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Artificial Intelligence and Audit Practice of Public Audit Firms in Nigeria: Does Audit Experience and Expertise Matter?

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Abstract: *This study investigates the moderating role of auditors' expertise and experience on the relationship between artificial intelligence (AI) adoption and audit quality in audit firms in Nigeria. Grounded on Task-Technology Fit (TTF) theory, a quantitative method was employed using data collected from a structured questionnaire administered to 237 respondents after validity and reliability tests. The structural equation modelling (SEM) shows a significantly positive relationship between expert systems of AI, neutral network of AI, machine learning of AI, 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' expertise and experience 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. Based on the findings, the paper concludes that artificial intelligence is a significant determinant of audit quality in Nigeria. The findings suggest that auditors' expertise and experience significantly moderate the association between artificial intelligence as a significant determinant of audit quality of audit firms in Nigeria. The study highlights the consequences of human capital in the digital transformation of audit practices and demands better investment in auditor training, digital literacy, and continuous professional development. This valuable knowledge gained suggests very useful implications for audit policymakers, regulatory bodies, and institutions, pointing to the improvement of audit quality through AI integration.*

Keywords: artificial intelligence, audit practice, audit experience, audit quality, Nigeria

INTRODUCTION

The future of audit practice is being reshaped by the rapid advancement in Information and Communication Technology (ICT), particularly the evolution of artificial intelligence. This transformative technology is designed to restructure audit practices, bringing about a new beginning of efficiency, effectiveness, and accuracy in audit opinions. According to Ghanoun and Alaba (2020), improvement in ICT tools is becoming noticeable in the contemporary corporate environment and hence more data is generated by businesses, making public accountancy firms stay up to date with this revolution with equivalent funding of cutting-edge ICT tools to effectively scrutinise large volume of financial data being produced. Isaa et al (2016) argue that cutting-edge ICT tools can be applied to automate audit practice by creating highly proficient audit process of pre-engagement activities, preliminary planning, development of overall audit plan, performing audit procedures, evaluation of results of tests, perform review of events subsequent to the statement of financial position date, perform review of financial statements, obtain management representation, issue audit report and management letter (Appah, 2017). Consequently, the application of cutting-edge ICT tools will continue to improve the efficiency and effectiveness in audit practice (Raschke et al., 2018). So cutting-edge ICT tools will change audit practice from reactive to proactive, allowing audit processes to be performed more effectively, efficiently, and reliably (Yebi & Cudjoe, 2022). Accordingly, audit practice is fine-tuning into this revolution with the incorporation of artificial intelligence systems to improve audit process and audit quality. Kokina and Davenport (2017) maintained that artificial intelligence (AI) systems are appropriate for organized and unorganized data to advance insight into the financial and non-financial performance of firms.

AI tools and methods are fundamental to the advancement and growth of audit practice. Issa et al. (2016) defined AI in audit as a blend of technologies enhancing and altering audit practice. 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 the audit practice, as wellas the detection of likely matters with a firm's financial reports and to detect possiblefraud 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 (Kaplan and Haenlein 2019). 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 (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). 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.

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 (Akinbuli, 2010). 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 organization's financial transactions and other data collected, recorded, and processed (Mansour, 2016). 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 experience and expertise level of auditors. Audit experience, often described in terms of years of professional practice, industry exposure, and accumulated expertise, plays an important role in shaping auditors' ability to exercise professional judgment and interpret AI outputs effectively. Experienced auditors possess deep-rooted knowledge of audit procedures, client behaviour, and risk indicators that cannot be easily replicated by algorithms. Their ability to identify inconsistencies, interpret patterns, and challenge AI-generated insights is crucial to maintaining audit integrity. Audit experience - comprising years of practice, exposure to complex engagements, and judgmental maturity may significantly influence how AI is understood, trusted, and applied in audit processes. However, existing 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), Linaand Kloviene (2019), Khamis (2021), Albawwat and Yaser (2021), Chukwuani andEgiyi(2020), Chukwudi, et al (2018), Lee andTajudeen (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 experience and expertise moderates the relationship between AI and audit practice, particularly within developing economies like Nigeria. While several scholars have tried to guide managers in the implementation of AI (Heavin & Power, 2018), information on the AI-HRM interface remains limited in the literature (Basu et al., 2022; Minbaeva, 2021) provoking a 'growing concern that research on AI could experience a lack of cumulative building of knowledge' (Collins et al., 2021). The gap in knowledge seems to be particularly intense regarding the specific relationships between AI and management skills, which needs to be trusted (Ramchurn et al., 2021; Razmerita et al., 2021). 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 audit experience and expertise 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 auditor experience and expertise 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 neutral 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; and evaluate the moderating role of auditor expertise and experience on the relationship between AI and audit quality of public audit firms in Nigeria. The following null hypotheses were tested in this investigation:

Ho$_1$: Expert systems of AI does not significantly influence audit quality of public audit firms in Nigeria.

Ho$_2$: Neutral networks of AI does not significantly influence audit quality of public audit firms in Nigeria.

