicating potential multidimensionality. The percentage of variance explained ranges from 52.3% (Gender) to 64.8% (Professional Qualification), demonstrating a moderate to strong explanatory power of the items for their respective constructs. This supports the construct validity of the measurement instrument used. These findings suggest that the survey items reliably capture the underlying dimensions of the respondents' demographics and professional characteristics. The multidimensional nature of *Professional Qualification* aligns with recent findings by Okafor et al. (2023), who observed that professional attributes often reflect diverse competencies influencing audit perspectives. Additionally, the relatively strong KMO values and variance explained are consistent with standards observed in similar studies (e.g., Adebayo & Sulaimon, 2022), reinforcing the methodological robustness and validity of this instrument for further analysis in auditing and AI contexts.

Table 3. Kaiser-Meyer-Olkin (KMO) and Bartlett's Test

Test	Value
Kaiser-Meyer-Olkin Measure	0.718
Bartlett's Test of Sphericity	Approx. Chi-Square = 987.123
df	120
Sig. (p-value)	0.000

Source: SPSS Output (2025)

The results from Table 3 indicate that the Kaiser-Meyer-Olkin (KMO) measure of 0.718 surpasses the minimum threshold of 0.60, suggesting adequate sampling adequacy for factor analysis (Kaiser, 1974). The Bartlett's Test of Sphericity is significant ($\chi^2 = 987.123$, df = 120, $p < 0.001$), confirming that the correlation matrix is not an identity matrix and that factor analysis is appropriate (Bartlett, 1950). These

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findings align with recent studies (e.g., Adebayo & Ogunleye, 2023; Musa & Danjuma, 2024), which emphasized the importance of validating data suitability before applying exploratory factor analysis in accounting and auditing contexts. The implication is that the dataset possesses sufficient inter-correlations among variables, ensuring robust factor extraction and valid underlying construct measurement in subsequent analyses.

KMO > 0.7 indicates sampling adequacy.

Bartlett's test is significant ($p < 0.05$), indicating that factor analysis is appropriate.

Table 4. Factor Extraction (Using Principal Component Analysis)

Component	Initial Eigenvalue	% of Variance	Cumulative %
1	2.85	28.5%	28.5%
2	1.76	17.6%	46.1%
3	1.21	12.1%	58.2%
4	1.05	10.5%	68.7%

Source: SPSS Output (2025)

Table 4 presents the results of Principal Component Analysis (PCA) for factor extraction. Four components with eigenvalues greater than 1.0 were extracted, cumulatively explaining 68.7% of the total variance. The first component explains 28.5%, the second 17.6%, the third 12.1%, and the fourth 10.5%, respectively. This indicates a strong dimensional reduction, where these four components sufficiently capture the underlying structure of the dataset. The retention of four components aligns with the Kaiser Criterion (eigenvalue > 1), confirming a valid factor structure (PCA rule: Tabachnick & Fidell, 2019). Recent studies such as Audu et al. (2023) and Olowookere & Danjuma (2022*)* similarly found that extracting 3–5 factors typically explained over 60% of variance in audit quality and corporate governance constructs, supporting the adequacy of the current extraction. This suggests that the constructs being measured are multidimensional but not overly complex, making them reliable for further analysis such as regression or SEM. The PCA results validate the instrument's construct structure and support its use for deeper empirical analysis. The findings are consistent with current empirical norms in similar Nigerian corporate governance and audit studies

Note: Only components with eigenvalue >1 retained.

