

Moderating Role of Auditors Attitude and Perception On Artificial Intelligence and Audit Practice of Audit Firms in Nigeria

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Abstract: *This study explores the moderating role of auditors' attitude and perception on the relationship between artificial intelligence (AI) and audit quality of audit firms in Nigeria. Grounded on the Technology Acceptance Model and the study utilized cross-sectional survey research design and a population of all audit firms licensed by ICAN and Taro Yamene formula was used to derive the sample size. Questionnaire was used as the primary source of data collection from 237 respondents after validity and reliability tests. The data obtained from the questionnaire administered were analysed using univariate, bivariate, and multivariate analysis to discover if the change in auditors' attitude and perception, expert systems, neutral network, machine learning and fuzzy logic influence audit quality in Nigeria. The finding from the structural equation modelling (SEM) shows a significantly positive relationship between expert systems of AI on audit quality of public audit firms in Nigeria, a significantly positive relationship between neutral network of AI on audit quality of public audit firms in Nigeria, a significantly positive relationship between machine learning of AI on audit quality of public audit firms in Nigeria, a significantly positive relationship between fuzzy logic of AI on audit quality of public audit firms in Nigeria, and a significantly positive relationship between auditors' expertise and experience on audit quality of public audit firms in Nigeria. The study also revealed that auditors' attitude and perception moderate a significantly positive relationship between artificial intelligence (expert systems, neutral network, machine learning and fuzzy logic) on audit practice (audit quality) on audit quality of public audit firms in Nigeria. Hence, based on the findings, the paper concludes that artificial intelligence is a significant determinant of audit quality in Nigeria and auditors' attitude and perception moderate significantly positive association between artificial intelligence is a significant determinant of audit quality of public audit firms in Nigeria. The study offers practical implications for audit regulators, professional bodies and audit firms aiming to improve audit outcomes through the effective integration of AI technologies.*

Keywords: artificial intelligence, audit quality, auditors' perception and attitude, technology acceptance model.

INTRODUCTION

In recent years, the rapid advancement of artificial intelligence (AI) has begun to reshape the landscape of audit practice globally. AI technologies such as machine learning, data analytics, natural language processing and robotic process automation are increasingly being integrated into audit tasks – ranging from risk assessment and anomaly detection to audit evidence analysis and fraud identification (Yoon et al, 2015). These technologies are expected to enhance audit quality, efficiency, and coverage. According to Albawwat and AlFrijat (2021), AI can support data to be mined and pooled to provide better audit processes at various stages. Owonifari et al (2023) argued that AI structures have the benefit of being able to analyze whole set of data, generate audit tests, and prepare audit reports. Kokina and Davenport (2017) assert that auditing is particularly well-matched to data analytics and AI applications. Noordin (2022) maintain that client consulting, providing of services such as audit and fraud detection, and improvement of audit firms' internal processes are all likely AI applications in audit practice. Owonifari et al (2023), Chukwuani and Egiyi (2020), Chukwudi, et al (2018) explains that AI tools and methods enhances the accuracy and proficiency of audit practice, as well as the detection of likely matters with a firm's financial reports and to detect possible fraud on the accounting records. Kaplan and Haenlen (2019) also argue that AI assists to enhance the accuracy of a firm's accounting processes even further. According to Raji and Buolamwini (2019), several auditing procedures that formerly required human efforts are now automated by AI, which comprises data entry processes. Noordin et al (2022) noted that AI tools and methods, as distinct from human auditors, can inspect 100% of accounting data, generate audit tests and prepare audit reports. AI can discover false accounting entries and make available attention at the head office, thereby reducing human intervention in the audit process (Moffitt et al. 2018; Lee & Tajudeen, 2020). As AI systems become more advanced, their potential to revolutionize audit practice is increasingly acknowledged, particularly in areas such as anomaly detection, fraud prediction and substantive testing (Dongre et al, 2020). However, the adoption and practical impact of AI on audit practice are not uniform and may depend significantly on huma elements, particularly the perception of auditors (Zhang et al, 2020; Hassan, 2022)

The integration of AI into audit practice has been globally recognized to enhance audit efficiency, accuracy, and fraud detection (Yoon et al, 2015). In developed economies, AI-driven tools have transformed how auditors perform data analytics, assess risk and form audit judgments. However, in developing countries like Nigeria, the adoption and effective application of AI in auditing remain inconsistent and underutilized (Asante & Nasir, 2021). Despite increasing availability of AI-enabled solutions, their practical impact on audit quality is yet to be fully realized. In the context of Nigeria, the adoption of AI in auditing is still at a nascent stage, hindered by structural, infrastructural, and educational constraints (Okoye et al, 2021). While bigger audit firms operating within Nigeria may have begun integrating AI tools, many small and medium-sized practices (SMPs) lack the resources, technical skills, and digital infrastructure necessary to fully embrace AI-driven audit solutions (Lee & Tajudeen, 2020). This uneven pace of technological adoption raises concerns about audit quality, regulatory compliance, and the overall effectiveness of audit

processes in the country. Consequently, it is beneficial for auditors to be knowledgeable and prepared with AI tools and methods that can monitor the exploration of organisation's financial transactions and other data collected, recorded, and processed (Hassan, 2022). Hence, implementing AI tools and methods in audit practice meets this challenge for auditors with the likelihood of computerization of auditing procedure from stage to stage (Moffitt et al, 2018). AI can remove important information from accounting data assisting auditors to devote sufficient time and energy on areas that call for high-level decision and is also being used by numerous auditing firms to study and review the total population of records than conducting sampling (Kokina & Davenport, 2017).

A critical factor influencing the successful implementation of AI in audit practice is the perception of auditors. Auditors' perception refers to the way auditors understand, interpret, and form judgments about audit-related information, clients and environment. It is a subjective mental process shaped by personal experiences, professional background, ethics and situational awareness during an audit engagement (Appah, 2024). Auditors' perceptions towards AI can influence their willingness to adopt and integrate AI into audit practice. These perceptions of usefulness, ease of use and trustworthiness of AI tools significantly shape auditors' willingness to adopt and apply emerging technologies (Curtis & Payne, 2008). However, prior studies Ugo (2023), Owonifari et al (2023), Fedyk et al (2022), Noordin (2022), Kwarbai and Omojoye (2021), Emetaram and Uchime (2021), Balios et al. (2020), Lina and Kloviene (2019), Khamis (2021), Albawwat and Yaser (2021), Chukwuani and Egiyi (2020), Chukwudi, et al (2018), Lee and Tajudeen (2020), Chassignol et al. (2018), Ukponget al (2019), Lin and Hazelbaker (2019), Deniz and Sorenson (2022), Solaimani et al. (2020), Albawwat and AlFrijat (2021) have largely ignored how auditors perception moderates the relationship between AI and audit practice, particularly within developing economies like Nigeria. Hence, understanding this moderating effect is particularly relevant in Nigeria's audit environment, where the regulatory framework is still adapting to technological disruptions and where auditor training in AI remains limited. This study seeks to fill a gap in existing body of knowledge by investigating how auditors' perception interacts with AI implementation to influence audit effectiveness, judgment quality and risk assessment. The findings from this study could provide valuable insights for policymakers, audit practice, regulators and professional bodies such as ICAN and ANAN in designing targeted training programs and AI adoption strategies that align with auditors' perception levels. Specifically, the objectives of the study are to: investigate the association between expert systems and audit quality of public audit firms in Nigeria; determine the association between neural network and audit quality of public audit firms in Nigeria; evaluate the association between machine learning and audit quality of public audit firms in Nigeria; investigate the association between Fuzzy logic and audit quality of public audit firms in Nigeria; examine the relationship between auditors perception on audit quality of public audit firms in Nigeria and evaluate the moderating role of auditors' perception on the relationship between AI and audit quality of public audit firms in Nigeria. The following null hypotheses were tested in this investigation:

H01: Expert systems of AI does not significantly influence audit quality of public audit firms in Nigeria.

