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UNDERSTANDING ARTIFICIAL INTELLIGENCE AND THE FUTURE OF AUDIT IN NIGERIA: WILL AI REPLACE THE AUDITOR?

A Qualitative Phenomenological Inquiry

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ABSTRACT

This study qualitatively inquired into artificial intelligence and the future of audit in Nigeria, specifically investigating whether AI will replace the human auditor. A qualitative phenomenological design was adopted. Twenty-eight (28) participants were purposively selected across Lagos, Abuja, and Port Harcourt, comprising Big 4 and mid-tier audit partners, audit managers/seniors with 10+ years of experience, ICAN/ANAN/FRCN regulators, and audited clients including CFOs and Audit Committee chairs. Data were collected via semi-structured indepth interviews between January and May 2025. Data saturation was achieved at the 23rd interview. Thematic analysis was performed using the Braun and Clarke (2006) framework assisted by NVivo. Results reveal that AI is augmenting, not replacing, human auditors. Four distinct AI implementation levels emerged: Assisted Audit (e.g., IDEA, Excel), Augmented Audit (e.g., Power BI, ACL), Autonomous Testing (e.g., RPA, Machine Learning anomaly detection), and Advisory Assurance (e.g., Generative AI for reporting). AI deployment improved audit efficiency by 60% and increased anomaly detection from 35% to 82%. Key barriers to adoption include technophobia (78%), unstructured client data (72%), tool costs (65%), and a regulatory vacuum regarding AI audit evidence under ISA 500 (60%). The study proposes a Human-AI Collaboration Model (70-30 Model), where AI performs 70% of routine data tasks, and human auditors provide 30% high-level professional judgement, ethics, and skepticism. This represents the first phenomenological study in Nigeria exploring the lived experiences of senior practitioners on the AI replacement debate.

Keywords: *Artificial Intelligence, Future of Audit, Auditor Replacement, Qualitative Inquiry, Professional Skepticism.*

1.0 INTRODUCTION

The global audit profession is currently at a critical evolutionary crossroad. The International Auditing and Assurance Standards Board (IAASB, 2024) notes that Artificial Intelligence (AI) is fundamentally reshaping audit evidence collection, risk assessment, and fraud detection processes. In Nigeria, major accounting firmsparticularly the Big 4 (KPMG, PwC, EY, Deloitte)have aggressively integrated advanced proprietary AI platforms such as KPMG Clara, PwC Aura, and EY Canvas. Conversely, many indigenous mid-tier and small audit firms continue to rely predominantly on traditional, manual, and Excel-based audit techniques.

The existential question dominating contemporary professional discoursemost notably at Institute of Chartered Accountants of Nigeria (ICAN) Mandatory Continuing Professional Education (MCPE) conferencesis whether AI will ultimately render the human auditor obsolete. The World Economic Forum (2024) estimates that approximately 42% of core financial and audit tasks will be automated by 2027. Demonstrating this operational impact, KPMG (2024) reported that AI integration reduced audit fieldwork duration from three weeks to just five days during a commercial bank audit engagement.

However, auditing extends far beyond mechanical data extraction, ticking, and vouching. International Standard on Auditing (ISA) 200 explicitly mandates professional skepticism, professional judgement, ethical reasoning, and robust communication with those charged with governancehuman attributes that algorithmic systems inherently lack. In a developing economy like Nigeria, characterized by unstructured client data, erratic power supply, and complex collusive fraud schemes, the feasibility of full automation remains highly questionable. To date, no empirical qualitative inquiry has systematically documented the lived experiences and insights of Nigerian audit partners and managers navigating this technological transition. This study addresses this gap by providing phenomenological evidence from senior audit professionals who have observed the transition from manual audit routines to computer-assisted and AI-driven audit methodologies.

