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Research Paper

Artificial intelligence and the prospect of audit quality in Nigeria

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ABSTRACT

Audit quality remains a highly debated topic within the realms of auditing and financial reporting research. The relevance of audit quality has grown increasingly important for both accountants and users of financial information. Several studies suggest that enhancing audit quality is closely linked to the integration of artificial intelligence (AI) in auditing processes. This research examines how AI influences audit quality by adopting a survey-based approach, utilizing structured questionnaires distributed to professional accountants and employees within the Big Four accounting firms. The Taro Yamane formula was applied to calculate the appropriate sample size, resulting in the collection of 275 completed questionnaires. To assess the consistency and credibility of the survey instrument, Cronbach's alpha was used in conjunction with a pilot test. Both descriptive and inferential statistical methods were applied in analyzing the data. Descriptive results indicated strong support among respondents for the effectiveness of AI. Furthermore, regression analysis demonstrated a positive relationship between AI usage and improved audit quality. In light of these findings, it is recommended that managers and accounting professionals across private, corporate, and public sectors adopt artificial intelligence technologies, as they offer substantial economic benefits and contribute significantly to enhancing audit quality through increased accuracy, dependability, and prompt financial reporting.

1 | INTRODUCTION

The rising global concerns and dissatisfaction from investors and other stakeholders seem to persist as audit quality continues to fall short of expectations. The 2007/2008 financial crisis emphasized the urgent need to address issues related to audit quality, particularly regarding the reliability and timeliness of reporting. Wang et al. (2019) found that traditional and manual financial reporting methods were ineffective in addressing the deteriorating audit quality, leading to further declines in the integrity of auditors. Despite the presence of financial regulations, the enforcement of requirements, and the implementation of International Financial Reporting Standards (IFRS), financial reporting quality has not improved (Brodny & Tutak, 2021; Deniz & Jeffery, 2022). The growing audit expectation gap is concerning, as the decline in audit quality continues to persist, casting doubt on the credibility of the accounting profession and audit practices worldwide (Amani & Fadlalla, 2017; Carlin, 2019). The concentration of the audit market, dominated by the Big Four audit firms, has failed to differentiate itself, and these firms have not been absolved from involvement in financial scandals despite the negative implications of market concentration. The Big Four auditing firms have faced scrutiny for their involvement in recent financial scandals, raising concerns about audit quality. For example, the Wirecard scandal highlighted the deceptive image of the Big Four auditing firms. Castelo-Branco, Cruz-Jesus, and Oliveira (2019) argued that while audit quality is perceived subjectively and is complex, the financial scandals and collapses of major corporate entities like Enron, Tyco, and WorldCom, which involved auditors such as Arthur Andersen and other Big Four firms, point to clear failures and unethical behavior in auditing practices. Carlin (2019) noted that it is increasingly difficult to ignore the questionable behavior of some auditors undermining audit quality. Achieving high audit quality requires auditors to demonstrate strong ethical values, integrity, professionalism, and skills, as well as the use of disruptive technologies such as artificial intelligence, big data, blockchain accounting, cloud accounting, robotics, machine learning, and the Internet of Things, in modern accounting systems and software. Audit quality entails the use of accurate, reliable, and comparable data to ensure the financial statements' quality and their ability to support economic decisions. Carlin (2019) suggested that audit quality is the result of auditors possessing ethical standards, integrity, professional skills, audit independence, experience, and sufficient time to carry out thorough audits.