Ho$_3$: Machine learning of AI does not significantly influence audit quality of public audit firms in Nigeria.

Ho$_4$: Fuzzy logic of AI does not significantly influence audit quality of public audit firms in Nigeria.

Ho$_5$: Auditor expertise and experience does not significantly influence audit quality of public audit firms in Nigeria.

Ho$_6$: Auditor expertise and experience does not significantly moderate on the relationship between AI and audit quality of public audit firms in Nigeria.

LITERATURE REVIEW

Conceptual Review

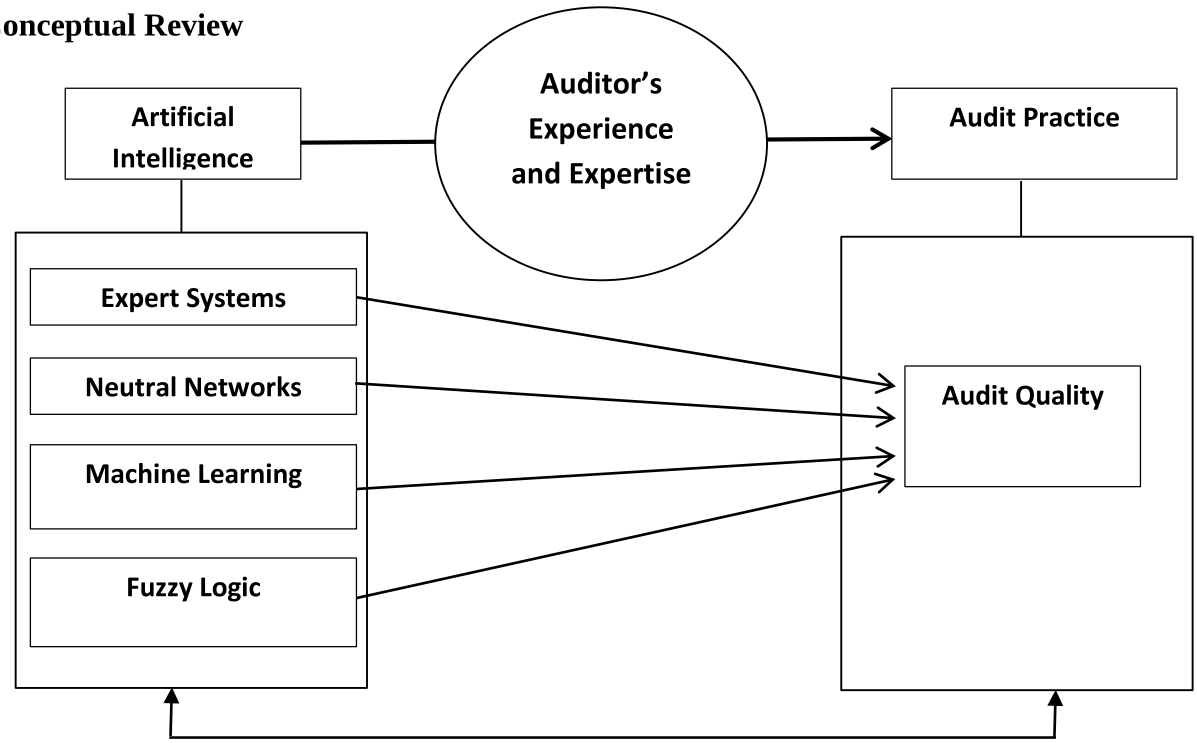

Figure 1: Conceptual Framework
Source: Author Creation

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. AIare 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 neutral 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), neutral 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.

Auditor Experience and Expertise: Audit experience refers to the accumulated knowledge, skills and competences gained by an auditor through repeated exposure to audit engagements over time. It reflects not just the number of years spent in the profession, but also the depth and variety of practical exposure to different audit clients, industries, standards, and challenges (Appah, 2024). Auditors with more experience and expertise in AI may be more effective in integrating AI into audit practice (Ugo, 2023). Auditor expertise and experience are critical factors that can significantly impact the quality and effectiveness of audits (Hassan, 2022). According to Appah (2024), there are several factors that affect audit practice such as length of service, industry expertise, audit type, client size and complexity, technical skills, professional certifications, continuing professional education and soft skills. Hassan (2022), Ugo (2023), Kwarbai and Omojoye (2022), Owonifari et al, (2023) stated that auditor experience and expertise provides several benefits such as improved audit quality, enhanced client satisfaction, increased efficiency, and better risk assessment. Similarly, Appah (2024) stated that audit experience matters in audit practice as experienced auditors are better at exercising skepticism, interpreting ambiguous evidence, and making complex decisions. Familiarity with audit processes enables quicker and more effective task execution. Through pattern recognition and contextual knowledge, experienced auditors more readily detect risk factors (Kwarbai & Omojoye, 2022; Owonifari et al, 2023). Auditors' expertise refers to the depth and breath of knowledge, technical skills, and accumulated experience an auditor possesses in performing audit tasks, especially in complex or high-risk environments. AI is changing auditing by automating routine tasks, improving fraud detection, and enhancing audit accuracy. However, these benefits are achieved only when auditors possess the right and necessary expertise to supervise, interpret, and validate AI. Luo et al (2022) explained that AI use in auditing improves quality, but its effectiveness depends significantly on the auditor's domain knowledge, interpretative skills, and ability to apply professional judgment. In addition, Minbaeva (2021) noted that auditors' expertise remains vital in exercising cynicism and relative decision-making even with advanced AI tools.