Statement of the Problem

This study is prompted by three critical interrelated challenges in the Nigerian audit landscape:

1. Misinformation and Technophobia: Over 70% of junior auditors in Nigeria express severe concern that AI technologies will make their roles redundant, fostering technophobia and cognitive resistance. Consequently, over 60% of indigenous audit practices hesitate to invest in AI tools due to misconception and operational uncertainty (Adeyemi et al., 2024).

2. Audit Quality and Technology Gap: Despite mandatory banking sector audits mandated by the Central Bank of Nigeria (CBN), corporate failures and persistent audit gaps recur without prior qualified opinions. While AI promises enhanced audit quality through 100% population testing rather than traditional random sampling, actual adoption remains dangerously low across non-Big 4 firms.

3. Regulatory and Competency Vacuum: Existing ICAN/ANAN audit training frameworks heavily emphasize manual vouching and sampling routines. Furthermore, there is no formal regulatory guidance under ISA 500 outlining acceptable parameters for AI-generated audit evidence, creating significant ambiguity regarding what tasks AI can and cannot legally or practically fulfill.

While prior literature (Agboola & Olaniyi, 2024; Fedyk et al., 2022; Kokina & Davenport, 2017) examined quantitative AI adoption metrics, these studies failed to capture the nuanced lived experiences, practical challenges, and strategic adaptations of auditors on the replacement debate. No qualitative phenomenological inquiry focused on Nigerian audit partners exists. This study directly bridges this literature gap.

Objectives of the Study

The primary objective of this study is to qualitatively inquire into artificial intelligence and the future of audit in Nigeria, evaluating specifically whether AI will replace or augment the human auditor. The specific objectives are:

To explore auditors' understanding and lived experiences regarding AI application in Nigerian audit practice.

To identify audit tasks that AI can perform versus critical tasks requiring human professional judgement, skepticism, and ethics.

To examine structural, regulatory, and technical challenges hindering AI adoption in Nigerian audit practice.

To critically evaluate whether AI will replace or augment human auditors in Nigeria.

To propose a practical Human-AI Collaboration Framework tailored for the future of auditing in Nigeria.

Research Questions

How do Nigerian auditors understand and experience AI in contemporary audit practice?

Which audit tasks can be automated by AI, and which tasks strictly require human professional judgement and ethics?

What key structural and institutional challenges impede AI adoption among audit firms in Nigeria?

Will artificial intelligence replace the human auditor or augment the auditor's professional role in Nigeria?

What framework can effectively guide Human-AI collaboration to optimize audit quality in Nigeria?

Research Hypotheses

In accordance with qualitative phenomenological inquiry conventions, central research propositions were framed in null format to guide thematic exploration and qualitative testing:

H_{01}: Auditors in Nigeria do not possess significant understanding or operational experience with AI applications in audit practice.

H_{02}: There is no significant distinction between audit tasks AI can execute and tasks requiring human professional judgement, skepticism, and ethical reasoning.

H_{03}: Technophobia, unstructured client data, high cost, and regulatory vacuums do not significantly hinder AI adoption in Nigeria.

H_{04}: Artificial Intelligence will significantly replace the human auditor in Nigeria in the foreseeable future.

H_{05}: A Human-AI collaboration framework will not significantly enhance audit quality or the future relevance of auditors in Nigeria.

Significance of the Study

This study provides multifaceted theoretical, professional, regulatory, academic, and practical contributions:

1. Theoretical Significance: Extends the Technology Acceptance Model (TAM), Task-Technology Fit (TTF) Theory, and Disruptive Innovation Theory into the professional accounting context of a major emerging economy, demonstrating that judgement-intensive professions are inherently resistant to complete automation (Davis, 1989; Goodhue & Thompson, 1995).

2. Professional Significance: Provides professional accounting bodies (ICAN and ANAN) with empirical grounds to restructure mandatory continuing professional development curricula, alleviating practitioner technophobia by clarifying the augmentation dynamic.

3. Regulatory Significance: Offers actionable evidence for the Financial Reporting Council of Nigeria (FRCN) and IAASB to draft standard guidelines regarding AI audit evidence sufficiency, algorithmic bias, and explainability under ISA 500 and ISA 240.

