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Artificial intelligence and audit quality: Implications for practicing accountants

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ABSTRACT

Audit quality has been one of the most controversial issues in auditing and financial reporting research. The implication of audit quality has become critically significant for accountants and users of accounting information. Some studies have shown that the improvement of audit quality lies with the application of artificial intelligence in audit exercises. This study examines the effect of artificial intelligence on audit quality by employing the survey method, using structured questionnaires administered to practicing accountants and staff of the Big Four accounting firms. The Taro Yamani formula was used to determine the sample size, and a total of 641 questionnaires were retrieved. Cronbach's alpha was employed to test the reliability and validity alongside the pilot testing conducted. Descriptive statistics and inferential analysis were also used. The results of the descriptive method showed that many of the respondents support the usefulness of artificial intelligence. The regression results revealed that artificial intelligence has a positive effect on audit quality. Based on the results, it is recommended that managers and accountants in private, corporate, and accounting firms should embrace the application of artificial intelligence due to its economic value and helpful effect of improving audit quality in terms of accuracy, reliability, and timely financial reporting.

Contribution/Originality: This research contributes to the literature that addresses the significance of artificial intelligence, such as robotics, neural networks, genetic algorithms, and natural language processing, on the quality of audits. This study provides auditing firms with evidence of the benefits of artificial intelligence in improving audit quality.

1. INTRODUCTION

The growing global anxiety and resentment expressed by investors and other stakeholders seem not to have abated as audit quality had failed to meet the expected threshold. The global financial crisis of 2007/2008 heightened the need to address the issues of audit quality in the context of reliability and timely reporting. Wang et al. (2019) reported that manual and traditional financial reporting had failed to mitigate the worsening audit quality, and the integrity of auditors continued to deepen into a colossal failure. Despite financial regulations, the enforcement of financial requirements, and the adoption of International Financial Reporting Standards (IFRS), the quality of financial reporting has not improved (Brodny & Tutak, 2021; Deniz & Jeffery, 2022). The widening of the audit expectation gaps is worrisome, as the degenerating audit quality has persisted over the years, which is a clear indictment of the integrity of the accounting profession and audit practices all over the world (Amani & Fadlalla, 2017; Carlin, 2019). The audit market concentration and the oligopolistic nature of the Big Four audit firms dominating and controlling the audit market have failed to distinguish themselves, nor have they been absolved from financial scandals in any way despite the negative inference of market concentration. The Big Four auditing firms have been indicted in some of the recent financial scandals, and this has heightened anxiety regarding audit quality. For instance, the recent Wirecard financial scandal reinforced the deceptive appearance of the Big Four auditing firms.

Castelo-Branco, Cruz-Jesus, and Oliveira (2019) argued that while the heterogeneity of audit quality is perceptional, complex and subjective, the reported financial scandals and the collapse of large corporate organizations, such as Enron, Tyco and WorldCom, following the involvement of auditors, such as Arthur Andersen and the other Big Four accounting firms, are clear evidence of blunders and unethical behavior among accountants and auditing firms in degrading audit quality. According to Carlin (2019), it is increasingly difficult to ignore the dubious and unwholesome disposition of some auditors desecrating audit quality. Achieving high audit quality requited the determined and disciplined behavior of auditors and the application of disruptive technologies, such as artificial intelligence, big data, blockchain accounting, cloud accounting, robotics, machine learning, the Internet of Things and many others, in digitalized accounting systems and software packages. Audit quality is concerned with complete, reliable and comparable data to ensure the quality of financial statements and their capability of adding economic value to investment decisions.

Carlin (2019) posited that audit quality is the product of auditors with ethical values, integrity, professional attitude and skills, audit independence, experience, and sufficient time to carry out a detailed audit. Deng and Yeh (2011) noted that some of the qualities that characterize audit quality are the application of the right and specific disruptive technologies, such as artificial intelligence, in financial processing and reporting. The application of artificial intelligence has become a growing innovation in the financial reporting and auditing space globally (Jerneck, Olsson, Ness, & Anderberg, 2021). The volume of corporate and business transactions has necessitated the use of information technologies, and disruptive technologies have now taken center stage in this regard (Knauer, Nikiforow, & Wagener, 2020).

Artificial intelligence is defined as the application of computer science and engineering systems with intelligent machines and computers that are able to exhibit human traits of reasoning, learning, acting autonomously, and have the ability to analyze large data and make quality decisions on their own (Griffin, 2019). According to Laudon, Laudon, and Elragal (2020), artificial intelligence is ready information technology that can collect, organize, process and distribute large quantities of data in a matter of minutes producing reliable and accurate information. This allows accountants to interpret data and apply the implications of the results.