H02: Neutral networks of AI does not significantly influence audit quality of public audit firms in Nigeria.

H03: Machine learning of AI does not significantly influence audit quality of public audit firms in Nigeria.

H04: Fuzzy logic of AI does not significantly influence audit quality of public audit firms in Nigeria.

H05: Auditor's perception does not significantly influence audit quality of public audit firms in Nigeria.

H06: Auditors' perception does not significantly moderate on the relationship between AI and audit quality of public audit firms in Nigeria.

LITERATURE REVIEW

Conceptual Review

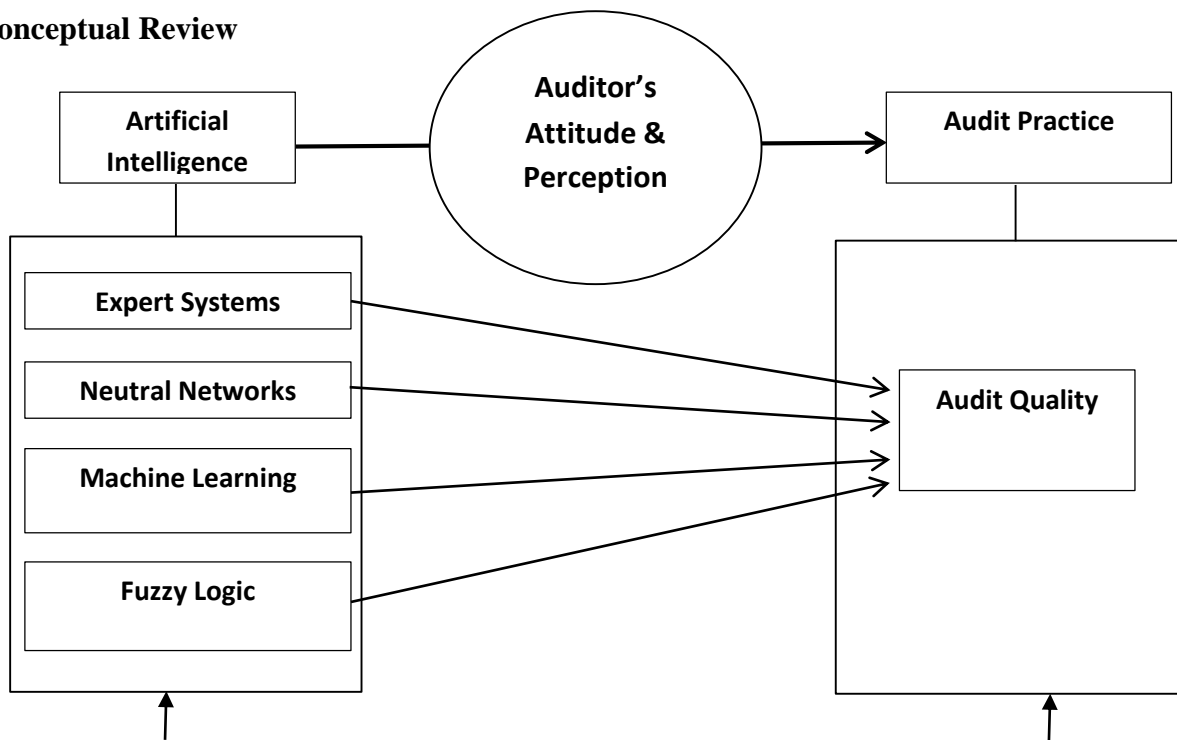


Figure 1: Conceptual Framework

Source: Author Creation

Concept of Artificial Intelligence: The concept of AI was coined by John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude E. Shannon (McCarthy et al, 2006). AI is an aspect of computer science and engineering designed with evolving smart technologies proficient in cognitive, knowledge and performing independently. AI systems can examine enormous quantities of data, identify configurations, and make decisions on their own (Hemin 2017). Hassan (2022) argued that AI consists of arranging, interpreting, and transferring the data, information, and intelligence to qualified parties in the form of reliable intelligence. Zemánková (2019) defined AI as the capacity of a mechanical system to precisely comprehend outside data, learn from it, and use what it has learned to accomplish definite objectives and responsibilities through flexible adaptation. Similarly, Zhang et al. (2020) described AI as the effective use of big data and machine learning (ML) know-how to understand the past and predict the future by means of enormous volumes of data. Lee and Tajudeen (2020) also examined AI as the use of machines that learn from their errors, adjust to new input, and perform human-like tasks. Dongre et al (2020) described AI as computerized systems that are programmed to reason and work as human intelligence and performs tasks better than humans through the experimental feature of computer science applied in programming an intelligent device that can function on numerous tasks by using its intelligence. According to Smith (2020), AI is characteristically assumed as a mix of hardware and software technologies that react to simulation in ways consistent with typical human reactions, given the human capability for reasoning, decision, and objective. AI are software packages that attempts to emulate human behaviour and capability and then accumulation human understanding and capability and convert it into instructions it applies to explain accounting issues and accomplish several accounting jobs (Stancheva- Todorova, 2018). Kwarbai and Omojoye (2022) argue that AI targets to create an intelligent software mechanism that can respond in ways akin to human behaviour and reasoning. The authors further noted that it also encompasses the capacity to review, comprehend associations, and create unique opinions. Baldwin et al (2006) listed the use of AI on auditing such as neural network for analytical review procedures, genetic algorithm for classification, fuzzy expert system for materiality assessment, internal control evaluation and risk assessment, hybrid system and statistical models for going concern decisions, non – linear model and classification trees for bankruptcy prediction and belief functions and probability for aggregating audit evidence. Consequently, this study used expert systems (ES), neural networks (NN), machine learning (ML), and fuzzy logic (FL) as dimensions for AI.