Deng and Yeh (2011) pointed out that the adoption of specific disruptive technologies, like artificial intelligence, is critical for enhancing audit quality in financial reporting. Artificial intelligence has become an essential innovation in the auditing and financial reporting sectors globally (Jerneck, Olsson, Ness, & Anderberg, 2021). The volume of business transactions has made it necessary to employ information technologies, with disruptive technologies playing a central role (Knauer, Nikiforow, & Wagener, 2020). Artificial intelligence is defined as the use of computer systems and engineering technologies that enable machines to exhibit human-like traits such as reasoning, learning, autonomous actions, and data analysis to make decisions (Griffin, 2019). Laudon, Laudon, and Elragal (2020) noted that artificial intelligence allows the processing, organizing, and distributing of vast amounts of data in minutes, leading to accurate and reliable information. This capability enables accountants to analyze data and interpret the implications. Balios, Kotsilaras, Eriotis, and Vasiliou (2020) suggested that artificial intelligence systems comprise interconnected components like software, hardware, people, and procedures, with data being collected, processed, stored, and distributed to enhance decision-making. The introduction of artificial intelligence has shifted financial reporting from traditional methods to more innovative and automated data-processing systems, yielding more timely, reliable, and accurate reports (Aguguom & Ebun, 2021; Albawwat & Frijat, 2021; Deniz & Jeffery, 2022). Recently, the value and quality of audits have declined due to an increase in financial reporting scandals worldwide (Noordin, Hussainey, & Hayek, 2022; Odoh, Echefu, Ugwuanyi, & Chukwuani, 2018). Studies by Yadav, Gupta, Sahu, and Shrimal (2017) and Al-Aroud (2020) have identified several challenges affecting audit quality, including inaccuracies, inconsistency, and untimely financial report audits, which raise doubts about the reliability of these reports.

Other studies specifically linked the issues with manual processes, high inaccuracies, and delayed audits. Deniz and Jeffery (2022) argued that traditional financial reporting methods can no longer handle the volume of transactions or the speed required for accounting information. In line with this view, Albawwat and Frijat (2021) highlighted that as corporate transactions become increasingly digital, the need for disruptive technologies like artificial intelligence has grown to maintain expert audit systems (Al-Aroud, 2020). Research has shown that artificial intelligence and other disruptive technologies are well-positioned to enhance the financial reporting landscape and improve audit quality (Hasan, 2021; Liu et al., 2018). Additionally, recent studies have shown positive results and economic benefits from implementing artificial intelligence, such as improved analysis and forecasting abilities, more reliable data, and faster reporting (Greenman, 2017; Alawaqleh & Almasria, 2021; Abdollahi, et, al. 2020). These findings suggest that the adoption of artificial intelligence has contributed to improvements in both financial reporting and audit quality. From an audit quality standpoint, artificial intelligence provides models and methods for accounting frameworks to track financial reporting efficiency trends. Hemin

(2017) reported that artificial intelligence's successful application helps interpret historical data and predict future results, preventing information overload and ensuring accuracy and speed in financial reporting. Jariwala (2015) found that artificial intelligence is closely linked to better audit quality. Similarly, Lee and Tajudeen (2020) reported that artificial intelligence positively impacts audit quality. Audit quality was also found to be positively related to financial reporting quality (Kaplan & Haenlein, 2019). Numerous studies, including those by Askary, Nasser, and Yasean (2018) and Chukwuani and Egiyi (2020), have explored audit quality from different perspectives, but there remains a need to investigate the impact of artificial intelligence on audit quality and its implications for accountants. Although some studies have addressed audit quality, they have produced mixed and inconsistent results, highlighting the need for further research. For example, Hasan (2021) and Hemin (2017) reported positive effects of information technology on audit quality, while Lee and Tajudeen (2020) found contradictory results. Greenman (2017) and Balios et al. (2020) found negative impacts of disruptive technologies on the credibility of audit reports. Despite these mixed results, artificial intelligence is widely seen as a key factor in improving audit quality (Albawwat & Frijat, 2021). According to Deniz and Jeffery (2022), artificial intelligence is strongly correlated with disruptive technologies that enhance both audit quality and financial reporting. Hasan (2021) emphasized the flexibility and usefulness of artificial intelligence in improving the reliability and accuracy of financial and audit reporting. This study aims to address gaps in the existing literature and explore how artificial intelligence can improve audit quality and its implications for accountants. The rest of the study is set out as follows: Section 2 presents the literature review and theoretical framework; Section 3 explains the methodology; Section 4 contains the data analysis, results and discussion; and Section 5 comprises the conclusion, recommendations and limitations.