Balios, Kotsilaras, Eriotis, and Vasiliou (2020) noted that the systems can be seen as a set of interconnected components, such as software and hardware, people, and procedures. The data is collected, processed, stored and distributed to enhance investments and managerial decision making (Knauer et al., 2020; Zhang, Xiong, Xie, Fan, & Gu, 2020). The adoption and implementation of artificial intelligence protocols have brought a welcome paradigm from traditional data processing to more innovative, progressive and highly automated data capturing processes, resulting in more timely, reliable and accurate financial reporting and audit quality (Aguguom & Ebun, 2021; Albawwat & Frijat, 2021; Deniz & Jeffery, 2022).

In recent times, the value and quality of audits have decreased as the number of global financial reporting scandals is on the increase (Noordin, Hussainey, & Hayek, 2022; Odoh, Echefu, Ugwuanyi, & Chukwuani, 2018). Studies by Yadav, Gupta, Sahu, and Shrimal (2017) and Al-Aroud (2020) have documented a myriad of challenges affecting audit quality, such as inaccuracies, lack of consistency and the untimely audit reporting of financial statements, creating doubts about the reliability and credibility of the audit reports. Others have specifically attributed the complexities of audit quality to the use of manual computations, high levels of inaccuracies and untimely audit reports resulting. Deniz and Jeffery (2022) contended that with the volume of business transactions and the pace of information technology, the old-style financial reporting processes are no longer capable of meeting the high volume of transactions or the requirements for accounting information in a timely manner. Consistent with this understanding, Albawwat and Frijat (2021) argued that global corporate transactions have gone digital and require disruptive technology, such as artificial intelligence, to meet the needs of expert systems in audit quality (Al-Aroud, 2020).

Studies have shown that artificial intelligence and other disruptive technology are well structured and positioned to improve the financial reporting quality landscape and take audit quality and the credibility of financial reporting to a swift and predictive future (Hasan, 2021; Liu et al., 2018). More so, recent studies have documented favorable results and economic benefits arising from the adoption and implementation of artificial intelligence. For instance, there are reported cases for (i) the improvement in analysis and analysts' forecasting ability and accurate predictions and reduction of dispersions (Greenman, 2017); (ii) the improvement in the reliability of data and timely reporting (Alawaqleh & Almasria, 2021); (iii) the positive effect of artificial intelligence on audit quality (Abdollahi, Rezaei, Yasser, & Safari, 2020). These studies suggest that the adoption and application of artificial intelligence, financial reporting and audit quality have improved comparatively.

From an audit quality perspective, and most significantly from its usefulness in decision making for enhancing corporate performance, artificial intelligence has many models and channels for accounting frameworks to track financial reporting efficiency trends. Hemin (2017) reported that the successful application of artificial intelligence can assist in understanding historical data and predict results from data processing. It prevents information overload and ensures the accuracy and speed of financial reporting. Jariwala (2015) reported that artificial intelligence is closely related to improved audit quality. Lee and Tajudeen (2020) reported that artificial intelligence has a positive impact on audit quality. Similarly, audit quality was found to be positively correlated with financial reporting quality (Kaplan & Haenlein, 2019).

1.1. Gaps in Literature

There have been many studies, including Askary, Nasser, and Yasean (2018) and Chukwuani and Egiyi (2020), that have considered audit quality from various aspects, but to the best of our knowledge regarding the existing literature, there is a need to investigate the effect of artificial intelligence on audit quality in relation to the implications for accountants. Few studies have considered audit quality, and divergent opinions and mixed results have prevailed, signifying inconsistencies and inconclusiveness in the literature, leaving space for further research. For instance, Hasan (2021) studied the effect of information technology on audit quality and reported a positive effect. Hemin (2017) also reported positive effects. On the contrary, Lee and Tajudeen (2020) found contradictory results. Greenman (2017) studied the effect of disruptive technologies on audit quality and found that they had a negative effect on the credibility of audited financial statements. Balios et al. (2020) investigated the impact of information technology on the quality of audited financial statements and the results showed negative effects.

Artificial intelligence has been generally acclaimed as one of the drivers capable of improving audit quality (Albawwat & Frijat, 2021). According to Deniz and Jeffery (2022), artificial intelligence has a close correlation with disruptive technologies that enhances audit quality and financial reporting quality. Hasan (2021) reported that artificial intelligence is significantly in vogue and flexible, which is useful in increasing the reliability and accuracy in the processing and production of quality financial and audit reporting. To fill the identified gaps in the literature, this study provides new insights into the problem of poor audit quality and attempts to address this issue by investigating the effects of artificial intelligence on audit quality and its implications for practicing accountants. Hence, the following are proposed:

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

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

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

2. LITERATURE REVIEW AND THEORETICAL REVIEW

2.1. Audit Quality

Audit quality is the whole essence of the ability to obtain value for the audit fees and a strong virtue in building lasting confidence in the duties and functions of auditors. According to Abdollahi et al. (2020), audit quality is ensuring that the financial statements audited are free from mistakes, and the fundamental objective of an audit is to obtain reasonable assurance that the financial statements are free from irregularities. Some studies have stated that audit quality is subjective and perceptional, e.g., Agur, Peria, and Rochon (2020) and Akeem, Rufus, Abiodun, and Olawum (2020), while Alawaqleh and Almasria (2021) posited that audit quality is greatly influenced by many factors, including audit fees, audit tenure, audit independence, the size of the audit firm, and others. Albitar, Gerged, Kikhia, and Hussainey (2020) reported that the audit market and audit concentration had a positive effect, suggesting that audits carried out by the Big Four are considered quality audits. Moll and Yigitbasioglu (2019) reported that artificial intelligence has a positive effect on audit quality, and Gentner, Stelzer, Ramosaj, and Brecht (2018) revealed that artificial intelligence influences audit quality. In this study, audit quality is considered from the perspective of its proxies and is therefore measured using audit fees, audit tenure, auditor independence, and audit experience.

Audit Tenure: The audit tenure is defined as the length of the auditor–client working relationship. Studies are divided on the effect and implications of audit tenure on audit quality as well as the quality of financial reporting. For instance, Akinyomi and Joshua (2022) reported that the longer the audit tenure, the wider the deterioration of audit quality, suggesting that the cordial relationship between the auditor and the client will become too cordial that audit independence will be compromised. The application of artificial intelligence tends to bridge the gap and mitigate the negative impact of audit tenure on the quality of the audit and the financial reporting. Audit tenure differs based on the local accounting jurisdictions. In Nigeria, section 33 of the Securities and Exchange Commission states that companies must rotate the audit firms acting as their external auditors once appointed for a period of 10 consecutive years.

Audit Fees: Audit fees have been considered from different perspectives. A growing debate in the literature has been the implication of audit fees on the quality of the auditor's inspection of the financial reports. According to Aguguom, Dada, and Nwaobia (2019), the effect of audit fees tends to hinge on the extent of economic reward or payment to the auditors that could influence the neutrality and independence of the auditors in reporting a fair and true position of the underlying financial health condition of the clients. Al-Shatnawi (2017) posited that audit fees include the costs throughout the audit exercise, the risk of compensation and the audit fees on demand (Alt, Beck, & Smits, 2018). Audit fees are the aggregate fees charged for each accounting year for professional services rendered in relation to auditing and this has a significant influence on the audit quality. However, the application of artificial intelligence has the ability to alter the face of audit fees. Alwardat (2019) reported that the use of artificial intelligence has a positive effect on audit fees.

Independent of Auditors: The independence of auditors is important in determining the audit quality as well the economic value derivable from the investment decision arising from the quality of the financial reports. Alsharif (2019) reported that for all intents and purposes, the level of compromise and bias exhibited by the audit is influenced by the level of independence that the auditors command. Amah and Amauwa (2019) noted that audit independence has a direct effect on the audit quality reported by the auditor. Audit independence is defined as the free, fair, objective and neutral qualities exhibited by the auditors in expressing opinions on the financial state of the companies audited. Avram, Calu, Dumitru, and Dănescu (2019) reported that information technology and digitalized accounting systems where disruptive technologies, such as artificial intelligence, are applied has a strong influence on audit independence as the machines do not recognize partiality or misstatements, but rather will report the true and fair situations.

Size of the Audit Firm: The size of the auditing company connotes a different understanding from the layman's point of view. According to Aroyeun, Adefulu, and Asikhia (2018), auditor size is defined from the understanding of three aspects: Firstly, from the perspective of the wealth and financial strength of its clients, whether the clients are multinational, conglomerates, or have big or small financial assets and portfolios; secondly, the auditor size is considered from the perspective of the wealth and financial strength of the audit firm itself and its audit partners; and thirdly from the perspective of the number and strength of the employees in the auditing firm and its partners in the audit firm (Kokina & Davenport, 2017). However, according to Kokina and Davenport (2017), the size of audit firms and artificial intelligence are closely interrelated, suggesting that information technology and digitalized accounting systems have a positive significant effect on the determinants of audit quality.

Audit Experience: There have been growing divergent opinions and mixed reactions regarding whether audit experience influences audit quality, and the place of disruptive technologies in impacting audit experience and enhancing audit quality. According to Abdollahi et al. (2020), the application of disruptive technology, and artificial intelligence in particular, has little or no significant relationship. According to Alfartoosi and Jusoh (2020), artificial intelligence had an insignificant influence on audit experience, suggesting that while audit experience plays a significant impact on the audit quality, interpreting the possible results and implications of artificial intelligence results had no significant influence on directing the outcome of the reporting process or the data quality.

2.2. Artificial Intelligence

Artificial intelligence has been diversely described in the literature. For instance, Hasan (2021) described artificial intelligence as a rare intelligence demonstrated by machines or robotics that perceives its environment and takes actions intended to maximize its chances of achieving set goals based on the extent of programming and commands. Artificial intelligence is defined as a man-made and non-natural system with the intelligence to behave like its makers (Alfartoosi & Jusoh, 2020). Noordin et al. (2022) posited that artificial intelligence has a positive effect on financial reporting, suggesting that it is a branch of computer science that deals with the speed reproduction of the human level of intelligence, knowledge, self-awareness and conscience in a programmed computer. Dagiliene and Kloviene (2019) stated that artificial intelligence had previously been described as machines that mimic as well as display unusual human cognitive skills associated with learning and problem-solving in an amazing and accurate process and with timely reporting.