Theoretical Review: This study is anchored on the Task-Technology Fit (TTF) theory advanced by Goodhue and Thompson in 1995. The theory suggests that Information and Communication Technology (ICT) will most likely impact positively on individual performance and be used if the proficiencies of information communication and technology (ICT) match the tasks that the user must perform (Chukwunulu, 2019). Hsiao (2019) posited that the theory evaluates how ICT leads to performance, evaluate usage effects, and judge the match between the task and technology features (Wu &Chen, 2017). This theory states that ICT should be a good fit with the tasks it supports to be utilized and to positively influence user performance (El Said, 2015). Hsiao (2019) noted that both task characteristics and technology characteristics can affect the task-technology fit, which in turn defines users' utilization of technology and their task performance. TTF theory is extensively applied in various fields, including technological innovation (Irum & Ismail, 2017), commercial bank (Abbas et al.,2018), information processing and network directional behavior (Xia & Zhao, 2019).TTF is applied in this study to reveal the degree to which AI software tools can automate and perform processes that auditors hitherto performed manually. Malik & Jabbar (2023), Hassan (2022), Ugo (2023), Kwarbai and Omojoye (2022), Owonifari et al, (2023) stated that the benefits of TTF theory are TTF theory helps identify the optimal technology for specific tasks, leading to improved performance; by selecting technology that fits tasks requirements, users are more likely to be satisfied with the technology; TTF theory can help organizations optimize technology use, leading to increased productivity; by understanding the fit between task and technology, organizations can make more informed technology adoptions decisions; and TTF theory considers the specific task and technological context, providing a nuanced understanding of technology use. However, the TTF theory suffers from several criticisms. Chukwunulu (2019), Malik & Jabbar (2023), Hassan (2022), Ugo (2023) listed some of the limitations of the theory as: TTF theory may not be applicable to all contexts or tasks, limiting its generalizability; TTF theory can be complex to apply requiring a deep understanding of both task and technological requirements; The concept of fit is subjective and can vary depending on individual perspectives and experiences; TTF theory primarily focuses on task and technological factors, overlooking social factors that can influence technological adoption and use. This theory is applicable to this study since AI can automate routine tasks, freeing auditors to focus on higher value tasks; AI can improve audit quality by detecting anomalies, identifying risks and providing insights; AI can help auditors identify and assess risks more efficiently enabling proactive risk management; and AI can assist auditors in tasks like data analysis, reporting and documentation, increasing productivity and reducing workload. Consequently, by applying TTF theory, auditors and audit firms can better understand the relationship between AI and audit practice, ensuring that AI is used effectively to support audit tasks and improve overall audit quality.

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	The study used survey research design and	The multiple regression analysis results revealed that

	accounting profession.	questionnaire as the primary source of data collection. The population consisted of big 4 operating firms in Nigeria. 500 questionnaires were distributed and 277 were collected and used for data analysis using multiple regression.	AI positively and significantly affects accounting profession in Nigeria. The study recommends amongst 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 sizeof 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	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.

		collected were analysed using reliability and validity tests, descriptive analysis and independent samples t-test.	
Dagunduro et al (2023)	The study analysedthe 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 as the primary source of data collection and univariate and multivariate analysis was used for data analysis.	The finding from the multiple regression analysis indicated that expert systems, machine learning and intelligent agents positively and significantly influence audit practice in Nigeria.
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	The findings of the investigation indicated that expert systems and neutral

		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.	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 analysedthe 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 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 univariateanalysis 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 professional skepticism and judgment in Oman	This research employed survey research design using a target population of auditors' in Oman and only 200 respondents were sent questionnaires while	The findings of the study revealed that AI and ML significantly improves the quality, reliability and efficiency of audit; significant and positive correlation

		only 169 responded. Questionnaire was the primary source of data collection while descriptive and correlationanalysis were used for data analysis.	between AI and ML on the quality, reliability and efficiency of audit; and AI and ML enhanced professional skepticism and judgmentpositively 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	The results from the regression analysis indicated that AI positively and significantly influences the effectiveness of accounting information system.

		analysed using descriptive, exploratory factor analysis and multiple regression.	
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 audit firms; employment of AI workers. The data collected were analysed using descriptive and multiple regression analysis.	The results from the study indicated that the adoption of AI assists audit firms to advance 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 South East 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	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 South East Nigeria.

		data collected from the questionnaire responses were analysed using descriptive and regression analysis.	