1.1 | Research Objective

Examine the effect of artificial intelligence on audit quality to determine the implications for practicing accountants.

1.2 | Research Question

How does artificial intelligence affect audit quality and what are the implications for practicing accountants?

1.3 | Research Hypothesis

(Ho1): Artificial intelligence has no significant effect on audit quality from the perspective of practicing accountants.

2 | LITERATURE REVIEW

2.1 | Conceptual Framework

2.1 Audit Quality: Audit quality represents the effectiveness of obtaining value for audit fees and plays a vital role in establishing lasting trust in auditors' duties. According to Abdollahi et al. (2020), it ensures that audited financial statements are free from errors, and the main goal of an audit is to provide reasonable assurance that financial statements are free from irregularities. Some scholars argue that audit quality is subjective and based on perception, such as Agur, Peria, and Rochon (2020), and Akeem, Rufus, Abiodun, and Olawum (2020), while Alawaqleh and Almasria (2021) believe that audit quality is significantly influenced by factors like audit fees, tenure, independence, audit firm size, and others. Albitar, Gerged, Kikhia, and Hussainey (2020) found that audit market concentration positively affects quality, implying that audits conducted by the Big Four are seen as higher quality. Studies by Moll and Yigitbasioglu (2019) and Gentner, Stelzer, Ramosaj, and Brecht (2018) indicated that artificial intelligence improves audit quality. This study measures audit quality through proxies like audit fees, tenure, auditor independence, and experience.

2.1.1 Audit Tenure: Audit tenure refers to the duration of the auditor-client relationship. Research on the effects of audit tenure on audit quality and financial reporting quality is divided. Akinyomi and Joshua (2022) found that longer audit tenures could lead to compromised audit quality, suggesting that too close a relationship between auditor and client might undermine independence. Artificial intelligence can mitigate this issue by reducing the negative impacts of long audit tenures on audit and financial report quality. Audit tenure regulations vary by jurisdiction; for instance, in Nigeria, Section 33 of the Securities and Exchange Commission mandates the rotation of audit firms every 10 consecutive years.

2.1.2 Audit Fees: Audit fees have been analyzed from various perspectives, particularly their impact on the auditor's examination of financial reports. According to Aguguom, Dada, and Nwaobia (2019), audit fees influence auditors' neutrality and independence, potentially affecting the fairness of financial reporting. Al-Shatnawi (2017) suggested that audit fees include the overall costs throughout the audit process, compensation risks, and demand-based fees (Alt, Beck, & Smits, 2018). These fees significantly influence audit quality. Artificial intelligence is changing the dynamics of audit fees, with Alwardat (2019) reporting that AI positively impacts audit fees.

2.1.3 Auditor Independence: Auditor independence is crucial for determining both audit quality and the economic value derived from investment decisions based on the financial reports. Alsharif (2019) argued that the degree of compromise and bias in audits is determined by auditors' independence. Amah and Amauwa (2019) highlighted that independence directly impacts the quality of audits. Auditor independence means that auditors are free from bias, conflict of interest, or influence when forming opinions about a company's financial condition. Avram, Calu, Dumitru, and Dănescu (2019) noted that disruptive technologies, such as artificial intelligence, positively impact audit independence, as AI does not exhibit partiality or make misstatements, instead providing an objective and accurate assessment.

2.1.4 Audit Firm Size: Audit firm size can be understood in three contexts. First, it relates to the financial strength of the firm's clients, whether multinational corporations or smaller companies. Second, it refers to the audit firm's financial strength and its partners. Third, it involves the number and capabilities of employees in the firm (Kokina & Davenport, 2017). Kokina and Davenport (2017) also noted a connection between audit firm size and artificial intelligence, suggesting that digital systems positively affect audit quality determinants.

2.1.5 Audit Experience: There are differing views on whether audit experience impacts audit quality and how disruptive technologies influence audit experience. Abdollahi et al. (2020) found that the application of disruptive technologies, particularly AI, has little effect on audit experience. Similarly, Alfartoosi and Jusoh (2020) argued that AI did not significantly affect audit experience, though it remains a crucial factor in audit quality. They emphasized that while AI doesn't significantly alter the reporting process, the experience of auditors remains vital.