Concept of Audit Quality: Auditing is described as a systematic procedure of collecting information on the financial events of an organisation and communicating the outcomes to all interested parties. According to Owonifari et al (2023), to audit an organization involves an independent examination of the accounting books, which include financial statements such as statement of financial position, income statement, statement of changes in equity, cash flow statement, and notes explaining accounting policies. The primary objective of the audit is to provide an independent opinion on whether the financial information in the financial statements presented truly reveals the organization's financial state as at a specific date (Appah, 2017). Audit quality is described as the capacity of an auditor to ascertain accounting and regulatory gaps and explain the gaps for the attention of diverse stakeholders. Knechel and Salterio (2016) described

audit quality with two features of competence (expertise) and independence (objectivity). This provides that audit quality hinge on the expertise and proficiencies of the audit team and in what way the objective the audit team is in carrying out the audit process. According to The International Auditing and Assurance Standard Board (IAASB, 2014), it is imperative for members of the audit team to be objective in their composition and conduct of the audit effectively and efficiently. The IAASB (2014) state that audit quality consists of input factors, process factors, output factors and contextual factors. Consequently, audit quality can only be achieved when input and processes are conducted accurately with the excellent human resources, ICT technology and techniques to create the sought after ending. Nonetheless, AI is enhancing the quality of audit that prevails over the capabilities of humans. Kokina and Davenport (2017) maintain that AI can extract relevant information from accounting data assisting auditors to devote more time on aspects that call for advanced judgment to enhance audit quality and be able complete massive quantities of data and perform analysis quicker and which can be said to be impossible for auditors. Issa et al (2016) noted that AI is assisting auditors to perform effective audit testing by ascertaining if all risks identified have been solved. The use of machine learning would enable auditors to detect risk and misstatement faster during the audit process.

Auditors Perceptions and Attitude: Auditors' perception refers to the way auditors understand, interpret, and form judgments about audit-related information, clients, and environment. It is a subjective mental process shaped by personal experiences, professional background, ethics and situational awareness during an audit engagement (Appah, 2024). Auditors' perceptions towards AI can influence their willingness to adopt and integrate AI into audit practice. According to Appah (2024), that auditors' attitudes and perceptions play a crucial role in shaping the behaviour of auditors, decision making and overall performance. Hassan (2022), Ugo (2023), Kwarbai and Omojoye (2022), Owonifari et al, (2023) stated that auditors' attitude and perception provides several benefits such as training and experience, firm culture, client relationships and regulatory environment. Appah (2024) further argued that in audit practice, perception influences how auditors assess risk, interpret evidence, detect fraud, and make decisions regarding audit opinions. Because audits often involve complex, ambiguous, and judgment-based situations, how an auditor perceives these elements can significantly affect audit quality. Kwarbai and Omojoye (2022), Owonifari et al, (2023) stressed that perception plays a key role in determining how an auditor responds to audit situations. Auditor's attitude refers to the mental disposition, mindset, or behavioural tendency that an auditor holds toward their professional duties, ethical standards, technologies, and audit practice in general. It encompasses beliefs, feelings, and intended behaviours that may influence how auditors approach audit tasks, make judgments, or accept and use new tools. Okolie et al (2019) explained that auditors' attitude is the mindset or behavioural tendency that determines the quality of audit judgment and their willingness to adopt new technologies.

Theoretical Review: This study is grounded on the Technology Acceptance Model (TAM) theory advanced by Fred Davis (1986). The TAM is a theoretical framework that explains how users form attitudes and intentions to use technology. TAM proposes two key factors that determine whether

a person will adopt a new technology (Davis, 1989). **Perceived Usefulness:** The degree to which a user believes a technology will enhance their performance or productivity. **Perceived Ease of Use:** The degree to which a user believes a technology is easy to use and requires minimal effort (Davis, 1989). TAM offers several advantages such as predict user acceptance and adoption of technology, helps understand the factors that influence user behaviour and technology adoption, inform system design and development to create more user-friendly and effective systems, understanding the factors that influence user acceptance, help create systems that are more intuitive and user-friendly, leading to a better user experience. However, TAM suffers from several limitations such as oversimplifying complex factors that influence technology adoption, focuses primarily on perceived usefulness and ease of use, neglecting other important factors, it may not account for contextual factors such as organizational culture and social influences and the assumption that users are homogenous, neglecting differences in personality, motivation and ability. Several empirical evidence reveals the application of TAM in audit and accountancy practice. Yoon et al (2015) findings revealed that auditors were more likely to adopt big data analytics when they perceived them as useful in enhancing audit evidence. Asante and Nasir (2021) study findings indicated that audit firms perceived use and usefulness strongly predicated auditors' intention to use digital audit tools. In addition, Curtis and Payne (2008) investigation showed that auditors were likely to adopt new technologies when they believed the tools would increase efficiency and effectiveness.

Empirical Review

Table 1: Web metric Analysis of Reviewed Literature

Author(s)	Objective of the Study	Methodology	Findings and Recommendations
Malik & Jabbar (2023)	The study investigated the effects of fuzzy logic on enhancing audit procedures for the preparation of audit report.	The study employed cross sectional survey research design and data was obtained from a research questionnaire administered to the respondents. A total of 100 questionnaires were distributed and 87 were obtained for analysis using statistical analysis.	The results from the statistical analysis disclosed a statistical positive and significant association between fuzzy logic and audit processes in preparing audit report.
Kwarbai & Omojoye (2021)	The study examined the effects of AI on accounting profession.	The study used survey research design and questionnaire as the primary source of data collection. The population consisted of big 4 operating firms in	The multiple regression analysis results revealed that AI positively and significantly affects accounting profession in Nigeria. The study recommends amongst

		Nigeria. 500 questionnaires were distributed and 277 were collected and used for data analysis using multiple regression.	others that accounting software of accounting firms should learn from prior tagging decisions and integrate AI into sampling system
Owonifari et al (2023)	The study analysed the effects of AI and its efficacy on audit practice in Nigeria	This study used survey research design and the population comprised of 82 accounting firms and a sample size of 62 firms. The research used questionnaire as the primary source of data collection and 310 questionnaires were distributed to the sampled firms and the data obtained were analysed using univariate, bivariate and multivariate analysis.	The results from the multiple regression analysis indicated that data mining, machine learning and image recognition positively and significantly affect audit practice in Nigeria.
Noordin et al (2022)	The study investigated external auditors' perception of the application of AI on audit quality in UAE.	The study employed cross sectional online survey research design. The study used primary data from questionnaire from 22 domestic and 41 foreign audit firms in UAE and the primary data collected were analysed using reliability and validity tests, descriptive analysis and independent samples t-test.	The results from the study revealed that a non-significant difference in the perception of AI on audit quality between domestic and foreign audit firms.
Dagunduro et al (2023)	The study analysed the effects of AI on audit practice in Nigeria.	The study adopted survey research design and the population comprised 178 accounting firms and a sample size of 125 using non-probability sampling method. Questionnaire was used	The finding from the multiple regression analysis indicated that expert systems, machine learning and intelligent agents positively and significantly influence audit practice in Nigeria.

		as the primary source of data collection and univariate and multivariate analysis was used for data analysis.	
Falana et al (2023)	This study investigated the effects of big data on information quality of firms in Nigeria	The investigation employed survey research design and a population of 157 firms listed on the Nigeria Exchange Group (NGX) and a sample of 20 firms using purposive sampling method and descriptive and multiple regression analysis were used for data analysis.	The results from the multiple regression analysis indicated that data volume, data variety and data velocity positively and significantly affects the quality of information in Nigeria.
Ugo (2023)	This investigation studied the effects of AI on accounting practice in Nigeria.	This research employed survey research design and the population comprised of 148 respondents in Abuja. The study used questionnaire as the primary source of data collection and descriptive and multiple regression analysis were employed for data analysis.	The findings of the investigation indicated that expert systems and neutral networks positively and significantly affects the accounting practice in Nigeria.
Fijabi & Lasisi (2023)	This study analysed the effects of digitalization on accounting practice in Nigeria.	The study used survey research design and the population made up of 100 and a sample size of 86. The study used questionnaire as the primary source of data collection while univariate and multivariate analysis were used as methods of data analysis.	The multiple regression analysis discovered that digitalization positively and significantly influences audit practice efficiency, tax services and financial advisory services in Nigeria. The study further indicated that accounting practices positively and significantly affects digitalization in Nigeria.