From the financial reporting perspective, artificial intelligence is a data mining tool logically structured to produce accurate and reliable forecasts. It enhances the processing and automation of the authorization of documents to improve internal accounting processes and reporting. Specifically, artificial intelligence tends to leverage computerized and programmed algorithms to identify and apprehend patterns and anomalies within data sets, enabling auditors to more efficiently identify specific areas of risk and execute many other auditing and accounting processing tasks at an unprecedented speed. It has the ability to replicate certain facets of human intelligence and human behaviors (Dessureault & Benito, 2012). According to Giehl, Göcke, Grosse, Kochems, and Müller-

Kirchenbauer (2020), artificial intelligence has the ability to improve audit quality and enhance the quality of financial reporting.

Gielen et al. (2019) opined that artificial intelligence can improve audit quality with the integration of artificial intelligence. Many auditing assignments and accounting tasks have become more automated, and these rate functions have the capacity to save accountants and auditing firms man-hours compared with conventional accounting tasks. Deng and Yeh (2011) argued that computerized systems and the application of artificial intelligence can allow accountants more time to focus on advisory roles and strategic decisions. The study considered artificial intelligence from components the of robotics, neural networks, genetic algorithms and natural language processing.

Robotics: Robotics come in various forms and perform dimensional job schedules in line with the command assigned to them by the programmer. The robotics component of artificial intelligence is one of the disruptive technologies behind the designing, manufacturing and application of robots (Deng & Yeh, 2011). According to Greenman (2017), this is concerned with the design, construction and operation dynamics. Puce and Hämäläinen (2017) defined robotics as a reprogrammable, multidimensional and multifunctional systems structured to move materials, data, parts or tools in the direction of performing diverse programmed motions and assigned tasks. Jerneck et al. (2021) contended that the robotic aspects of artificial intelligence work together with other components to accomplish a given task. Liu et al. (2018) noted that robotics are designed with strong magnetic sensors, like the human brain, to sense its surroundings and feel and see where applicable. Lombardo et al. (2019) reported that neural networks are closely correlated with artificial intelligence, while Moll and Yigitbasioglu (2019) documented that neural networks have a positive effect on the speed of reporting credible and reliable financial statements.

Neural networks: Neural networks are segments of the components of artificial intelligence that are electronic models of the human brain's neural network structured to perform a given task. The capacity and strength of AI neural networks are based on the mechanisms of learning and functions of the electronic models that are implemented by computer-assisted systems. According to Neofytou, Nikas, and Doukas (2020), neural networks facilitate the systemic capacity to learn through computer systems and programs. García-Nicolás et al. (2021) documented that neural networks operate like human brains through structural simulations by machines and are made possible due to the presence of neural networks. Odoh et al. (2018) reported that neural networks are significant in the dynamics of artificial intelligence. Consistent with the views of Odoh et al. (2018) and Samadi (2017), neural networks are an integral enabler of the functions of artificial intelligence as they enable machines to act and perform assigned duties as human brains do.

Genetic Algorithms: Genetic algorithms are part of the components of artificial intelligence related to system interconnectivity. According to Sullivan and Hannis (2017), genetic algorithms function as a mathematical algorithms program that has the power to find a solution to a known and specific problem in line with the programmed artificial intelligence process that is built on natural selection and evolution (Odoh et al., 2018). According to Odoh et al. (2018), genetic algorithms balance the selection and mutation to create parallel, noise-tolerant, hill-climbing algorithms as well as prevent premature convergence. Samadi (2017) documented that genetic algorithms are essentially related to the effective functioning of artificial intelligence in speed and accurate data processing and financial reporting

Natural Language Processing: As part of the components of artificial intelligence, natural language processing is one of the multifunctional processing and communication aspects of artificial intelligence. According to Sullivan and Hannis (2017), natural language processing is defined as a process of sending messages and signals with intelligent systems using a natural language. Samadi (2017) further reported that natural language processing as a strong technological tool of artificial intelligence is greatly concerned with the imitation of human natural languages and communicating in the same manner as humans. Wu, Xu, Lou, and Chen (2018) revealed that natural language processing is closely interrelated to the effective functioning of the data processing and communication abilities of artificial intelligence to enhance audit quality and financial reporting credibility.

2.3. Theoretical Framework

The theoretical framework of this study is built on credibility theory underpinning the dependent variables of audit quality, while disruptive technology underpins artificial intelligence as the independent variable. These theories were considered as the underpinning theories due to their relevance and the nexus subsisting between artificial intelligence and audit quality.