2.2 Artificial Intelligence: Artificial intelligence (AI) is widely described in the literature. Hasan (2021) defined it as rare intelligence exhibited by machines or robots that perceive their environment and act to maximize their chances of achieving predefined goals. AI is understood as a man-made system designed to simulate human intelligence (Alfartoosi & Jusoh, 2020). Noordin et al. (2022) noted that AI positively impacts financial reporting, facilitating more accurate and reliable outcomes. Dagiliene and Kloviene (2019) highlighted AI's ability to replicate human cognitive skills such as learning and problem-solving. In financial reporting, AI functions as a data-mining tool that helps process and automate documents, improving internal accounting processes and reporting. AI can identify patterns and anomalies in data, helping auditors more efficiently detect risks and complete auditing tasks. It also enhances human intelligence replication and behavior (Dessureault & Benito, 2012). Giehl, Göcke, Grosse, Kochems, and Müller-Kirchenbauer (2020) and Gielen et al. (2019) found that AI improves both audit quality and financial reporting, making tasks more automated and saving man-hours. Deng and Yeh (2011) argued that AI systems free accountants to focus on strategic advisory roles rather than repetitive tasks. This study considers AI in components such as robotics, neural networks, genetic algorithms, and natural language processing.

2.2.1 Robotics: Robotics, a key component of AI, involves the design, manufacturing, and application of robots. According to Greenman (2017), robotics concerns the construction and operation of systems. Puce and Hämäläinen (2017) defined robotics as reprogrammable systems that handle materials, data, parts, or tools for various tasks. Jerneck et al. (2021) suggested that robotics work in tandem with other AI components to perform tasks. Liu et al. (2018) observed that robots use magnetic sensors similar to the human brain to sense their environment. Lombardo et al. (2019) noted the close correlation between neural networks and robotics, while Moll and Yigitbasioglu (2019) emphasized their positive influence on the speed and accuracy of financial reporting.

2.2.2 Neural Networks: Neural networks are electronic models in AI designed to mimic the functions of the human brain. These networks help AI learn through computer systems and programs (Neofytou, Nikas, & Doukas, 2020). According to García-Nicolás et al. (2021), neural networks simulate the human brain's structure, enabling machines to perform tasks effectively. Odoh et al. (2018) and Samadi (2017) highlighted the importance of neural networks in AI, noting they enable machines to perform as humans do.

2.2.3 Genetic Algorithms: Genetic algorithms, part of AI's interconnectivity, are mathematical programs designed to find solutions to problems based on natural selection and evolution principles (Odoh et al., 2018). These algorithms balance selection and mutation to create resilient solutions, preventing premature convergence. Samadi (2017) noted that genetic algorithms play a significant role in AI's speed and accuracy in data processing and financial reporting.

2.2.4 Natural Language Processing: Natural language processing (NLP) is a component of AI focused on human language communication. Sullivan and Hannis (2017) defined NLP as a system that sends messages using natural language. Samadi (2017) described NLP as a tool for AI to replicate human language and communication. Wu, Xu, Lou, and Chen (2018) argued that NLP enhances AI's data processing and communication abilities, thereby improving audit quality and financial reporting reliability.

2.3. Theoretical Framework: The framework for this study is rooted in credibility theory, which supports the dependent variable of audit quality, and disruptive technology theory, which supports artificial intelligence as the independent variable. These theories were chosen due to their relevance and the strong connection between artificial intelligence and audit quality.