Emetaram & Uchime (2021)	The study investigated the impact of AI on accountancy profession in Nigeria	The investigation used descriptive survey research design and the population consisted of 176 and a sample size of 122 using Taro Yamene model. Questionnaire was the primary source of data collection and t-test was used for data analysis.	The findings from the analysis indicated that AI positively and significantly affects accountancy profession in Nigeria.
Balios et al (2020)	This study analysed the impact of big data and data analytics on external auditing	This study used descriptive analysis and secondary sources of data collection for the investigation.	The descriptive analysis of the documentary evidence provides that big data and data analytic positively impact on the audit process.
Al-Arooud (2020)	This study analysed the impact of AI technologies on audit evidence in Jordan	This study adopted quantitative research design and a population of 582 licensed auditors while the sample size consisted of 314. The study used questionnaire as the primary source of data collection and univariate and multivariate analysis was applied for data analysis.	The results from the analysis indicated that expert systems positively and significantly impact on audit evidence while neutral network revealed a positive and insignificant effect on audit evidence in Jordan.
Ali et al (2022)	The study examined the effects of AI techniques on internal auditing activities	The study employed survey research design and population consisted of 100 respondents and 66 were collected from the respondents and univariate analysis were used for data analysis.	The findings from the data analysis indicated that AI techniques positively and significantly influences internal audit efficiency, provide better understanding and create competitive advantages.
Puthukulam et al (2021)	This research analysed the effects of auditors' perception on AI on	This research employed survey research design using a target population of auditors'	The findings of the study revealed that AI and ML significantly improves the quality,

	professional skepticism and judgment in Oman	in Oman and only 200 respondents were sent questionnaires while only 169 responded. Questionnaire was the primary source of data collection while descriptive and correlation analysis were used for data analysis.	reliability and efficiency of audit; significant and positive correlation between AI and ML on the quality, reliability and efficiency of audit; and AI and ML enhanced professional skepticism and judgment positively with the detection of errors and misstatements.
Albawat and Al-Frijat (2021)	The study examined the effects of AI techniques on audit quality in Jordan	This study adopted survey research design and the study population consisted of 250 questionnaires were administered and 124 were used for analysis. The primary data collected from questionnaire were tested using univariate and multivariate analysis.	The findings from the analysis of the responses indicated that auditors perceived assisted and augmented AI systems are ease of use in auditing while perceiving autonomous AI systems are complex. The results further showed a significant difference between perceived contribution to audit quality by the assisted, augmented and autonomous AI systems.
Solikin & Darmawan, (2023).	This study analysed the impact of AI on the effectiveness of accounting information systems in India	The study adopted survey research design and primary data using questionnaire was administered to 250 respondents were randomly selected while the responses from the questionnaire were analysed using descriptive, exploratory factor analysis and multiple regression.	The results from the regression analysis indicated that AI positively and significantly influences the effectiveness of accounting information system.
Fedyk et al (2022)	This study investigated the effects of AI on audit process in USA.	The study employed content analysis of 310,000 detailed individual resume for 36	The results from the study indicated that the adoption of AI assists audit firms to advance

		audit firms; employment of AI workers. The data collected were analysed using descriptive and multiple regression analysis.	audit quality, reduction of audit fees and displaces human auditors.
Chukwuani & Egiyi (2020)	The study examined the effects of AI on the automaton of accounting processes in Nigeria	The study employed descriptive research design and secondary sources of data collection for descriptive analysis.	The descriptive analysis indicated that the adoption of AI improves the quality of accounting information system, avoid the possibility of financial fraud and promote the transformation of traditional accounting and auditing.
Chukwudi et al (2018)	This research investigated the effects of AI on the accounting operations among accounting firms in Southeast Nigeria.	This study used survey research design and a population of 25 firms with 193 employees and census sampling method was used for sample size determination. The study used questionnaire as the primary source of data collection and data collected from the questionnaire responses were analysed using descriptive and regression analysis.	The results from the regression analysis indicated that expert systems and intelligent agents positively and significantly affects the performance of accounting functions of accounting firms in Southeast Nigeria.

Source: Compiled by the researchers (2024)

METHODOLOGY

This investigation on AI and audit practice in Nigeria used quantitative cross-sectional survey and correlational and exploratory research designs. These designs are appropriate to examine the direct effect of AI on audit practice and the moderating impact of audit experience. The population of this present study consists of one thousand five hundred (1500) audit firms licensed by the Institute of Chartered Accountants of Nigeria as at 22nd February, 2023 and Taro Yamene formula was

used to derive a sample size of three hundred and sixteen (316) audit firms. The study used primary and secondary sources of data collection. The secondary sources of data included textbooks, journals, accounting professional pronouncements and magazines. The primary source of data was the questionnaire entitled “Artificial Intelligence and Audit Practice in Nigeria Questionnaire”, which was cautiously designed and administered to various respondents across the states in Nigeria Using Google Scholar Form with the assistance of stratified random sampling technique, therefore, responses of the respondents emanated from a five-point Likert rating scale ranging from strongly disagree (1), disagree (2), neutral (3), agree (4) and strongly agree (5). The first section of the questionnaire contains items on demographic features of audit firms. The second section of the questionnaire consists of five (5) parts. The first part of the second section consists of five (5) items for measuring expert systems adopted from Chukwudi et al (2018), Al-Arooud (2020), Emetaram & Uchime (2021), Ugo (2023); the second part consists of five (5) items for measuring neutral networks adopted from Al-Arooud (2020); Emetaram & Uchime (2021), Ugo (2023); the third part consists of five (5) items for measuring machine learning adopted from Owonifari et al (2023); the fourth part consists of five (5) items for measuring fuzzy logic adopted from Emetaram & Uchime (2021), Malik & Jabbar (2023); and the fifth part consists of five (5) items for measuring audit practice adopted from Noordin et al (2022), Malik & Jabbar (2023), Owonifari et al (2023) while the sixth part consists of five (5) items for measuring audit attitude and perception adopted from Abiola and Iredele (2021), Asante and Asir (2021), Dabor and Dabor (2015). The questionnaire was validated using content and construct validity while it was pre-tested using twenty (20) respondents in Port Harcourt, Rivers State and a reliability test was done on the data collected using Cronbach Alpha test, to explore the internal consistency of the questionnaire (Appah, 2020). The result of the reliability test shows that the designed questionnaire is highly reliability at 0.872, 0.835, 0.843, 0.816 and 0.856. The questionnaires were administered to partners and audit seniors of sampled audit firms. The data obtained from respondents was presented and analyzed using univariate, bivariate and multivariate analysis. The multiple regression was guided by the model below:

$$AUQ = \beta_0 + \beta_1 EXS + \beta_2 NEN + \beta_3 MAL + \beta_4 FUL + \beta_5 AAP + + \mu \text{ -----1}$$

$$AUQ = \beta_0 + \beta_1 EXS + \beta_2 NEN + \beta_3 MAL + \beta_4 FUL + \beta_5 AAP + \beta_6 EXS * AAP + \beta_7 NEN * AAP + \beta_8 MAL * AAP + \beta_9 FUL * AAP + \mu \text{ -----2}$$

Where: β_0 = intercept; β_1 = coefficient of parameter Expert System (EXS); β_2 = Coefficient of parameter Neutral Networks (NEN); β_3 = Coefficient of parameter Machine Learning (MAL); β_4 = Coefficient of parameter Fuzzy Logic (FUL); AAP = Auditors Attitude and Perception and μ : random error term. The a priori expectation: $\beta_1 - \beta_4 > 0$, while $\beta_5 - \beta_9$ is the relationship between the moderator variable and independent variable.

RESULTS AND DISCUSSION**Table 2: Questionnaire Distribution**

	Frequency	Percent	Valid Percent	Cumulative Percent
Valid Number returned and correctly filled	237	75	75	75
Number returned and not correctly filled	28	8.9	8.9	83.9
Number not returned	51	16.1	16.1	100.0
Total	316	100.0	100.0	

Source: Field Survey (2025) Via SPSS Output

Table 2 shows that a total of three hundred and sixteen (316) copies of the questionnaire were distributed to the respondents. Out of this number, Two Hundred and Thirty-seven (237), representing 75% response rates, were correctly filled and returned, while Twenty-Eight (28) copies, representing 8.9% were returned but not correctly filled. However, fifty-one (51), representing 16.1% were not returned. The implication is that the analysis of data will be based on Two Hundred and thirty-seven (237) copies of the questionnaire, representing 75% response rates that were returned and correctly filled.

Table 3: Descriptive Statistics on Expert Systems

S/N	Items	N	Min	Max	Mean	Std. D
1	Expert systems are applied to accumulate audit evidence by redesigning them in the form of computer-hosted software	237	1.00	5.00	3.682	1.543
2	Expert systems are applied to remove knowledge to resolve problems with the gathering of audit evidence for efficient and effective quality of audit.	237	1.00	5.00	3.528	1.255
3	Expert systems are applied to be able to advise and make the right decisions regarding audit quality.	237	1.00	5.00	3.326	1.256
4	Expert systems are applied as a hierarchical framework that shows the accounting knowledge set for audit quality.	237	1.00	5.00	3.321	1.253
5	Expert systems are implemented to gather audit evidence in a program and are stored in the system's knowledge base for better audit quality.	237	1.00	5.00	3.327	1.365
	Valid No.	237			3.437	1.334

Source: Field Survey (2025)

The results in Table 3 represent the descriptive statistics of the mean and standard deviation responses on an expert systems variable using five questionnaire items that were designed on a five-point Likert scale. Thus, the questionnaire items labelled above and the mean and standard deviation of the five items were calculated to determine the overall mean and standard deviation responses on expert systems. Notwithstanding, all the items are above the cut-off point of 2.5.

However, the grand mean and standard deviation responses on the questionnaire items disclosed (**Mean =3.437; Std. D =1.334**) respectively. This implies that an expert system is a significant predictor of audit quality in Nigeria.

Table 4: Descriptive Statistics of Neutral Networks

S/N	Items	N	Min	Max	Mean	Std. D
1	Neutral networks of AI can explain the steps of collecting audit evidence to reach the solution and the reasons behind this solution.	237	1.00	5.00	3.248	1.537
2	Neutral networks of AI add to providing explanations and recommendations to the user in a strong and correct depiction of audit evidence for increased audit quality.	237	1.00	5.00	3.271	1.245
3	Neutral network of AI is applied to complete the collection and practical implementation of integrated electronic audit evidence for increased audit quality.	237	1.00	5.00	3.432	1.256
4	Neutral network of AI is implemented to store information about the gathering of audit evidence for the collection of links and communication for improved audit quality.	237	1.00	5.00	3.574	1.272
5	Neutral network of AI is implemented to process information on audit evidence and provide solutions to difficult problems in parallel for improved audit quality.	237	1.00	5.00	3.274	1.375
Valid N (listwise)		237			3.360	1.337

Source: Field Study (2025)

The results in Table 4 show the descriptive statistics of the mean and standard deviation responses on the neutral network AI variable using five questionnaire items that were designed on a five-point Likert scale. Thus, the questionnaire items labelled above and the mean and standard deviation of the five items were calculated to determine the overall mean and standard deviation responses on neutral network AI. Notwithstanding, all the items are above the cut-off point of 2.5. However, the grand mean and standard deviation responses on the questionnaire items disclosed (**Mean =3.360; Std. D =1.337**) respectively. Therefore, this implies that neutral network AI is a significant predictor of audit quality in Nigeria.

Table 5: Descriptive Statistics of Machine Learning

S/N	Items	N	Min	Max	Mean	Std. D
1	Do you agree that the use of computer technology for predicting output values from given input data is effective?	237	1.00	5.00	3.421	1.432
2	Does your firm use Automatic help lines or chatbots in which customers or clients don't speak to humans, but instead interact with a machine?	237	1.00	5.00	3.365	1.318
3	Does your firm use algorithms that use machine learning and natural language processing, with the bots learning from records of past conversations to come up with appropriate responses?	237	1.00	5.00	3.318	1.423
4	Does your firm have a pool of training data where your machine or software learn and improve with experience?	237	1.00	5.00	3.724	1.252
5	Does your firm use machine learning to reduce the cost and time of conducting an audit?	237	1.00	5.00	3.236	1.412
Valid N (listwise)		237			3.413	1.367

Source: Field Study (2025)

The results in Table 5 display the descriptive statistics of the mean and standard deviation responses on the machine learning AI variable using five questionnaire items that were designed on a five-point Likert scale. Thus, the questionnaire items labelled above and the mean and standard deviation of the five items were calculated to determine the overall mean and standard deviation responses on machine learning AI. Notwithstanding, all the items are above the cut-off point of 2.5. However, the grand mean and standard deviation responses on the questionnaire items disclosed (**Mean =3.413; Std. D =1.367**) respectively. Therefore, this implies that machine learning AI is a significant predictor of audit quality in Nigeria.