Source: Compiled by the researcher (2025)

METHODOLOGY

This investigation on AI and audit practice in Nigeria used a quantitative cross-sectional survey and correlational and exploratory research designs. This design is 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 on 22nd February, 2023 and the Taro Yamane 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 experience adopted from Asante and Asir (2021), Olowookere and Inneh (2016), AI. Luo et al (2022). 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 the 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 reliable at 0.872, 0.835, 0.843, 0.816 and 0.856. The questionnaires were administered to partners and audit seniors of the sampled audit firms. The data obtained from respondents was presented and analysed using univariate, bivariate and multivariate analysis. The multiple regression was guided by the model below:

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

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

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); AUE = Auditors Experience; Audit Quality (AUQ), and μ: random error term. The a priori expectation: $\beta 1$- $\beta 4>0$, while β_5- β_9 is the relationship between the moderator variable and the 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.

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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
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 demonstrate 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 Experience and Expertise

S/N	Items	N	Min	Max	Mean	Std. D
1	The number of years an auditor has been practicing can impact their experience and expertise.	237	1.00	5.00	3.753	1.325
2	Auditors with experience in a specific industry can provide valuable insights and knowledge.	237	1.00	5.00	3.521	1.352
3	Experience with different types of audits such as financial statement audits or internal control audits can influence an auditor's expertise.	237	1.00	5.00	3.423	1.423
4	Auditors with experience working with clients of varying sizes and complexities can adapt to different audit environments.	237	1.00	5.00	3.573	1.315
5	Auditors need to possess technical skills such as accounting, auditing and financial analysis.	237	1.00	5.00	3.213	1.413
Valid N (listwise)		**237**			**3.497**	**1.366**

Source: Field Study (2025)

The results in Table 8 explain the descriptive statistics of the mean and standard deviation responses on the audit experience and expertise 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 experience and expertise. 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 =3.497; Std. D =1.366**) respectively.

Table 9: Correlation Matrix

		AUQ	EXS	NEN	MAL	FUL	AUE
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	
AUE	Pearson Correlation	0.735	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 = 0.735, P = 0.00) relationship between auditor experience and expertise 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)	0.528	0.568	0.092	5.739	0.000

Source: Authors' Computation (2025)

Table 10 reveals the adjusted R – Square of the moderating role of auditors' experience and expertise on the relationship between artificial intelligence and audit practice of public audit firms in Nigeria. The adjusted R^2 of 0.528 suggested that the model explains 52.8% of the variance in audit quality.

Table 11: Artificial Intelligence, Audit Quality and Auditors Experience and Expertise

	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**
AUE -> AUQ	1.232	1.413	0.448	2.751	**0.005**	**Ha_5 Supported**
EXS * AUE -> AUQ	0.390	0.407	0.134	2.920	**0.003**	**Ha_6 Supported**
NEN * AUE -> AUQ	1.323	1.491	0.620	2.135	**0.036**	**Ha_7 Supported**
MAL * AUE -> AUQ	1.095	1.196	0.402	2.379	**0.012**	**Ha_8 Supported**
FUL * AUE -> AUQ	1.014	1.041	0.500	2.028	**0.042**	**Ha_9 Supported**

Source: Authors' Computation (2025)

Table 11 demonstrates the first hypothesis (**H_{01}**), 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 (**Ha_1**). For the second hypothesis (**H_{02}**), 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 (**Ha_2**). For (**H_{03}**), 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 (β = 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 (**Ha_3**). For (**H_{04}**), 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 (β = 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 (**Ha_4**). The moderation analysis showed that (**H_{05}**) which posited that auditor expertise and experience does not significantly influence audit quality of public audit firms in Nigeria. The finding indicated a significantly positive (β = 1.232, t = 2.751, p = .005), relationship between auditors' expertise and experience of public audit firms in Nigeria. Thus, result supports the acceptance of the alternative hypothesis (**Ha_5**).

For (**H_{06}**), concerning auditors' expertise and experience 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' expertise and experience does moderate significantly and positively (β = 0.390, t = 2.920, p = .003), 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 (**H_{07}**), concerning auditors' expertise and experience 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' expertise and experience does moderate significantly and positively (β = 1.323, t = 2.135, p = .036), 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 (**H_{08}**), concerning auditors' expertise and experience 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' expertise and experience does moderate significantly and positively (β = 1.095, t = 2.379, p = .012), 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 (**H_{09}**), concerning auditors' expertise and experience 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' expertise and experience does moderate significantly and positively (β = 0.390, t = 2.920, p = .003), 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 Oduwole 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' experience and expertise on the relationship between artificial intelligence and audit quality. The findings suggest that auditor experience and expertise had a significantly positive moderating effect on the relationship between artificial intelligence and audit quality. The finding is supported by Olojede and Ogunsemi (2022), Sirois and Bedard (2018). The study carried out by Olojede and Ogunsemi (2022) study in Nigeria revealed that auditor experience significantly moderates the link between audit technology and audit quality. However, the finding negates the studies of Westermann et al (2020), Olojede and Ayinde (2022). According to Westermann et al (2020), that the more experienced auditors were more skeptical or resistant to AI based output, often rely solely on their professional judgment. This behaviour weakens the effectiveness of AI tools, demonstrating a negative and significant moderating effect on audit quality.