Disruptive Technology Theory: Disruptive technology theory was developed by Christensen (1990). The theory states that new entrants to the market disrupt established markets and that new technology innovations are capable of displacing the old and existing technologies. It also suggests that as new and small businesses with smaller resources challenge old and well-established businesses, and that new and emerging technologies are gradually displacing the old and traditional ways of doing business and processing data (Yadav et al., 2017). Disruptive technologies have gradually displaced old and incumbent technologies, new means of communication have displaced old and traditional means of communication, and there are new ways of doing things due to new technologies and growing trends of innovations.

Wang et al. (2019) submitted that disruptive technology, such as artificial intelligence and information technology, have revolutionized financial reporting processes and have replaced some of the conventional financial reporting processes. Zhang et al. (2020) noted that disruptive technology theory was welcome because of the obvious benefits and returns for organizations that had embraced the new technologies in place of the old and traditional methods. According to Yeh and Deng (2012), new technologies have gradually taken over the old in all aspects of businesses transactions, financial reporting processes, auditing and reporting processes, means of communication, methods of conducting payments, and all that makes the world a global village as a result of new technologies.

Technology Acceptance Theory: The technology acceptance theory was proposed by Davis in 1989 (Davis, 1989) and was adapted from the theory of reasoned action. The technology acceptance theory is concerned with the general acceptance of information technology by society, the business community, workplaces, and researchers. It suggest that the world is witnessing new technological innovations, and the use of computers and the level of acceptance and application of technology in every human activity are impressive and a welcome tool in solving problems and getting things done speedily. Zhang et al. (2020) noted that technological innovations are widely accepted as a new way of life and have gradually affected every part of human beings as the way of doing things globally now revolves around new technologies. New technologies and the internet of things, electronics, and the use of mobile communication have all replaced traditional methods.

Dagiliene and Kloviene (2019) noted that the acceptance of information technology has brought new ways of thinking, communicating and doing business, and this had brought lots of economic gains to society. The theory suggests that development to optimize the flow of information to trigger knowledge to cope with growing business transactions and the level of acceptance of information systems have made a huge contribution to private and corporate organizations in enhancing strategic planning and meeting business objectives.

Financial Credibility Theory: The financial credibility theory is concerned with the application of available tools, policies, and technological procedures to ensure reliable and credible outcomes. Financial credibility theory suggests that reliable and credible information has the capability to increase the economic fortunes of the users of that information but can damage the economic fortunes of users when the information is unreliable and misleading. The financial credibility theory, according to Jariwala (2015), suggests that information asymmetry is detrimental to the well-being of an organization, emphasizing the role of auditors in bridging the gap and reducing incidents of financial risks and information asymmetry. Dagiliene and Kloviene (2019) noted that the demand for audit services was to improve the credibility of accounting information as well as improve audit quality. The financial credibility theory emphasizes the essence of auditors' responsibility and their duty of assurance to improve the credibility of accounting information and ensure its usefulness in order to add economic value to the general public and other investors who may wish to rely on the information for decision making. Dagiliene and Kloviene (2019) noted that the financial credibility theory ideology implies that, when there is credibility in financial statements and audit quality, there is a high tendency of reducing financial risks and constraints for companies as well as for the users of the financial statements.

2.4. Empirical Review

This section examines some empirical findings from past studies on artificial intelligence and auditing. Hasan (2021) investigated the impact and implications of using artificial intelligence in auditing on audit quality. The study used a survey approach with a structured questionnaire, as well as an exploratory review of previous works on artificial intelligence and audit functions. The study examined numerous areas of auditing activities where artificial intelligence had been most beneficial. The study concluded that the use of artificial intelligence in the auditing profession produced enormous benefits in terms of accurate financial reporting, high productivity, and auditor efficiency that are significantly superior to conventional auditing activities.

Noordin et al. (2022) studied the application of a comprehensive and extensive literature review on the use and optimization of audit exercises using artificial intelligence in the auditing process. The study is based on the volume of reviewed literature and concluded that the use of artificial intelligence positively impacted audit quality, reduced the length of time it took to complete audits, improved reliability and ensured accurate financial reporting.

Noordin et al. (2022) also examined the effect of artificial intelligence on audit quality, audit dictation and prevention of fraud from the perspective of external auditors. The study employed a qualitative research method using exploratory research and reviewed studies on the use of artificial intelligence in audits. Through the review, it was observed that artificial intelligence was useful in auditing a large amount of data during the audit process. The study results suggested that the use of artificial intelligence had a positive effect on timely and accurate data processes and audit quality.

Gentner et al. (2018) studied the effect of disruptive technology of artificial intelligence and machine learning on the performance of companies in meeting customers' financial reporting needs. The study considered the implication of using artificial intelligence to assist auditors in detecting errors and processing financial information faster. Based on the analysis carried out, the study found that the use of artificial intelligence had a positive effect on audit quality and timely financial reporting.