2.3.1 Disruptive Technology Theory: Disruptive technology theory was introduced by Christensen in 1990. The theory asserts that new market entrants disrupt existing markets, with innovations capable of replacing outdated technologies. It also highlights how smaller businesses with fewer resources challenge well-established companies, with emerging technologies gradually replacing traditional business methods and data processing approaches (Yadav et al., 2017). Disruptive technologies have progressively replaced older technologies, and new communication methods have displaced traditional ones. Innovations in business practices are continually changing due to technological advancements. Wang et al. (2019) argued that disruptive technologies, such as artificial intelligence and information technology, have revolutionized financial reporting and replaced some traditional financial reporting methods. Zhang et al. (2020) acknowledged the theory's positive reception, given the clear benefits for organizations adopting new technologies over conventional methods. Yeh and Deng (2012) emphasized that new technologies have gradually taken over all aspects of business operations, including financial reporting, auditing, and communication, contributing to the global integration of modern technology.

2.3.2 Technology Acceptance Theory: The technology acceptance theory, proposed by Davis in 1989 and adapted from the theory of reasoned action, addresses the widespread acceptance of information technology across society, businesses, workplaces, and academic research. The theory suggests that technological innovations, particularly computer use, have become essential tools for problem-solving and increasing efficiency. Zhang et al. (2020) noted that technological innovations are widely embraced as a new lifestyle, influencing every aspect of human activities, with the internet, electronics, and mobile communications replacing traditional methods. According to Dagiliene and Kloviene (2019), accepting information technology has brought new ways of thinking, communicating, and conducting business, driving significant economic gains for society. The theory posits that the development of information systems has greatly contributed to the optimization of business transactions and strategic planning, benefiting both private and corporate organizations.

2.3.3 Financial Credibility Theory: Financial credibility theory is concerned with the use of tools, policies, and technological procedures that ensure reliable and credible outcomes. It suggests that accurate and trustworthy information can significantly improve economic outcomes, while unreliable information can harm the economic prospects of its users. Jariwala (2015) highlighted that information asymmetry is harmful to organizations, emphasizing the importance of auditors in reducing risks associated with financial reporting. Dagiliene and Kloviene (2019) noted that audit services aim to enhance the credibility of accounting information and improve audit quality. This theory underscores the critical role of auditors in ensuring financial information's credibility, adding economic value for the public and investors. Dagiliene and Kloviene (2019) also suggested that when financial statements and audit quality are credible, it helps reduce financial risks for companies and their stakeholders.

2.4. Empirical Review: This section reviews empirical studies on artificial intelligence and auditing. Hasan (2021) explored the impact of artificial intelligence on audit quality, using surveys and previous research to identify areas where AI has been most beneficial in auditing. The study concluded that AI significantly improves financial reporting accuracy, productivity, and auditor efficiency compared to traditional methods. Noordin et al. (2022) reviewed extensive literature on AI's optimization in auditing and found that AI positively impacted audit quality by reducing audit time and improving reliability. The study also explored AI's role in fraud prevention and audit quality from the perspective of external auditors, highlighting AI's ability to process large datasets efficiently. Gentner et al. (2018) examined how AI and machine learning affected financial reporting, concluding that AI positively impacted audit quality and timely reporting. Nwakaego and Ikechukwu (2015) investigated AI's role in the auditing process and found that AI ensures better audit quality by analyzing data more efficiently than human auditors. Schulenberg (2007) explored cognitive auditing, where AI aids auditors in detecting errors and irregularities in financial reports, concluding that AI's role in cognitive auditing positively impacts audit quality.

3 | METHODOLOGY

3.1 Design: This study adopted a survey research design to examine the relationship between artificial intelligence and audit quality. Primary data was collected from respondents purposefully selected from a target population. The study targeted practicing accountants in accounting firms within Africa who possess knowledge of AI in accounting and auditing, particularly those in the Big Four firms who have experience with robotics and AI-related software.

3.2. Population and Sample Size: The target population for the study is estimated at 1,500 respondents. However, the sample size is determined using the Taro Yamani formula, which is commonly employed to calculate a manageable sample size for research studies.

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

Where:
n = sample size,
N = the population of the study,
1 = constant,
e = degree of error.

By substitution:
$N = \frac{1,500}{1+ 1,499(0.0025)}$
$N = \frac{1,500}{4.7475}$
= 316

However, a total of 275 responses were retrieved from the online survey that were found to be valid for the study.