Table 6: Descriptive Statistics of Fuzzy Logic

S/N	Items	N	Min	Max	Mean	Std. D
1	Fuzzy logic of AI is applied to accumulate audit evidence by redesigning it in the form of computer-hosted software	237	1.00	5.00	3.583	1.324
2	Fuzzy logic of AI is applied to be able to advise and make the right decisions regarding audit quality.	237	1.00	5.00	3.438	1.323
3	Fuzzy logic of AI is implemented to gather audit evidence in a program and stored in the system's knowledge base for better audit quality.	237	1.00	5.00	3.125	1.532

4	Fuzzy logic of AI is implemented to gather audit evidence in a program and stored in the system's knowledge base for better audit quality.	237	1.00	5.00	3.548	1.421
5	Fuzzy logic of AI improves the judgment and decision-making process of external auditors to improve audit quality.	237	1.00	5.00	3.338	1.437
Valid N (listwise)		237			3.406	1.407

Source: Field Study (2025)

The results in Table 6 present the descriptive statistics of the mean and standard deviation responses on the fuzzy logic AI variable using five questionnaire items that were designed on a five-point Likert scale. Thus, the questionnaire items labelled above and the mean and standard deviation of the five items were calculated to determine the overall mean and standard deviation responses on fuzzy logic AI. Notwithstanding, all the items are above the cut-off point of 2.5. However, the grand mean and standard deviation responses on the questionnaire items disclosed (**Mean =3.406; Std. D =1.407**) respectively. Therefore, this implies that fuzzy logic AI is a significant predictor of audit quality in Nigeria.

Table 7: Descriptive Statistics of Audit Quality

S/N	Items	N	Min	Max	Mean	Std. D
1	AI technology in auditing will aid my professional skepticism.	237	1.00	5.00	3.373	1.254
2	AI technology in auditing will automate routine audit processes	237	1.00	5.00	3.521	1.337
3	AI technology in auditing will facilitate robust risk assessment through the analysis of entire populations.	237	1.00	5.00	3.426	1.516
4	AI technology in auditing will facilitate the focus of audit testing on the areas of the highest risk through the stratification of large populations.	237	1.00	5.00	3.837	1.231
5	AI technology in auditing will enable me to perform tests on large or complex datasets where a manual approach would not be feasible.	237	1.00	5.00	3.517	1.623
Valid N (listwise)		237			3.535	1.392

Source: Field Study (2025)

The results in Table 7 illustrate the descriptive statistics of the mean and standard deviation responses on the audit quality variable using five questionnaire items that were designed on a five-point Likert scale. Thus, the questionnaire items labelled above and the mean and standard deviation of the five items were calculated to determine the overall mean and standard deviation

of responses on audit quality. Notwithstanding, all the items are above the cut-off point of 2.5. However, the grand mean and standard deviation responses on the questionnaire items disclosed (**Mean =3.535; Std. D =1.392**) respectively.

Table 8: Descriptive Statistics of Audit Attitude and Perception

S/N	Items	N	Min	Max	Mean	Std. D
1	Auditors' attitudes towards professional skepticism can impact their ability to identify and assess risks.	237	1.00	5.00	3.373	1.254
2	Auditors' risk tolerance can influence their willingness to challenge management or identify potential issues.	237	1.00	5.00	3.521	1.337
3	Auditors' attitudes towards quality can impact their attention to detail and overall audit performance, and auditors' perceptions of the effectiveness of audit procedures can impact their confidence in the audit results.	237	1.00	5.00	3.426	1.516
4	Auditors' perceptions of the importance of the audit can impact their motivation and engagement.	237	1.00	5.00	3.837	1.231
5	Auditors' perceptions of the level of risk associated with the audit can influence their audit approach and procedures.	237	1.00	5.00	3.517	1.623
Valid N (listwise)		237			3.535	1.392

Source: Field Study (2025)

The results in Table 8 illustrate the descriptive statistics of the mean and standard deviation responses on the auditor attitude and perception variable using five questionnaire items that were designed on a five-point Likert scale. Thus, the questionnaire items labelled above and the mean and standard deviation of the five items were calculated to determine the overall mean and standard deviation of responses on auditor attitude and perception. Notwithstanding, all the items are above the cut-off point of 2.5. However, the grand mean and standard deviation responses on the questionnaire items disclosed (**Mean =3.535; Std. D =1.392**) respectively.

Table 9: Correlation Matrix

		AUQ	EXS	NEN	MAL	FUL	AAP
AUQ	Pearson Correlation	1					
	Sig. (2-tailed)	0.00					
	N	237					
EXS	Pearson Correlation	0.674	1				
	Sig. (2-tailed)	.000	.000				
	N	237	237				
NEN	Pearson Correlation	0.628	0.523	1			
	Sig. (2-tailed)	.000	.000	.000			
	N	237	237	237			
MAL	Pearson Correlation	0.618	0.629	0.569	1		
	Sig. (2-tailed)	.000	.000	.000	.000		
	N	237	237	237	237		
FUL	Pearson Correlation	0.557	0.635	0.624	0.694	1	
	Sig. (2-tailed)	.000	.000	.000	.000	.000	
	N	237	237	237	237	237	
AAP	Pearson Correlation	0.714	0.588	0.695	0.622	0.506	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000
	N	237	237	237	237	237	237

Source: Computed by Author Via SPSS (2025)

The bivariate analysis was carried out using Pearson's Product-Moment Correlation Coefficient (PPMC), showing the relationship between artificial intelligence (expert system, neutral network, machine learning, and fuzzy logic), audit practice (audit quality) and auditor experience and expertise as the moderator of public audit firms in Nigeria. Table 9 displays a strong and positive ($r = 0.674$, $P = 0.00$) relationship expert system (EXS) AI and audit quality (AUQ) of public audit firms in Nigeria. a strong and positive ($r = 0.628$, $P = 0.00$) relationship between neutral network (NEN) AI and audit quality (AUQ) of public audit firms in Nigeria. a strong and positive ($r = 0.618$, $P = 0.00$) relationship between machine learning (MAL) AI and audit quality (AUQ) of public audit firms in Nigeria. a moderate and positive ($r = 0.557$, $P = 0.00$) relationship between fuzzy logic (FUL) and audit quality (AUQ) of public audit firms in Nigeria and a strong and positive ($r = 0.714$, $P = 0.00$) relationship between auditor attitude and perception (AAP) and audit quality (AUQ) of public audit firms in Nigeria.

Table 10: R-Square Adj.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Audit Quality (AUQ)	0.628	0.648	0.104	6.0385	0.000

Source: Authors' Computation (2025)

Table 10 reveals the adjusted R – Square of the moderating role of auditors' attitude and perception (AAP) on the relationship between artificial intelligence and audit practice of public audit firms in Nigeria. The adjusted R² of 0.628 suggested that the model explains 62.8% of the variance in audit quality.