CONCLUSION, POLICY IMPLICATIONS, LIMITATIONS AND FURTHER RESEARCH

This paper investigated the moderating role of auditors' experience and expertise 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' experience 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' expertise and experience 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' expertise and experience 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, Nigerian tertiary institutions and professional institutions should reform and revive accounting and auditing curricula to integrate AI and emerging audit technologies such as robotic process automation (RPA), natural language processing (NLP) and predictive analytics, government policies should provide tax incentives or grants to audit firms that invest in upskilling staff in AI technologies, regulators should adopt a risk-based approach in evaluating audit quality with particular focus on the integration of AI by experienced audit teams, government should strengthen capacity building in public sector audit institutions such as office of the Auditor-General to adopt AI with experienced personnel and ICAN and ANAN and other bodies should include AI-related ethics in their codes of conduct and disciplinary frameworks.

The study presented noteworthy and insightful results, but with limitations. The findings from this study on public audit firms may not be generalizable because of differences in structure, culture, funding and accountability mechanisms, some audit firms may be reluctant to disclose vital information on internal operations, AI adoption, and staff competences and skills limiting data richness. This could lead to reliance on self – reported data, which may introduce bias. Also, auditors' expertise and experience measured on years of service, qualifications are subjective which may not fully capture AI and technological competences. Similarly, the study utilized cross – sectional survey and cannot establish causality. Further studies should focus on the examination of how experienced auditors navigate ethical dilemmas and professional skepticism when interpreting AI-generated outputs, examination of how regulatory frameworks and government policy influence the capacity of experienced auditors to leverage AI in improving audit outcomes, investigate how organizational culture, management support, and change readiness in audit firms moderate the relationship between auditor experience, AI and audit quality. Additionally, further studies should develop more comprehensive metrics for auditor expertise, including digital literacy, prior exposure to AI systems and training in audit analytics and the use of qualitative methods such as interviews and case studies to gain deeper insights into how experienced auditors interact with AI in real audit settings.

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REFERENCES

Abbas, S. K., Hassan, H. A., & Asif, J. (2018). Integration of TTF, UTAUT, and ITM for mobile banking adoption. *International Journal of Advanced Engineering, Management and Science, 4(5),*89-101.=

Ahmad, N., & Shabbir, M. S. (2018). The role of fuzzy logic in audit evidence evaluation: An empirical insight. *Asian Journal of Accounting Research,* 3(2), 78 – 89.

Albawwat, I., & Al Frijat, Y. (2021). An analysis of auditors' perceptions towards artificial intelligence and its contribution to audit quality. *Accounting, 7*(4), 755-762.

Akinbuli, S. F. (2010). The effect of audit experience on auditors' performance in Nigeria. *Journal of Social Sciences,* 2(3), 199 – 205.

Ali, M.M., Abdullah, A.S. & Khattab, G.S. (2022). The effects of activating artificial intelligence techniques on enhancing internal auditing activities "Field Study", *Alexandra Journal of Accounting Research, 6(3),* 1 – 40.

Al-Aroud, S.F. (2020). The impact of artificial intelligence technologies on audit evidence, *Academy of Accounting and Financial Studies Journal*, 24(3), 1- 11.

Alles, M., & Gray, G. L. (2016). The prospects and limitations of big data analytics for auditing: Research opportunities. *Auditing: A Journal of Practice & Theory*, 35(4), 147 – 155. https://doi.org/10.2308/ajpt-51468

Appah, E. (2024). *Auditing and assurance services (2nd Edition),* Peroscopic Media and Publishing Company.

Appah, E. (2020). *Research Methodology: Integration of Principles, Methods & Techniques,* Ezevin Printing & Publishing Company.

Asante, J., A., & Asir, M., B. (2021). Artificial intelligence and audit quality: The moderating role of auditor attitude. *Journal of Accounting and Taxation*, 13(3), 61 – 71.

Baldwin, A. A., Brown, C. E., & Trinkle, B. S. (2006). Opportunities for artificial intelligence development in the accounting domain: The case for auditing. *Intelligent Systems in Accounting, Finance and Management, 14,* 77-86.https://doi.org/10.1002/isaf.277

Balios, D., Kotsilaras, P., Eriotis, N. & Vasiliou, D. (2020). Big data, data analytics and external auditing. *Journal of Modern Accounting and Auditing 16,* 211–19.

Basu, S., Majumar, B., Mukherjee, K., Munjal, S., & Palaksha, C. (2022). Artificial intelligence-HRM interactions and outcomes: A systematic review and causal configurational explanation. Human Resource Management Review, 33(1), Article 100893. https://doi.org/10.1016/j.hrmr.2022.100893

Brown-Liburd, H., Issa, H., & Lombardi, D. (2015). Behavioural implications of big data's impact on audit judgment and decision-making. Accounting Horizons, 29(2), 409 – 422. https://doi.2308/acch-51023.