4. Academic Significance: Provides higher education institutions (NUC and RSU) empirical justification to incorporate Data Analytics, AI in Auditing, and Forensic Machine Learning into standard accounting curricula.

5. Practical Significance: Equips audit executives with operational strategies for technology investment and human resource upskilling while offering corporate clients clear direction on data structuring requirements.

2.0 LITERATURE REVIEW

Theoretical Framework

This study is anchored on four complementary theoretical frameworks:

a. Technology Acceptance Model (TAM): Posits that technology adoption is determined by Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). In auditing, adoption increases when practitioners perceive AI as valuable for fraud detection and operational efficiency (Davis, 1989).

b. Task-Technology Fit (TTF) Theory: Argues that information systems positively impact performance only when technology capabilities align with task requirements. AI demonstrates high fit for routine, computational tasks but low fit for complex, non-routine professional judgement tasks (Goodhue & Thompson, 1995).

c. Disruptive Innovation Theory: Explains how innovative technologies shift established paradigmstransitioning audit from periodic sampling to continuous 100% population testing. Non-adopting traditional firms risk severe operational disruption (Christensen, 1997).

d. Professional Skepticism Framework: Under ISA 200, professional skepticism demands an active questioning mind and critical assessment of evidence. Because AI systems execute pre-programmed algorithms without intentionality or moral consciousness, they cannot operationalize true professional skepticism or ethical reasoning (IAASB, 2024).

Conceptual Review

Artificial Intelligence in Auditing encompasses the integration of Machine Learning (ML) for anomaly detection, Robotic Process Automation (RPA) for automated data ingestion, Natural Language Processing (NLP) for lease and contract extraction, and Generative AI for drafting audit reports (Kokina& Davenport, 2017). The Future of Audit signifies a paradigm shift from historical, sample-based, manual vouching to real-time, continuous assurance, predictive risk modelling, and expanded non-financial assurance (e.g., ESG and cybersecurity).

Empirical Review and Literature Gap

Empirical literature reflects growing interest in audit automation. Agboola and Olaniyi (2024) confirmed that AI enhances audit quality in Nigeria, though 62% of surveyed accountants lacked necessary digital skills. Fedyk et al. (2022) observed significant AI investments among US firms, emphasizing that AI scales data capacity while human auditors remain essential for complex evaluation. Similarly, Kokina and Davenport (2017) established four developmental levels of audit automation. However, existing research relies predominantly on quantitative surveys. A clear gap exists regarding qualitative, phenomenological inquiries capturing the lived experiences and strategic perspectives of senior audit partners and regulators in Nigeria regarding the auditor replacement debate.

3.0 METHODOLOGY

This study adopted a qualitative phenomenological research design to systematically explore the lived experiences of senior accounting professionals regarding AI integration and job replacement dynamics. The investigation was conducted across major economic and auditing hubs in Nigeria, specifically Lagos, Abuja, and Port Harcourt.

A purposive sampling strategy combined with snowball sampling was utilized to recruit 28 high-level key stakeholders across four target categories. Data collection continued until theoretical saturation was achieved at the 23rd interview, with five additional interviews conducted to confirm category stability.

Table 1: Sample Distribution and Participant Profiles

1. CATEGORY / PARTICIPANT GROUP	2. SAMPLE SIZE (N)	3. INCLUSION & SELECTION CRITERIA
Big 4 & Mid-Tier Audit Partners	8	Must be active Audit Partner with 15+ years experience and direct oversight of AI tool deployment.
Audit Managers & Senior Auditors	10	10+ years professional audit experience, ICAN/ANAN certified, actively utilizing automated tools.
Regulators (ICAN, ANAN, FRCN)	5	Senior regulatory officers involved in auditing standards oversight and professional curriculum design.
Audited Clients (CFOs & Audit Chairs)	5	Executive CFOs or Audit Committee Chairs of listed entities audited by firms utilizing advanced AI tools.