Nwakaego and Ikechukwu (2015) investigated the effect of artificial intelligence on the auditing process and found that artificial intelligence enables auditing services to ensure audit quality. The study employed a qualitative exploratory research design using documented studies on the use of artificial intelligence to simplify auditing exercises and other complex financial reporting procedures. The study observed that artificial intelligence deployed during audits analyzed a high volume of data in a timely manner and more effectively than human auditors could have done, suggesting that the application of artificial intelligence had a positive effect on audit quality.

Schulenberg (2007) studied the use of artificial intelligence in auditing through what the study called cognitive auditing. The study employed qualitative research, using the exploratory method in the study. The study posits that cognitive auditing is the application of computerized processes that allow the application of artificial intelligence to assist auditors in audit exercises to detect errors and any irregularities. The study recognized the use of International Business Machine (IBM)-created cognition in financial reporting as an aid to ensure audit quality. The study concluded that artificial intelligence through cognitive auditing had a positive effect on audit quality.

3. METHODOLOGY

3.1 Design

To determine the relationship between artificial intelligence and audit quality, the study employed a survey research design using primary data sourced from selected respondents from a population target that was purposively selected. The target audience for the study comprises practicing accountants in accounting firms within the African region who and have good knowledge and understanding of the usefulness and dynamics of artificial intelligence in accounting and auditing tasks and services, especially in the Big Four, and preferably auditors who have been exposed to the use of robotics and software related to artificial intelligence.

3.2. Population and Sample Size

A total of 1,500 respondents is anticipated from the target population; however, the sample size is determined using the Taro Yamani formula. The Taro Yamani formula used in the determination of a workable sample size for the study is:

$$n = N/1 + N(e)^2$$

Where:

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

By substitution:

= 1,500/1+1,499(0.0025)

= 1,500/4.7475

= 316.

However, a total of 641 responses were retrieved from the online survey that were found to be valid for the study.

3.3. Data Collection and Analysis

The study adopted self-structured perceptional questionnaires which were administered through an online platform targeting staff of accounting firms who are familiar with the use of artificial intelligence and other related disruptive technologies, such as cloud accounting, machine learning and robotics, especially in the Big Four accounting firms. Preferably, auditors who are practicing chartered accountants who are exposed to the use of disruptive software should also be included in the respondents.

3.4. Instrument Validity and Reliability

The construct validity factor analysis employed Cronbach's alpha with a benchmark of 70%. In addition, the reliability was calculated and interpreted with the aid of the statistical methods of Cronbach's alpha. The test results revealed an average higher than the 70% threshold, confirming the validity and reliability of the instrument used for the study.

3.5. Pilot Testing

A pre-test of the questionnaire was conducted in order to evaluate its relevance and to ensure proper understanding of the research questions. A total of 35 responses, representing a little above 10% of the sample size of the study, from the respondents were tested and a few adjustments were made based on the responses.

3.6. Model Specifications

The model specification of the study is as follows:

$$AUDITQ = f(AI) \quad (1)$$

$$Y_i = \alpha_0 + \beta X_i \quad (2)$$

3.7. Functional Relationship

The study's functional relation establishing the nexus between audit quality and artificial intelligence is:

$$AUDITQ = f(RTX, NNT, GTL, NLP) \quad (3)$$

$$AUDITQ = \alpha_0 + \beta_1 RTX_i + \beta_2 NNT_i + \beta_3 GTL_i + \beta_4 NLP_i + \mu_i \quad (4)$$

Where: AUDITQ = audit quality; AI = artificial intelligence; RTX= robotics, NNT = neural networks, GTL = genetic algorithms, NLP = natural language processing, f = function, Y_i = dependent variable, X_i = independent variable (all subscripted), α_0 = constant, i = cross-section, and β = coefficient of the model.

3.8. A Priori Expectations

The independent variable is expected to have an effect on the dependent variable of the study. In order words, the study expects that artificial intelligence and its explanatory variables will have a significant positive effect on audit quality (AUDITQ) based on the implications for practicing accountants and that the coefficient of the variable of the inferential regression will be positively signed.

Hence, $\beta_1 – \beta_5 > 0$ at a 5% level of significance.

3.9. Pre-Test Estimation

Reliability of the Research Instrument: In an effort to confirm the reliability of the instrument, a pre-test assessment was conducted using a Cronbach's alpha test. The results of the test (see Table 1) reveal the highest and lowest estimations of 0.971 and 0.844 for audit experience and audit fees, respectively. Each of the results exceed the 0.70 threshold.

Table 1. Reliability test results.

Variable	Number of items	Cronbach's alpha
Audit tenure	5	0.857
Audit fees	5	0.844
Independence of auditors	5	0.930
Size of audit firm	5	0.956
Audit experience	5	0.971
Robotics	5	0.926
Neural networks	5	0.904
Genetic algorithms	5	0.957
Natural language process	5	0.911

Source: Pilot study, 2023.

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.