Chassignol, M, Khoroshavin, A., Klimova, A., &Bilyatdinova, A. (2018). Artificial Intelligence trends in education: A narrative overview. *Procedia Computer Science 136*, 16–24.

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. International Journal of Information Management, 60, Article 102383. https://doi.org/10.1016/j.ijinformg.2021.102383

Chukwuani, V. N., & Egiyi, M. A. (2020). Automation of accounting processes: Impact of artificial intelligence. *International Journal of Research and Innovation in SocialScience (IJRISS), 4,* 444-449.https://www.rsisinternational.org/journals/ijriss/Digital-Library/volume-4-issue-8/444- 449.pdf

Chukwudi, O., Echefu, S., Boniface, U., &Victoria, C. (2018). Effect of artificial intelligence on the performance of accounting operations among accounting firms in South East Nigeria. *Asian Journal of Economics, Business and Accounting, 7,* 1-11.https://doi.org/10.9734/AJEBA/2018/41641

Chukwunulu, J.I. (2019). Effect of financial innovation on the Nigerian economy. *World Journal of Innovative Research, 6(5),* 15 – 21.

Dagunduro, M. E., Falana, G. A., Adewara, Y. M., & Busayo, T. O. (2023). Application of artificial intelligence and audit quality in Nigeria. *Humanities, Management, Arts, Education & the Social Sciences Journal.* 11(1), 39-56. https://dx.doi.org/10.22624/AIMS/HUMANITIES/V11N1P

Deniz, A. &Sorenson, J..(2022). Artificial Intelligence and the Auditor: Are you ready? https://idea.caseware.com/ai-auditor-are-you-ready/

Dongre, N., Pandey, A. & Gupta, O.P. (2020). Artificial intelligence in accounting: Opportunities and Challenges, *Journal of Xian University of Architecture and Technology, 7(5),* 20 – 33.

Dowling, C, & Leech, S. A. (2014). A Big 4 firm's use of information technology to control the audit process: How an audit support system is changing auditor behaviour. *Contemporary Accounting Research,* 31(1), 230 – 252. http://doi.org/10.1111/1911-3846.12010

Dzomira, S. (2021). Artificial intelligence and audit quality: Empirical analysis from a developing country perspective. Cogent Economics and Finance, 9(1), 1918906. http://doi.org/10.1080/23322039.2021.1918906

Ejiogu, A., & Uche, C. (2021). Artificial intelligence and auditor independence in Nigeria: A double-edge sword. *African Journal of Accounting, Economics, Finance and Banking Research,*17(2), 88 – 105.

El Said, G. R. (2015). Understanding knowledge management system antecedents of performance impact: Extending the task-technology fit model with intention to share knowledge construct. *Future Business Journal, 1,* 75–87.

Emetaram, E. &Uchime, H. N. (2021). Impact of artificial intelligence on accountancy profession.*Journal of Accounting and Financial Management, 7(2),* 15 – 25.

Falana, G. A., Igbekoyi, O. E., &Dagunduro, M. E. (2023). Effects of big data on accounting information quality in selected firms in Nigeria. *International Journal of Research and Innovation in Social Science.* 7(3),789-806. https://doi.org/10.47772/IJRISS

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

Fijabi, L.K. &Lasisi, O.R. (2023). Accounting practices in adigitalised world: Nigerian perspective, *African Journal of Accounting and Financial Research, 6(1),* 63 – 82.

Ghanoun, S. &Alaba, F.M. (2020). Integration of artificial intelligence in auditing: The effect on auditing process. Master of Science Thesis, Kristianstad University, Sweden.

Ghosh, A., & Scott, J. (2018). Black box AI and auditor skepticism: Evidence from neutral network-assisted audits. Contemporary Accounting Research Conference Proceedings.

Hassan, A.R. (2022). Artificial intelligence (AI) in accounting and auditing: A literature review. Open *Journal of Business and Management,* 10, 440 – 465. https://doi.org/10.4236/ojbm.2022.101026

Hemin, A. Q. (2017). Will artificial intelligence brighten or threaten the future science, Ethics, and Society. Available online:https://www.researchgate.net/publication/323535179_Will_Artificial_Intelligence_Brighten_or

Heavin, C., & Power, D. J. (2018). Challenges for digital transformation – towards a conceptual decision support guide for managers. *Journal of Decision Systems,* 27(3), 38 – 45. https://doi.org/10.1080/12460125.2018.1468697

Hsiao, M-H. (2018). A conceptual framework for technology-enabled and technology-dependent user behaviour toward device mesh and mesh app. *Future Business Journal, 4(1),* 130 – 138.