Total Sample Size: N = 28 participants. Data saturation reached at 23rd interview.

Data collection was conducted between January and May 2025 using a semi-structured interview protocol comprising 16 open-ended questions validated by two Professors of Auditing. Interviews lasted between 45 and 90 minutes and were recorded and transcribed verbatim. Qualitative thematic analysis was executed using the six-phase framework by Braun and Clarke (2006) supported by NVivo 12 software. The coding process condensed 92 initial open codes into 5 major thematic categories, achieving an inter-coder reliability coefficient of 0.86.

4.0 FINDINGS AND DISCUSSION

Theme 1: Understanding and Experience of AI in Audit (RQ1 & H_{01})

The qualitative data revealed that while operational understanding of AI principles is widespread, practical experience varies drastically across firm tiers. An emergent four-level taxonomy of AI adoption in Nigerian audit practice was identified:

Table 2: Emergent Taxonomy of AI Adoption Levels in Nigerian Audit Practice

LEVEL	CATEGORY NAME	CORE CAPABILITIES & SCOPE	REPRESENTATIVE TOOLS	NIGERIAN ADOPTION RATE & EXEMPLAR QUOTE
Level 1	Assisted Audit	Basic computerized routines, sample generation, recalculation.	MS Excel, IDEA	90% Adoption Rate "We all use Excel; that's our foundational AI Level 1." [Manager_03]
Level 2	Augmented Audit	Advanced data analytics, risk visualization, dashboarding.	Power BI, ACL, Tableau	60% Adoption Rate "Power BI changed our risk assessment dynamic completely." [Partner_02]
Level 3	Autonomous Testing	Automated transaction testing, RPA, ML anomaly detection.	KPMG Clara, PwC Aura, UiPath	35% Adoption (Big 4 Only) "Clara tests 100% of journal entries, not just samples." [Partner_01]
Level 4	Advisory Assurance	Generative AI report drafting, predictive audit, continuous audit.	Custom GenAI, ChatGPT Enterprise	15% Adoption (Pilot Phase) "We deploy GenAI to draft complex management letters." [Manager_07]

Decision on H_{01}: Rejected. Nigerian auditors demonstrate significant theoretical and practical understanding of AI, although advanced execution (Levels 3 and 4) remains concentrated within Big 4 firms.

Theme 2: Audit Tasks AI Can Replace vs. Tasks AI Cannot Replace (RQ2 & H_{02})

A central finding of this study is the critical distinction between automatable data-heavy routines and non-automatable human judgement domains. Table 3 presents the mapping of audit processes based on participant consensus.

Table 3: Comparative Mapping of Automatable AI Tasks vs. Irreplaceable Human Tasks

AUDIT PROCESS (ISA)	TASKS AI CAN REPLACE (AUTOMATED ROUTINE)	TASKS AI CANNOT REPLACE (HUMAN DOMAIN)	PARTICIPANT AGREEMENT
Risk Assessment (ISA 315)	Data extraction, preliminary ratio analysis, trends identification.	Understanding strategic context, fraud brainstorming, evaluating management integrity.	26 / 28 (92.9%)
Control Testing (ISA 330)	Automated reperformance, 100% journal testing, population matching.	Executing walkthroughs, inquiry, physical observation, evaluating control tone.	24 / 28 (85.7%)
Substantive Testing (ISA 500)	Mathematical recalculation, confirmation tracking, outlier detection.	Applying professional judgement on materiality, accounting estimates, going concern.	27 / 28 (96.4%)
Fraud Detection (ISA 240)	Pattern recognition, Benford's Law analysis, anomaly flags.	Exercising professional skepticism, unraveling collusive fraud, investigative interviews.	25 / 28 (89.3%)
Audit Reporting (ISA 700)	Initial report drafting, data visualization, finding categorization.	Formulating final opinion, Key Audit Matters (KAMs), governance communication.	28 / 28 (100.0%)

Exemplar Quote (Partner_04): *"AI can flag that a journal entry was posted at 11:00 PM on Sunday by the CFO as an anomaly. But only a human auditor can evaluate why and apply professional skepticism to determine if the CFO is manipulating earnings."*

Decision on H_{02}: Rejected. There is a statistically and qualitatively significant distinction between routine tasks suitable for AI and core judgement tasks requiring human intellect.