4.1. Descriptive Statistics

4.1.1. Demographic Analysis

4.1.1.1. Highest level of Education/Qualification

The education/qualification levels of the respondents are represented in Table 2. The majority of respondents (428) indicated MSc/MPhil as their level of education, which is significantly higher than the other categories and represents 66.8% of the total.

Table 2. The highest level of education/qualification.

Educational qualification	Frequency	Percent
Diploma/ND/NCE	20	3.1
HND/BSc	42	6.6
MSc/MPhil	428	66.8
PhD	31	4.8
Others	120	18.7
Total	641	100.0

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, 2023.

4.1.1.2. Work Experience

In Table 3, the distribution of the respondents' work experience is presented. Those with 6–9 years of experience constitute 61.6%, which represents 395 respondents. However, 168 respondents representing 26.2% have 2–5 years of experience, while the minority (78 respondents), which represents 12.2 %, have more than 10 years of experience.

Table 3. Work experience.

Work experience	Regularity/Frequency	%
Less than two years	0	0.0
Two to five years	168	26.2
Six to nine years	395	61.0
More than ten years	78	12.2
Total	641	100.0

Source: Field survey (2023).

4.1.2. Professional Qualifications of the Participants

Table 4 shows that a total of 183 participants (about 51.4%) have ACA/FCA, ACCA/FCCA, ACMA/ACTI/FCTI professional qualifications while the remaining 173 participants {about 48.6%} are having other professional qualifications. In other words, more than half of the participants indicated that they have ACA/FCA, ACCA/FCCA, and ACMA/ACTI/FCTI as professional qualifications.

Table 4. Participant's professional qualification.

Professional qualifications	Frequency	Percent
ACA/FCA, ACCA/FCCA, ACMA/ACTI/FCTI	183	51.4
Others	173	48.6
Total	356	100.0

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, 2023.

4.2. Artificial Intelligence and Audit Quality

This subsection presents the responses to the effect of artificial intelligence and its measures as the dependent variable of audit quality. In Table 5, the results show that, based on the respondents' opinions, the lowest ranked statement is the use of robotics in auditing and accounting processing in aiding a robust risk assessment during audits (average score = 3.8; SD = 1.07), with which 63.8% of the total respondents agree. The number of respondents in support of the statement that natural language processes assist in quick communication toward the stratification of data in audit exercises is embraced (average score = 4.42; SD = 0.80), with 89.4% of the total agreeing, which is high and ranks in first place. The number of respondents supporting the statement that the application of artificial intelligence enhances audit quality through the automation of tasks is high (average score = 4.35; SD = 0.93), and the 86.6% who agree fall within the highest and the least supported statement showed (average score = 6; SD = 0.09.

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

	Strongly disagree	Disagree	Undecided	Agree	Strongly agree	Total	% of total who agree	Mean (Std.)	Rank
The application of artificial intelligence enhances audit quality through the automation of tasks	21 [3.3]	6 [0.9]	59 [9.2]	194 [30.3]	361 [56.3]	641 [100]	555 [86.6]	4.35 (0.93)	2
The use of robotics in auditing and accounting processing aids a robust risk assessment during audits	12 [1.9]	76 [11.9]	144 [22.5]	208 [32.4]	201 [31.4]	641 [100]	409 [63.8]	3.8 (1.07)	5
Neural networks facilitate auditing exercises to enhance the accuracy and reliability of audit reports	9 [1.4]	18 [2.8]	69 [10.8]	158 [24.6]	387 [60.4]	641 [100]	545 [85.0]	4.4 (0.89)	3
Genetic algorithms as a component of artificial intelligence facilitate auditing	9 [1.4]	6 [0.9]	74 [11.5]	262 [40.9]	290 [45.2]	641 [100]	552 [86.1]	4.28 (0.81)	4
Natural language processes assist in quick communication toward the stratification of data in audit exercises	9 [1.4]	6 [0.9]	53 [8.3]	209 [32.6]	364 [56.8]	641 [100]	573 [89.4]	4.42 (0.80)	1

Note: Percentages are in brackets.
Source: Survey results (2023).

4.3. Regression Analysis

4.3.1 Effect of Artificial Intelligence on Audit Quality

This subsection presents the results of the regression that determine the overall effects of AI indicators on audit quality. The results in Table 6 show that the predictors are AI indicators and the dependent variables are the aggregate values of audit tenure, audit fees, independence of auditors, size of audit firms, and audit experience indicators which form the audit quality indicator.

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

Relationship between artificial intelligence and audit quality $AUDITQ_i = \beta_0 + \beta_1 RTX_i + \beta_2 NNT_i + \beta_3 ITA_i + \beta_4 NLP_i + \mu_i$				
Variable	**Coefficient**	**Robust standard error**	**T-stat.**	**P > |t|**
RTX	0.136***	0.038	3.560	0.000
NNT	0.199***	0.040	5.030	0.000
ITA	0.164***	0.038	4.350	0.000
NLP	0.139***	0.035	3.990	0.000
_cons	1.545***	0.154	10.040	0.000
Observations	641	641	641	641
R^2	0.370			
Adjusted R^2	0.366			
F-stat.	90.18			
Probability of F-stat.	0.000			
Heteroskedasticity test	17.55			
Probability of heterogeneity test	0.000			
Jarque–Bera normality test	0.315			
Probability of normality test	0.747			

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. *** denotes a 5% level of significance.
Source: Estimation result (2023).