Table 11: Artificial Intelligence, Audit Quality and Auditors Attitude and Perception

	Original Sample (O)	Sample Mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values	Remarks
EXS -> AUQ	1.936	1.990	0.824	2.349	0.024	Ha ₁ Supported
NEN -> AUQ	3.685	4.109	1.839	2.004	0.048	Ha ₂ Supported
MAL -> AUQ	4.900	5.177	1.691	2.897	0.004	Ha ₃ Supported
FUL -> AUQ	2.665	0.099	1.238	2.153	0.038	Ha ₄ Supported
AAP -> AUQ	1.342	1.413	0.537	2.499	0.023	Ha ₅ Supported
EXS * AAP -> AUQ	1.430	0.371	0.613	2.333	0.034	Ha ₆ Supported
NEN * AAP -> AUQ	1.457	1.491	0.652	2.235	0.038	Ha ₇ Supported
MAL * AAP -> AUQ	1.578	1.196	0.594	2.657	0.025	Ha ₈ Supported
FUL * AAP-> AUQ	1.647	1.451	0.627	2.627	0.032	Ha ₉ Supported

Source: Authors' Computation (2025)

Table 11 demonstrates the first hypothesis (**H₀₁**), which proposed that expert systems of AI does not significantly influence audit quality of public audit firms in Nigeria. The result showed a significantly positive ($\beta = 1.936$, $t = 2.349$, $p = .024$), relationship between expert systems of AI

on audit quality of public audit firms in Nigeria. The finding supports the acceptance of the alternative hypothesis (**H_{a1}**). For the second hypothesis (**H₀₂**), which proposed that neutral network of AI does not significantly influence audit quality of public audit firms in Nigeria. The findings indicated that a significantly positive ($\beta = 3.685$, $t = 2.004$, $p = .048$), relationship between neutral network of AI on audit quality of public audit firms in Nigeria. This result supports the acceptance of the alternative hypothesis (**H_{a2}**). For (**H₀₃**), which proposed that machine learning of AI does not significantly influence audit quality of public audit firms in Nigeria. The outcome of the analysis suggested a significantly positive ($\beta = 4.900$, $t = 2.897$, $p = .004$) relationship between machine learning of AI on audit quality of public audit firms in Nigeria. This result supports the acceptance of the alternative hypothesis (**H_{a3}**). For (**H₀₄**), **pertaining to fuzzy logic** of AI does not significantly influence audit quality of public audit firms in Nigeria. The result of the data analysis revealed a significantly positive ($\beta = 2.665$, $t = 2.153$, $p = .038$), relationship between fuzzy logic of AI on audit quality of public audit firms in Nigeria. This result supports the acceptance of the alternative hypothesis (**H_{a4}**). The moderation analysis showed that (**H₀₅**) which posited that auditor attitude and perception does not significantly influence audit quality of public audit firms in Nigeria. The finding indicated a significantly positive ($\beta = 1.342$, $t = 2.499$, $p = .023$), relationship between auditors' attitude and perception of public audit firms in Nigeria. Thus, result supports the acceptance of the alternative hypothesis (**H_{a5}**).

For (**H₀₆**), concerning auditors' attitude and perception does not moderate positively and significantly the relationship between expert system of AI and audit quality of public audit firms in Nigeria. The result showed that auditors' attitude and perception does moderate significantly and positively ($\beta = 1.430$, $t = 2.333$, $p = .034$), the relationship between expert systems of AI on audit quality of public audit firms in Nigeria. Thus, the findings support the acceptance of the alternative hypothesis (**H_{a6}**). For (**H₀₇**), concerning auditors' attitude and perception does not moderate positively and significantly the relationship between neutral network of AI and audit quality of public audit firms in Nigeria. The result showed that auditors' attitude and perception does moderate significantly and positively ($\beta = 1.457$, $t = 2.235$, $p = .038$), the relationship between neutral network of AI on audit quality of public audit firms in Nigeria. Thus, the findings support the acceptance of the alternative hypothesis (**H_{a7}**). For (**H₀₈**), concerning auditors' attitude and perception does not moderate positively and significantly the relationship between machine language of AI and audit quality of public audit firms in Nigeria. The result showed that auditors' attitude and perception does moderate significantly and positively ($\beta = 1.578$, $t = 2.657$, $p = .025$), the relationship between machine language of AI on audit quality of public audit firms in Nigeria. Thus, the findings support the acceptance of the alternative hypothesis (**H_{a8}**). For (**H₀₉**), concerning auditors' attitude and perception does not moderate positively and significantly the relationship between fuzzy logic of AI and audit quality of public audit firms in Nigeria. The result showed that auditors' attitude and perception does moderate significantly and positively ($\beta = 1.647$, $t = 2.672$, $p = .032$), the relationship between fuzzy logic of AI on audit quality of public audit firms in Nigeria. Thus, the findings support the acceptance of the alternative hypothesis (**H_{a9}**).

DISCUSSION OF FINDINGS

The paper explores the moderating impact of auditors' experience and expertise on the relationship between expert systems of AI on audit quality of public audit firms in Nigeria. First, the findings revealed a significantly positive relationship between expert systems of AI and audit quality of public audit firms in Nigeria. The result is consistent with the conducted by Dzomira (2021) in South Africa that found a significant positive link between the utilisation of AI-based expert systems and audit quality in selected firms. The research highlighted that AI systems assist auditors detect anomalies faster, reduce human error, and improve the objectivity of audit judgments. Similarly, a study carried out by Oduwale and Adesina (2022) in Nigeria found a statistically significant positive linkage between the implementation of expert systems in audit firms and audit quality, especially in areas like fraud detection, risk assessment and compliance checks. However, the finding disagrees with the study of Ejiogu and Uche (2021), Alles and Gray (2016), Dowling and Leech (2014), Sirois and Bedard (2018). The study carried out by Ejiogu and Uche (2021) in Nigeria found that while AI expert systems increased efficiency, auditors' over-reliance on them reduced their independence and critical audit skills, which adversely affected audit quality. Also, Alles and Gray (2016) suggested that auditors' over-reliance on expert systems and big data analytics can lead to a decline in critical thinking and professional skepticism, ultimately reducing audit quality. Hence, auditors may trust system – generated results blindly without thorough cross – verification. Hence, the empirical evidence of the present study supports the statement and further suggests that an increase in expert systems of AI would lead to an increase in the quality of audit in public audit firms. The second findings of this paper revealed that a significantly positive relationship between neutral network of AI and audit quality of public audit firms in Nigeria. This result is consistent with the investigation conducted by Li and Lin (2020), Vasarhelyi et al (2012). The study of Li and Lin (2020) in China found a positive and statistically significant linkage between the neutral network-based fraud detection system and enhanced audit effectiveness and accuracy. Similarly, Vasarhelyi et al (2012) study of the utilization of neutral networks on continuous auditing suggested that systems embedded with neutral network models improve auditor efficiency and enhanced audit quality, particularly in identifying unusual transactions in real time. Nevertheless, the findings of this study disagree with the investigation carried out by Olojede and Ayinde (2022), Westermann et al (2020), Ghosh and Scott (2018), and Brown-Liburd et al (2015). The study carried out by Olojede and Ayinde (2022) suggested that the implementation of neutral network-based systems without adequate training and interpretability led to misuse and misinterpretation of AI outputs, which had a significant negative effect on audit performance and reliability. The third findings of the paper disclosed that machine learning had a significantly positive link between machine learning of AI and audit quality of public audit firms in Nigeria. The findings of this study align with the prior studies of Olatunji and Ogunyemi (2022), Zhang and Zhuang (2020), Issa et al (2016). The study of Issa et al (2016) revealed that machine learning algorithms especially supervised models, significantly improved audit outcomes by identifying irregularities and assisting auditors in making better decisions. Their findings demonstrated a positive effect on audit effectiveness and quality. Zhang and Zhuang (2020) study from Chinese firms found that auditors who utilized machine learning classification