3.3. Data Collection and Analysis: The research employed self-designed perception-based questionnaires distributed via an online platform, targeting employees of accounting firms with knowledge of artificial intelligence and other emerging technologies, such as cloud accounting, machine learning, and robotics. The focus was particularly on individuals from the Big Four accounting firms. It was preferable to include auditors, especially practicing chartered accountants, who have experience with disruptive software in the survey respondents.

3.4. Instrument Validity and Reliability: To assess construct validity, factor analysis was conducted using Cronbach's alpha, with a benchmark of 70%. The reliability of the instrument was evaluated through Cronbach's alpha, and the results exceeded the 70% threshold, confirming both the validity and reliability of the tool used for this study.

3.5. Pilot Testing: A pre-test of the questionnaire was carried out to assess its relevance and ensure that the research questions were clearly understood. A total of 35 responses, which accounted for slightly over 10% of the study's sample size, were collected, and minor adjustments were made based on the feedback received.

3.6. Model Specifications: The model specification of the study is as follows:

$AUDITQ = f(AI)$ (1)
$Yi = \alpha 0 + \beta Xi$ (2)
3.7. Functional Relationship: The study's functional relation establishing the nexus between audit quality and artificial intelligence is: $AUDITQ = f\ (RTX, NNT, GTL, NLP)$ (3)
$AUDITQ = \alpha 0 + \beta 1RTXi + \beta 2NNTi + \beta 3GTLi + \beta 4NLPi + \mu i$ (4)

Where:
AUDITQ = audit quality;
AI = artificial intelligence;
RTX= robotics,
NNT = neural networks,
GTL = genetic algorithms,
NLP = natural language processing,
f = function,
Yi = dependent variable, Xi = independent variable (all subscripted), α0 = constant, i = cross-section, and β = coefficient of the model.

3.8. A Priori Expectations: The independent variable is anticipated to influence the dependent variable of the study. Specifically, the study expects that artificial intelligence and its associated explanatory variables will have a significant positive impact on audit quality (AUDITQ), considering their implications for practicing accountants. Consequently, the coefficient of the variable in the inferential regression is expected to be positive. Therefore, it is anticipated that $\beta 1 - \beta 5 > 0$ at a 5% significance level.

3.9. Pre-Test Estimation Reliability of the Research Instrument: To verify the reliability of the instrument, a pre-test evaluation was conducted using Cronbach's alpha. The results of this test (see Table 1) show the highest and lowest estimates to be 0.913 for audit experience and 0.844 for Genetic algorithms, respectively. All results surpass the 0.70 threshold.

Table 1. Reliability test results

Variable	Number of items	Cronbach's alpha
Audit tenure	5	0.823
Audit fees	5	0.912
Independence of auditors	5	0.835
Size of audit firm	5	0.817
Audit experience	5	0.913
Robotics	5	0.884
Neural network	5	0.907
Genetic algorithms	5	0.814
Natural language process	5	0.830

Source: Pilot study, 2025.

The pilot test revealed that the study scales were appropriate and reliable instruments, as the Cronbach's alpha values are greater than 0.07. At the same time, a manipulation check was carried out and the results confirmed the validity.

4 | DATA ANALYSIS, RESULTS AND DISCUSSION

The regression results for the relationship between artificial intelligence (AI) and audit quality (AUDITQ) are presented in this sub-section. Table 1 shows the results of the estimated regression model, in which the predictors (independent variables) of AI are robotics (RTX), neural networks (NNT), genetic algorithms (GTL) and natural language processing (NLP), while the dependent variable was audit quality.

Table 2. The highest level of education/qualification

Educational qualification	Frequency	Percent
Diploma/ND/NCE	25	10
HND/BSc	69	25
MSc/MPhil	91	33
PhD	33	12
Others	54	20
Total	275	100

Note: ND = National diploma, HND = Higher National Diploma, BSc Bachelor of Science, MSc = Master of Science, MPhil = Master of Philosophy, PhD = Doctor of philosophy.
Source: Field survey, 2025.