Irum, S., Ismail, K., & Ashfaq, M. (2017). Factors influencing post-adoption beahviour of technological innovation. *Advanced Science Letters,* 23(9), 8939 – 8941. https://doi.org/10.1166/asl.2017.9999

Issa, H., Sun, T., & Vasarhelyi, M. A. (2016). Research ideas for artificial intelligence in auditing: The formalization of audit and workforce supplementation. *Journal of Emerging Technologies in Accounting*, 13(2), 1-20. https://doi.org/10.2308/jeta.10511

Khamis, A. (2021). The Impact of Artificial Intelligence in Auditing and Accounting Decision Making. Available online:https://www.researchgate.net/publication/352166419_The_Impact_of_Artificial_Intelligence_inAuditing_and_Accounting_Decision_Making

Kaplan, A. & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of Artificial Intelligence. *Business Horizons 62*, 15–25.

Knechel, W. & Salterio, S. (2016). Auditing: Assurance and risk, Taylor & Francis.

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.

Kwarbai, J. D. &Omojoye, E.O. (2021). Artificial intelligence an accounting profession. *Babcock Journal of Accounting and Finance, 1(1),* 78 – 88.

Lee, C. S., &Tajudeen, F. P. (2020). Usage and impact of artificial intelligence on accounting: Evidence from Malaysian organisations. *Asian Journal of Business and Accounting, 13,* 213-240. https://doi.org/10.22452/ajba.vol13no1.8

Li, S., & Lin, Y. (2020). Using deep neutral networks for financial statement fraud detection: Empirical evidence from Chinese firms. *Journal Intelligence and Fuzzy Systems,* 38(3), 3013 – 3024. https://doi.org/10.3233/JIFS-179259

Lin, P. &Hazelbaker, T. (2019). Meeting the challenge of Artificial Intelligence. *CPA Journal 89:* 48–52. https://www.cpajournal.com/2019/07/03/meeting-the-challenge-of-artificial-intelligence

Lina, D., & Kloviene, L. (2019). Motivation to use Big Data and Big Data Analytics in external auditing. *Managerial Auditing Journal 34*, 750–82.

Luo, Y., Wong, N., & Yu, Y. (2022). Auditing with AI: Evidence from US audit firms' staff restructuring and financial outcomes. *Review of Accounting Studies,* 27, 1054 – 1086. https://doi.org/10.1007/s11142.022-09697x

Malik, Y.S., & Jabber, I.B.W. (2023). The role of fuzzy logic in enhancing audit procedures for preparing the audit report: An empirical study. *Akkad Journal of Contemporary Accounting Studies, 3(1),* 14 – 25.

Mansour, E. (2016). Factors affecting the adoption of computer assisted audit techniques in audit process. Findings from Jordan. Business and Economic Research, 200-269.

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A proposal for the Dartmouth Summer Research Project on Artificial Intelligence, August 31, 1955.AI Magazine, 27, 12.

Minbaeva, D. (2021). Disrupted HR? Human Resource Management Review, 37(4), Article 100820. http://doi.org/10.1016/j.hrmr.2020.100820

Moffitt, K. C., Rozario, A. M., &Vasarh, M. C. (2018). Robotic process automation for auditing. *Journal of Emerging Technologies in Accounting, 15(1),* 1-10.

Noordin, N.A., Hussainey, K. & Hayek, A.F. (2022). The use of artificial intelligence and audit quality: An analysis from the perspective of external auditors in the UAE. Journal of Risk and Financial Management, 15, 339.http://doi.org/10.3390/jrfm15080339

Oduwole, I. O.& Adesina, O. T. (2022). Artificial intelligence and audit quality: Evidence from Nigerian audit firms. International Journal of Accounting and Financial Reporting, 12(2), 100 – 115. http://doi.org/10.xxx/ijafr.v12n2

Okoye, P. V. C., Okoye, V. & Aniefor, S. J. (2021). Digital transformation of audit practice: Challenges and prospects for Nigerian Audit Firms. *Journal of Accounting and Financial Management*, 7(3), 45 – 55.

Olojede, I., & Ayinde, B. (2022). Audit technology in Nigeria: Challenges of adoption and effects on audit quality. *Nigerian Journal of Accounting Research,* 8(1), 22 – 34.

Olatunji, T. E., & Ogunyeni, T. (2022). Machine learning adoption and audit quality in Nigeria audit firms. African Journa of Accounting and Finance, 14(1), 45 – 61.

Owonifari, V.O., Igbekoyi, O.E., Awotomilusi, N.S & Dagunduro, M.E. (2023). Evaluation of artificial intelligence and efficacy of audit practice in Nigeria. *Asian Journal of Economics, Business and Accounting, 23(16),* 1 – 14.

Owonifari, V.O., Igbekoyi, O.E., Awotomilusi, N.S &Dagunduro, M.E. (2023). Evaluation of artificial intelligence and efficacy of audit practice in Nigeria. *Asian Journal of Economics, Business and Accounting, 23(16),* 1 – 14.