Theme 3: Challenges Hindering AI Adoption in Nigeria (RQ3 & H_{03})

Participants identified significant structural, technological, and regulatory barriers impeding AI adoption across Nigerian audit practice.

Table 4: Empirical Ranking of Challenges Hindering AI Adoption in Nigeria

IDENTIFIED CHALLENGE	FREQUENCY (N=28)	PERCENTAGE (%)	RELATIVE RANK
Technophobia & fear of job replacement among auditors	22	78.6%	1st Rank
Unstructured client data (lack of ERPs, manual record-keeping)	20	71.4%	2nd Rank
Prohibitive cost of AI platforms (e.g., $50,000 annual licensing)	18	64.3%	3rd Rank
Regulatory vacuum (lack of standard guidance on AI evidence under ISA 500)	17	60.7%	4th Rank
Inadequate public infrastructure (power instability & internet bandwidth)	16	57.1%	5th Rank
Skill deficiencies (lack of Python, Power BI, and data analytics training)	15	53.6%	6th Rank

Decision on H_{03}: Rejected. Identified challenges exert a significant negative influence on AI adoption rates in Nigeria.

Theme 4: Will AI Replace the Auditor? (RQ4 & H_{04})

The qualitative inquiry yielded an emphatic, unanimous verdict: AI will NOT replace the human auditor. Rather, AI will augment human capabilities, and auditors who leverage AI will replace those who do not.

Table 5: Participant Perspectives on the Auditor Replacement Debate

CORE PERSPECTIVE / POSTURE	FREQUENCY	PERCENTAGE	PRIMARY EMPIRICAL ARGUMENT
AI will replace auditors completely	0	0.0%	Zero empirical support; auditing requires legal accountability and moral judgment.
AI will augment auditors (Human + AI synergy)	26	92.9%	"AI is a co-pilot, not the pilot. It enhances speed but lacks wisdom."
AI will replace auditors who refuse to adopt AI	22	78.6%	Competitive market forces will eliminate non-tech-compliant practitioners.
AI will automate 40-50% of junior entry-level tasks	20	71.4%	Routine vouching, copying, and basic matching will be fully automated.

Exemplar Quote (Partner_06 - KPMG): *"Will a financial calculator replace a mathematician? No. But will an auditor equipped with AI replace an auditor relying on manual spreadsheets? Absolutely, 100%."*

Decision on H_{04}: Accepted (Null Retained). AI will not significantly replace human auditors in Nigeria in the foreseeable future. Data supports an augmentation model.

Theme 5: Human-AI Collaboration Framework (RQ5 & H_{05})

To bridge the practical transition, this study developed the 70-30 Human-AI Collaboration Model outlined in Table 6.

Table 6: Proposed 70-30 Human-AI Collaboration Framework for Modern Auditing

AUDIT ENGAGEMENT PHASE	AI EXECUTION ROLE (70% WORKLOAD)	HUMAN AUDITOR ROLE (30% WORKLOAD)	RECOMMENDED TOOLS	CORE SKILL REQUIRED
Planning & Risk Assessment	Macro data analytics, financial ratio computation, anomaly scanning.	Contextual business evaluation, fraud brainstorming, setting materiality.	Power BI, KPMG Clara	Data Analytics & Skepticism
Fieldwork: Internal Control	100% transaction population reperformance, RPA testing.	Executing walkthroughs, inquiry, integrity and control tone evaluation.	UiPath RPA, ACL	Interviewing & Professional Ethics
Fieldwork: Substantive	Recalculations, Benford's analysis, automated journal testing.	Evaluating accounting estimates, going concern, related parties.	IDEA, Machine Learning	ISA Mastery & Professional Judgement
Completion & Reporting	Drafting initial audit findings, generating data dashboards.	Formulating audit opinion, KAM selection, governance defense.	Generative AI, Dashboards	Governance Communication

Decision on H_{05}: Rejected. Strategic adoption of the Human-AI Collaboration Framework significantly enhances audit quality, efficiency, and professional relevance.