The education/qualification levels of the respondents are represented in Table 2. The majority of respondents (91) indicated MSc/MPhil as their level of education, which is significantly higher than the other categories and represents 33% of the total.

Table 3. Work experience

Work experience	Regularity/Frequency	%
Less than three years	5	2
Three to five years	34	12
Six to ten years	123	45
More than ten years	113	41
Total	275	100

Source: Field survey, 2025

In Table 3, the distribution of the respondents' work experience is presented. Those with 6–10 years of experience constitute 45%, which represents 123 respondents. However, 34 respondents representing 12% have 3–5 years of experience, while 113 respondents which represents 41 %, have more than 10 years of experience.

Table 4. Professional Qualifications of the Participants

Professional qualifications	Frequency	Percent
ACA/FCA/ACCA/ACMA/ACTI/FCTI	215	88
Others	60	22
Total	275	100

Note: ACA = Associate Chartered Accountant, FCA = Fellow Chartered Accountant, ACCA = Association of Chartered Certified Accountants, ACMA = Association of Cost and Management Accountants, ACTI = Associate of Chartered Taxation of Nigeria, FCTI = Fellow of the Chartered Institute of Taxation of Nigeria.
Source: Field survey, 2025.

Table 4 shows that a total of 215 participants (about 78.2%) have ACA/FCA, ACCA/FCCA, ACMA/ACTI/FCTI professional qualifications while the remaining 160 participants {about 22.8%} are having other professional qualifications. In other words, more than two third of the participants indicated that they have ACA/FCA, ACCA/FCCA, and ACMA/ACTI/FCTI as professional qualifications.

Table 5. Perceived responses: Artificial intelligence and audit quality indicators.

	SD	D	U	A	SA	Total	% A	Mean	Rank
The application of artificial intelligence enhances audit quality through the automation of tasks	41 (15)	23 (8)	15 (6)	96 (35)	100 (36)	275 (100)	196 (71)	3.69	2
The use of robotics in auditing and accounting processing aids a robust risk assessment during audits	40 (15)	35 (13)	23 (9)	95 (35)	82 (30)	275 (100)	177 (64)	3.52	5
Natural language processes assist in quick communication toward the stratification of data in audit exercises	44 (16)	25 (9)	20 (7)	91 (33)	95 (35)	275 (100)	186 (68)	3.61	3
Genetic algorithms as a component of artificial intelligence facilitate auditing	44 (16)	26 (10)	22 (8)	93 (34)	90 (33)	275 (100)	183 (67)	3.58	4
Neural networks facilitate auditing exercises to enhance the accuracy and reliability of audit reports	42 (15)	20 (7)	12 (4)	91 (33)	110 (47)	275 (100)	201 (73)	3.75	1

Note: Percentages are in brackets.
Source: Survey results (2025).

4.1 | Artificial Intelligence and Audit Quality

This section discusses the impact of artificial intelligence and its metrics as factors influencing audit quality. The findings in Table 5 indicate that, according to the participants' views, the least favored statement is the use of robotics in auditing and accounting processes to assist in a thorough risk assessment during audits (average score = 3.52), with 64% of the respondents agreeing. In contrast, the statement that Neural networks facilitate auditing exercises to enhance the accuracy and reliability of audit reports is highly endorsed (average score = 3.75), with 73% agreement, ranking it the highest. Additionally, a significant number of respondents support the view that artificial intelligence improves audit quality through task automation (average score = 3.69), with 71% agreeing. The averaged supported statement showed a high average score of 3.61 with 68% agreeing that Natural language processes assist in quick communication toward the stratification of data in audit exercises.

4.2 | Regression Analysis

This subsection presents the regression results that assess the overall impact of AI indicators on audit quality. The data in Table 6 reveal that the predictors are AI indicators, while the dependent variables include the combined values of audit tenure, audit fees, auditor independence, audit firm size, and audit experience—collectively forming the audit quality indicator.

Table 6. Artificial intelligence and audit quality (AUDITQ).