techniques experienced higher accuracy in fraud detection and better audit efficiency, leading to enhanced audit quality. Likewise, Olatunji and Ogunyemi (2022) in Nigeria found that the adoption of machine learning tools such as logistic regression models significantly improve audit judgment quality, especially in client risk profiling and fraud detection. The findings of this study negate the prior studies of Olojede and Ayinde (2022), Ghosh and Scott (2018), Westermann et al (2020). In the study of Westermann et al (2020), the findings revealed that in a controlled experimental setting, auditors who use ML tools demonstrated over confidence in the model outputs and were less likely to override incorrect predictions. They argued that this behaviour led to audit errors and compromised audit quality. Ghosh and Scott (2018) study demonstrated that auditors who interacted with opaque ML systems showed reduced critical thinking and limited audit inquiry, resulting in lower quality of audits. Likewise, Olojede and Ayinde (2022) in Nigeria found that the introduction of ML tools without proper integration and auditor readiness led to inconsistent audit results, misjudgment, and a statistically significant reduction in audit quality. The fourth findings of the paper disclosed that fuzzy logic had a significantly positive association between fuzzy logic of AI and audit quality of public audit firms in Nigeria. The findings of this study agree with prior studies of Ahmad and Shabbir (2018), Yudhawati and Susanto (2020). In the study of Yudhawati and Susanto (2020), the application of fuzzy logic-based decision support system improved auditor decision-making, specifically in evaluating incomplete and uncertain records, which significantly improved audit quality. The study of Ahmad and Shabbir (2018), disclosed that auditors using fuzzy systems reported more accurate evaluations of audit sufficiency and appropriateness, resulting in higher audit quality in judgment-based tasks. Nevertheless, the finding is not in line with the prior studies of Westermann et al (2020), Olojede and Ayinde (2022), Ghosh and Scott (2018). In the study of Westermann et al (2020), the investigation revealed that auditors using black-box AI models including fuzzy inference systems exhibited lower levels of skepticism and judgment quality, especially when they could not understand or question the model's logic. This had a negative effect on audit quality. The fifth contribution of this study is the moderating role of auditors' attitude and perception on the relationship between artificial intelligence and audit quality. The findings suggest that auditor attitude and perception had a significantly positive moderating effect on the relationship between artificial intelligence and audit quality. The finding from this study aligns with the studies of Tarek et al (2021), Asante and Asir (2021) and Rozario and Vasarhelyi (2018). The study of Tarek et al (2021) revealed that auditors with positive perceptions of AI were more inclined to utilize AI-based technologies confidently, which enhances more thorough and higher quality audits. The moderating effect of perception was significant at the 0.01 level, showing a strong interaction between perception and AI adoption in inducing audit quality. In addition, Asante and Asir (2021) study in Ghana suggested that positive auditor attitude toward AI significantly improved the effects of AI technologies on audit quality, particularly in areas of fraud detection and risk assessment. But several other studies (Tarek et al, 2021; Efiok and Eton, 2022; Issa et al, 2016) showed a negative moderating impact of auditors' attitude and perception on the relationship between AI and audit quality. The study of Efiok and Eton (2022) conducted in Nigeria disclosed that auditors with a resistant or indifferent mindset toward AI revealed poor engagement with AI-based technologies, leading to decreased audit

quality. Similarly, Tarek et al (2021) noted that in subgroup of auditors with strongly negative perceptions of AI-based technologies, the impact on audit quality significantly diminished.

CONCLUSION, POLICY IMPLICATIONS, LIMITATIONS AND FURTHER RESEARCH

This study explored the moderating role of auditors' attitude and perception on the relationship between artificial intelligence (expert systems, neutral network, machine learning and fuzzy logic) on audit practice (audit quality) of public audit firms in Nigeria. The study used univariate, bivariate, and multivariate analysis to discover if the change in auditors' attitude and perception, expert systems, neutral network, machine learning and fuzzy logic influence audit quality in Nigeria. The finding from the structural equation modelling (SEM) shows a significantly positive relationship between expert systems of AI on audit quality of public audit firms in Nigeria, a significantly positive relationship between neutral network of AI on audit quality of public audit firms in Nigeria, a significantly positive relationship between machine learning of AI on audit quality of public audit firms in Nigeria, a significantly positive relationship between fuzzy logic of AI on audit quality of public audit firms in Nigeria, and a significantly positive relationship between auditors' expertise and experience on audit quality of public audit firms in Nigeria. The study also revealed that auditors' attitude and perception moderate a significantly positive relationship between artificial intelligence (expert systems, neutral network, machine learning and fuzzy logic) on audit practice (audit quality) on audit quality of public audit firms in Nigeria. Hence, grounded on the findings, the paper concludes that artificial intelligence is a significant determinant of audit quality in Nigeria. Furthermore, auditors' attitude and perception moderate significantly positive association between artificial intelligence is a significant determinant of audit quality of public audit firms in Nigeria.

The policy implications of the moderating effects of auditors' expertise and experience on the relationship between artificial intelligence (AI) and audit quality in the context of an emerging country like Nigeria are regulators such as the Financial Reporting Council of Nigeria (FRCN), Institute of Chartered Accountants' of Nigeria (ICAN), Association of National Accountants of Nigeria (ANAN) should mandate continuous training in AI-related tools and technologies for auditors, professional development programs should not only teach AI skills and competences but also address behavioural resistance, mindset shifts and technology acceptance, regulatory and professional institutions should certify and endorse AI audit tools to build trust and credibility among auditors, regulatory and professional institutions should revise audit standards or best practice frameworks to recognize the role of auditor mindset in effective technology use.

The study presented noteworthy and insightful results, but with limitations. The findings from this study use self-reported questionnaires to measure auditors' attitudes and perceptions which introduced social desirability bias or response exaggeration. Hence, respondents might overstate their openness to AI due to institutional or peer pressure. The study used cross-sectional data which limits the ability to observe how attitudes evolve over time as auditors gain more exposure to AI tools. The study is based on audit firms in Nigeria, which may limit generalization to other contexts. The role of organizational culture, leadership support and technological infrastructure in

shaping auditors' attitude was also ignored. Therefore, further studies should be carried out using longitudinal studies, mixed methods research, cross-cultural and cross-sectional comparisons, role of organizational support and training and the integration of behaviorual theories to explain how perceptions and attitudes develop in the audit profession.

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