Puthukulam, G., Ravikumor, A., Sharma, R.V.K. &Meesaala, A. (2021). Auditors' perception on the impact of artificial intelligence on professional skepticism and judgment in Oman, *Universal Journal of Accounting and Finance, 9(5),* 1184 – 1190.

Raji, I. & Buolamwini, J. (2019). Actionable auditing: Investigating the impact of publicly naming biased performance results of commercial AI products. Paper presented at the 2019 AAAI/ACM Conference on Artificial Intelligence, Ethics, and Society, Honolulu, HI, USA, January 27–28.

Ramchurn, S.D., Stein, S., & Jennings, N. R. (2021). Trustworthy human-AI partnerships. iScience, 24(8), Article 102891. https://doi.org/10.1016/j.isci.2021.102891

Raschke, R. L., Saiewitz, A., Kachroo, P., & Lennard, J. B. (2018). AI -enhanced audit inquiry: A research note. *Journal of Emerging Technologies in Accounting, 15(2),* 111- 116.

Razmerita, L., Brun, A., & Nabeth, T. (2021). Collaboration in the Machine Age: Trustworthy Human-AI Collaboration. In M. Virvou, G. Tsihrintzis, & J. Lakhmi (Eds), Advances in Selected Artificial Intelligence Areas – World Outstanding Women in Artificial Intelligence (pp. 23 – 40). Springer https://doi.org/10.1007/978-3-030-93052-3_14

Sirois, L.-P., & Bedard, J. (2018). Use of technology in the audit process and its effect on audit quality. Accounting Perspective, 17(3), 245 -264. https://doi.org/10.1111/1911-3838

Smith, S. S. (2020). *Blockchain, artificial Intelligence and financial services: Implications and applications for finance and accounting professionals*. Springer.https://doi.org/https://doi.org/10.1007/978-3-030-29761-9

Solaimani, R., Rashed, F., Mohammed, S. & ElKelish, W.W.(2020). The impact of artificial intelligence oncorporate control. *Corporate Ownership and Control 17,* 171–78.

Solikin, I. & Darmawan, D. (2023).Impact of artificial intelligence in improving the effectiveness of accounting information systems, Journal of Wireless Mobile Networks, Ubiquitous Computing and Dependable Application, 14(2), 82 – 93.

Stancheva-Todorova, E.P (2018). How artificial intelligence is challenging accounting profession.*Journal of International Scientific Publications, 12(1),*1314-7242,

Taghizadeh, A., Mohammad, R., Dariush, S., and Jafar, M. (2013). Artificial intelligence, its abilities and challenges. *International Journal of Business and Behavioral Sciences*.

Ugo, C.A. (2023). An empirical investigation of the impact of artificial intelligence on accounting practice in Nigeria. *African Journal of Accounting and Financial Research, 6(3),* 22 – 35.

Ukpong, E. G., Udoh, I. I., &Essien, I. T. (2019). Artificial intelligence: Opportunities, issues and applications in banking, accounting, and auditing in Nigeria. *Asian Journal of*

Economics, Business and Accounting, 10, 1-6.https://doi.org/10.9734/ajeba/2019/v10i13009

Vasarhelyi, M. A., Kuenkaiew, S., & Littley, J. (2012). The acceptance and adoption of continuous auditing by internal auditors: A neutral network approach. *International Journal of Accounting Systems*, 13(3), 267 – 281. https://doi.org/10.1016/j.accinf.2012.06.001

Westermann, K., Cohen, J. & Trompeter, G. (2020). Artificial intelligence in auditing: The impact on auditor judgment. *Working Paper*, University of Mississippi.

Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior*, *67*, 221–232.

Xia, D. & Zhao, Y. (2019). A theoretical study of the rational behaviour of users' credit compliance willingness. *Advances in Computer Science Research, 94,* 79 – 82.

Yebi, D., K., & Cudjoe, E. K. (2022). *Artificial intelligence as a disruptive business model in auditing: A study of the impact of artificial intelligence on auditors' skills and competence, audit process, and audit quality* (Master's thesis, Umea University, Sweden). Umea School of Business and Economics. DiVA – Academic Archive Online

Yudhawati, M. P. & Susanto, A. (2020). Fuzzy-based audit decision support system: Emerging audit quality in SMEs. J*ournal of Applied Accounting Research*, 21(3), 456 – 472. https://doi.org/10.1108/JAAR-03-2020-0054

Zemánková, A. (2019). Artificial intelligence and blockchain in audit and accounting: Literature review. *WSEAS Transactions on Business and Economics, 16*,568-581. https://www.wseas.org/multimedia/journals/economics/2019/b245107-089.pdf

Zhang, Y., Xiong, F., Xie, Y., Fan, X., &Gu, H. (2020). The impact of artificial intelligence and blockchain on the accounting profession. IEEE, 110461-110477.https://doi.org/10.1109/ACCESS.2020.3000505

Zhang, J., & Zhuang, Z. (2020). Application of machine learning in financial audit: Evidence from Chinese listed companies. *Journal of Intelligent Systems*, 29(5), 841 – 854.