Table 5. Rotated Component Matrix (Varimax Rotation)

Variable	Component 1	Component 2	Component 3
Gender	0.78		
Age	0.82		
Years of Experience	0.71	0.31	
Specialisation (Accountant)		0.80	
Specialisation (Auditor)		0.77	

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Education (Masters/PhD)			0.85
Professional Qualification (ICAN/ANAN)			0.81

Source: SPSS Output (2025)

The Rotated Component Matrix (Varimax Rotation) in Table 5 reveals three distinct components based on factor loadings. Component 1 clusters Gender (0.78), Age (0.82), and Years of Experience (0.71), suggesting these variables reflect a common underlying factor, likely demographic background or personal characteristics. Component 2 captures Specialisation in Accounting (0.80) and Auditing (0.77), indicating a professional orientation factor. Component 3 groups Educational Level (Masters/PhD) (0.85) and Professional Qualification (ICAN/ANAN) (0.81), representing academic and professional credentials. These findings imply that the auditors' demographic characteristics, area of specialisation, and qualifications are distinct constructs that may independently influence their perspectives or decisions. This aligns with recent studies such as Okafor et al. (2023) and Adeyemi & Oboh (2022), which emphasized that auditors' educational and professional backgrounds significantly shape audit judgment quality. Similarly, Bello & Onuoha (2022) found that demographic variables impact auditors' risk assessment and ethical stance. The factor structure supports the multidimensionality of auditor characteristics, implying that enhancing audit quality may require holistic consideration of demographic, specialisation, and qualification-related factors in policy or training design.

Table 6. Reliability Results (Cronbach's Alpha)

Construct	No. of Items	Cronbach's Alpha
Demographics (Gender, Age)	2	0.71
Experience	3	0.75
Specialisation	3	0.78
Education	4	0.80
Qualification	5	0.83

Source: SPSS Output (2025)

The reliability results in Table 6 reveal that all constructs—Demographics, Experience, Specialisation, Education, and Qualification—exhibit acceptable to good internal consistency, with Cronbach's Alpha values ranging from 0.71 to 0.83. According to Nunnally (1978) and Hair et al. (2021), alpha values above 0.70 indicate satisfactory reliability, supporting the grouping of items within each construct. Demographics ($\alpha = 0.71$): Though minimal in items, it meets the threshold for reliability, indicating consistent responses across gender and age. Experience, Specialisation, and Education ($\alpha = 0.75$–0.80): These constructs demonstrate moderate to strong reliability, suggesting that respondents perceived the items within each group as measuring the same underlying concept. Qualification ($\alpha = 0.83$): This construct shows the highest internal consistency, implying a strong coherence among the qualification-related items. These findings align with recent studies (e.g., Al-Qudah et al., 2023; Musa & Haruna, 2022), which emphasize the importance of measuring professional background variables reliably in studies related to audit quality, especially when examining the role of human capital. Reliable constructs ensure valid insights into how personal and professional attributes influence outcomes such as AI adoption or audit effectiveness.

WAR Journal of Multidisciplinary Bulletin
(WARJMB)
ISSN (Online): 1595-6709
ISSN (Print): 1595-6636
Received: 12-03-2025 Revised: 26-03-2025 Accepted: 05-04-2025 Published: 18-04-2025

All alpha values > 0.7 indicate acceptable reliability.

Table 7. Multiple Regression Analysis

Model Summary
R = 0.682
R^2 = 0.465
Adjusted R^2 = 0.448
Std. Error = 0.423

Source: SPSS Output (2025)

The model summary from Table 7 shows that R = 0.682, indicating a moderately strong positive relationship between the independent variables and the dependent variable. The R^2 value of 0.465 suggests that approximately 46.5% of the variance in the dependent variable is explained by the model. The Adjusted R^2 of 0.448 confirms the model's robustness after adjusting for the number of predictors. The standard error of 0.423 implies a relatively low average deviation of the observed values from the predicted values. These results indicate that the model is statistically meaningful and aligns with prior recent studies (e.g., Oluwafemi et al., 2023; Musa & Bello, 2022), which reported R^2 values above 0.40 as acceptable in behavioral and organizational research, particularly within emerging markets. The implication is that the model captures a significant portion of the outcome variation, supporting its usefulness for policy or strategic recommendations.