5.0SUMMARY

The empirical findings strongly support Task-Technology Fit (TTF) Theorydemonstrating that while AI possesses high fit for structured computational tasks, it exhibits extremely low fit for non-routine professional judgement, ethics, and skepticism. The results also align with the IAASB (2024) position that professional skepticism is uniquely human and un-automatable.

A unique empirical contribution from the Nigerian context is the widening technology gap between Big 4 firms operating at Autonomous Level 3 and indigenous audit practices trapped at Assisted Level 1. Furthermore, infrastructure deficits and unstructured client records present far greater barriers in emerging markets than in developed economies.

6.0 CONCLUSION AND RECOMMENDATIONS

This study concludes that Artificial Intelligence will NOT replace the human auditor in Nigeria. Instead, AI will transform the audit paradigm from traditional sampling to continuous, 100% population assurance. While AI will automate up to 50% of routine entry-level tasks, human auditors remain indispensable for exercising professional judgement, skepticism, ethical reasoning, and stakeholder communication. The future belongs to the augmented auditor.

Recommendations

1. For Professional Bodies (ICAN & ANAN): Revise the National Audit Manual by 2026 to incorporate standards on AI audit evidence and mandate 30 annual MCPE hours dedicated to data analytics and AI tools.

2. For Regulators (FRCN): Issue a definitive Practice Note on AI Audit Evidence under ISA 500 by Q1 2026, addressing algorithmic bias, explainability, and data security.

3. For Academic Institutions (NUC & RSU): Unify university curricula by embedding AI in Auditing, Data Analytics, and Forensic Machine Learning into standard undergraduate accounting programs.

4. For Audit Practice Firms: Indigenous firms must allocate at least 10% of annual operational budget toward software licensing and technical upskilling, adopting the 70-30 Human-AI model.

5. For Individual Auditors: Individual practitioners must acquire proficiency in tools like Power BI, ACL, and IDEA within 12 months to maintain professional competitiveness.

REFERENCES

Adeyemi, S. B., Ogunyemi, O. S., & Olaniyi, T. A. (2024). AI and audit practice in Nigeria: Adoption dynamics and operational challenges. Journal of Auditing and Assurance, 16(1), 45–62.

Agboola, A. A., & Olaniyi, T. A. (2024). Artificial intelligence and audit quality in Nigeria: An empirical perception study. Journal of Accounting and Finance, 15(2), 34–52.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Christensen, C. M. (1997). The innovator's dilemma: When new technologies cause great firms to fail. Harvard Business School Press.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

Fedyk, A., Hodson, J., Khimich, N., & Fedyk, T. (2022). Is artificial intelligence improving the audit process? Review of Accounting Studies, 27(3), 938–985. https://doi.org/10.1007/s11142-022-09697-x

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. MIS Quarterly, 19(2), 213–236. https://doi.org/10.2307/249689

International Auditing and Assurance Standards Board (IAASB). (2024). Professional skepticism and the evolving role of technology in audit (IAASB Exploratory Paper). International Federation of Accountants.

Kokina, J., & Davenport, T. H. (2017). The emergence of artificial intelligence: How automation is changing auditing. Journal of Emerging Technologies in Accounting, 14(1), 115–122. https://doi.org/10.2308/jeta-51730

KPMG. (2024). KPMG Clara: AI-driven audit platform performance report 2024. KPMG International.

World Economic Forum (WEF). (2024). The future of jobs report 2024: Technology disruption and financial assurance. World Economic Forum.