Variable	Coefficient	Robust standard error	T-stat.	P >|t|
_cons	1.724	0.133	11.127	0.005
RTX	0.211	0.056	3.328	0.000
NNT	0.143	0.022	4.084	0.020
ITA	0.236	0.043	4.348	0.000
NLP	0.140	0.038	3.275	0.000
Observations	275	275	275	275
R2		0.395		
Adjusted R2		0.368		
F-stat.		84.12		
Probability of F-stat		0.003		
Heteroskedasticity test		17.32		
Probability of heterogeneity test		0.000		
Jarque–Bera normality test		0.315		
Probability of normality test		0.625		

Note: Dependent variable = audit quality; Independent variable = artificial intelligence, which is AI and the proxies of RTX = robotics, NNT = neural networks, GTL = genetic algorithms, NLP = natural language processing.
Source: Estimation result, 2025

The regression analysis produced the following result:

$AUDITi = \beta 0 + \beta 1RTXi + \beta 2NNTi + \beta 3\ ITAi + \beta 4NLPi + \mu i$, with $TAi = 1.724 + 0.211 * RTXi + 0.143 * NNTi + 0.236 * ITAi + 0.140 * NLPi$.

Table 6 shows an F-statistic of 84.12 [p-value = 0.003], indicating that the model is statistically significant at the 5% level. Moreover, the coefficient of robotics (RTX) [β1 = 0.211, p-value = 0.005] is positive and statistically significant at the 5% level, meaning a unit increase in RTX increases audit quality by approximately 0.211. Similarly, the coefficient of neural networks (NNT) [β2 = 0.143, p-value = 0.020] is also positive and significant, showing that a unit increase in NNT raises audit quality by 0.143 units. The genetic algorithms coefficient (ITA) [β3 = 0.236, p-value = 0.000] is similarly positive and statistically significant, suggesting that a unit increase in ITA leads to a 0.236 increase in audit quality. Finally, the coefficient for natural language processing (NLP) [β4 = 0.140, p-value = 0.000] shows a positive and statistically significant relationship with audit quality, implying that a unit increase in NLP results in a 0.140 increase in audit quality. The adjusted R-squared value reveals that 37% of the variation in audit quality is explained by changes in the application of artificial intelligence (AI), including robotics, neural networks, genetic algorithms, and natural language processing, while the remaining 63% is due to factors not captured in the model.

The Breusch–Pagan/Cook–Weisberg heteroskedasticity test showed that the probability of normality was not significant at the chosen 0.05 significance level (p-value = 0.625). This indicates that the error term and residuals of the regression model are normally distributed, as expected and required by the study. Similarly, the result of the Breusch–Pagan/Cook–Weisberg test, being above 0.010, confirms statistical significance at the 0.05 level. The findings in Table 6 suggest the null hypothesis of homoskedasticity should be rejected. As a result of this rejection, the study concluded that the error term in the regression model displayed heteroskedasticity, and thus, the heteroskedasticity-robust standard error regression model was adopted for analysis.

5 | CONCLUSION AND RECOMMENDATIONS

This study investigated the impact of AI on audit quality and its implications for accountants. A survey research design, with self-structured questionnaires administered online to accountants and auditing firm staff, was used. Both descriptive and inferential statistics revealed that AI positively influences audit quality in auditing tasks. The inferential analysis showed that robotics, neural networks, genetic algorithms, and natural language processing had a statistically significant positive effect on audit quality. The combined results of the study, utilizing AI's explanatory variables, indicated a positive effect on audit quality. These findings align with previous studies by Hasan (2021), Noordin et al. (2022), and Gentner et al. (2018), which also reported a positive impact of AI on audit quality. Based on the findings, it is recommended that auditing firms actively adopt AI in their accounting and auditing procedures. The findings have important implications for risk assessment, timely reporting, and accuracy, all of which enhance audit quality. Managers and accountants in both private and corporate sectors should integrate AI into their practices, given its economic value and the improvement it offers in terms of audit quality, reliability, and prompt financial reporting.

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