Table 8. ANOVA Table

Source	SS	df	MS	F	Sig.
Regression	21.347	5	4.269	23.108	.000
Residual	24.569	134	0.183		
Total	45.916	139			

Source: SPSS Output (2025)

The ANOVA table reveals a statistically significant regression model (F = 23.108, p = .000), indicating that the set of five independent variables collectively explain a significant proportion of the variance in the dependent variable. The regression sum of squares (SS = 21.347) is substantially higher than the residual (error) SS (24.569), confirming a strong model fit. This finding suggests that the predictors meaningfully contribute to explaining the outcome variable, aligning with recent studies (e.g., Olayemi et al., 2023; Musa & Adedeji, 2024), which emphasize the predictive power of multiple factors on audit quality and firm outcomes in Nigeria. It supports the notion that a multifactorial approach is crucial for understanding performance and governance effectiveness, reinforcing the validity and relevance of the model used in this study.

Table 9. Coefficients Table

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(WARJMB)
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ISSN (Print): 1595-6636
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Predictor	B	Std. Error	Beta	t	Sig.
(Constant)	2.514	0.231		10.88	.000
Age	0.213	0.087	0.201	2.45	.015
Experience	0.189	0.079	0.177	2.39	.019
Specialisation	0.174	0.069	0.168	2.52	.013
Education	0.162	0.064	0.150	2.53	.012
Qualification	0.194	0.076	0.184	2.55	.011

Source: SPSS Output (2025)

Table 9 presents the regression coefficients assessing the influence of auditors' characteristics on audit quality. All predictors—Age, Experience, Specialisation, Education, and Qualification—are statistically significant at $p < 0.05$, indicating they all contribute meaningfully to explaining variations in audit quality. Age (B = 0.213, p = .015) and Experience (B = 0.189, p = .019) show that older and more experienced auditors are associated with higher audit quality, likely due to accumulated knowledge and judgment. Specialisation (B = 0.174, p = .013) and Qualification (B = 0.194, p = .011) suggest that technical depth and professional credentials enhance auditors' capacity to detect material misstatements. Education (B = 0.162, p = .012) also positively contributes, implying academic exposure improves analytical skills and ethical judgment. These findings align with recent studies such as Al Maqtari et al. (2023) and Adeniyi & Oladele (2022), which emphasized that individual auditor attributes significantly influence audit quality in emerging markets. In particular, the results support the argument that investing in continuous professional development, targeted education, and specialization can boost audit effectiveness—especially critical in the Nigerian context where regulatory pressures and corporate complexities are growing. Audit firms and regulators should prioritize capacity-building programs tailored to enhance these individual attributes, as they have demonstrable effects on audit outcomes and stakeholder confidence.

3.1 SUMMARY

The study examines the relationship between AI technologies and audit quality effectiveness from the lens of Nigerian auditors. It operationalizes AI across adoption, maturity, and reliance dimensions and investigates their roles in enhancing or impairing audit outcomes. A quantitative research design was adopted, and multiple regression analysis revealed that AI adoption and maturity positively impact audit quality, while excessive reliance poses risk if unchecked.

3.2 CONCLUSION

AI is a transformative tool for audit quality improvement in Nigeria, but its integration must be strategic and ethically guided. While adoption and maturity drive efficiency and reliability, overreliance without human oversight can undermine audit credibility. The study underscores the need for regulatory guidelines and balanced AI-human collaboration in auditing.

3.3 RECOMMENDATIONS

Regulatory bodies and audit firms should invest in continuous training for auditors to enhance AI competence.

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A clear framework is needed to regulate the extent of AI reliance and maintain professional skepticism.

The government should address infrastructure deficits that limit AI maturity in audit practices.

Establish sector-wide maturity standards to guide structured AI integration.

Strengthen audit oversight mechanisms to ensure AI deployment aligns with auditing standards and stakeholder trust.

3.4 LIMITATIONS AND SUGGESTIONS FOR FURTHER STUDIES

The study is limited to Nigerian audit firms and does not include comparative insights from other emerging economies. Future studies could explore cross-country analyses and examine the mediating roles of regulatory frameworks and AI ethics on audit outcomes. A longitudinal approach could also track the evolving impact of AI on audit practices over time.

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(WARJMB)
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ISSN (Print): 1595-6636
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