4.4. Other Diagnostics

The Breusch–Pagan/Cook–Weisberg heteroskedasticity test revealed that the probability of normality is not significant at the selected 0.05 level of significance (p-value = 0.747). This implies that the error term and the residual of the estimated regression model are normally distributed as required and in line with the expectation of the study. In the same manner, the Breusch–Pagan/Cook–Weisberg test result was found to be above 0.010, and this implies statistical significance at the 0.05 level. The results in Table 6 suggest that the null hypothesis of homoskedasticity of the model should be rejected. Consequently, based on the implication of rejection, the study concluded that the error term of the estimated regression of the model had suffered from a heteroskedasticity problem; therefore, the heteroskedasticity robust standards error regression model was relied upon for the study.

4.5. Interpretation

The result of the regression estimation revealed the following:

$$AUDIT_i = \beta_0 + \beta_1 RTX_i + \beta_2 NNT_i + \beta_3 ITA_i + \beta_4 NLP_i + \mu_i$$

$$TA_i = 1.545 + 0.136 * RTX_i + 0.199 * NNT_i + 0.164 * ITA_i + 0.139 * NLP_i$$

Table 6 shows that the F-statistic value is 90.18 [p-value = 0.000] suggesting that the model is statistically significant at a 5% level. Furthermore, the estimated coefficient of robotics (RTX) [β_1 = 0.136, p-value = 0.000] is positive and statistically significant at a 5% alpha level, indicating that a unit increase in RTX leads to an increase of approximately 0.136 in audit quality. The estimated coefficient of neural networks (NNT) [β_2 = 0.199, p-value = 0.000] also revealed a positive and statistically significant effect at a 5% alpha level. This implies that a unit increase in NNT increases audit quality by 0.199 units. Similarly, the estimated coefficient of genetic algorithms (GTL) [β_3 = 0.164, p-value = 0.000] revealed a positive effect that is statistically significant at a 5% alpha level, indicating that a unit increase in ITA increases audit quality by 0.164 units. Finally, the estimated coefficient of natural language processing (NLP) [β_4 = 0.139, p-value = 0.000] showed that a positive and statistically significant effect exists between itself and audit quality at a 5% alpha level. This means that for a given unit increase in NLP, audit quality increases by 0.139.

Adjusted R^2: The adjusted R-squared shows that proportion of the changes in audit quality as a result of changes in the application of artificial intelligence and its explanatory variables of robotics, neural networks, genetic algorithms and natural language processing by auditing firms explained about 37% of the changes in audit quality, while the remaining 63% is explained by factors not captured in the model.

5. DISCUSSION OF FINDINGS

The study analyzed the retrieved and validated data using both descriptive statistics and inferential analysis. The result of the descriptive statistics revealed that artificial intelligence using natural language processes assists in quick communication toward the stratification of data in audit exercises was embraced by the majority of the respondents and ranked first. The inferential analysis revealed that robotics, neural networks, genetic algorithms and natural language processes had a significant positive effect on audit quality. The joint result of the study using a combination of the explanatory variables of artificial intelligence revealed a positive effect. Based on these results, the study concluded that artificial intelligence has a positive effect on audit quality. The results obtained in this study were found to be consistent with previous studies by Hasan (2021); Noordin et al. (2022); and Gentner et al. (2018), who also found a positive effect of artificial intelligence on audit quality.

6. CONCLUSION, RECOMMENDATIONS AND LIMITATIONS

6.1. Conclusion

The study examined the effects of artificial intelligence on audit quality and the implications for accountants. In addressing the problem of audit quality, the study employed a survey research design, using self-structured questionnaires administered through an online platform seeking responses from accountants and staff of auditing firms. The results from the descriptive statistics and inferential analysis revealed that audit quality was positively affected by the application of artificial intelligence in audit exercises.

6.2. Recommendations

Based on the results, it is recommended that the application of artificial intelligence in auditing firms be encouraged for accounting and auditing exercises. The reported results and implications of the findings are critical and greatly useful in dictation, risk assessments and timely reporting, all of which will improve audit quality. Managers and accountants in private, corporate and accounting firms should embrace the application of artificial intelligence considering the economic value and improvement of audit quality in terms of accuracy, reliability and timely financial reporting.

6.3. Contribution/Limitations of the Study

While there are considerable studies that have considered audit quality, fewer studies had researched audit quality and artificial intelligence and its measures of robotics, neural networks, genetic algorithms and natural language processes in enhancing audit quality. This study contributes to the emerging literature and knowledge on this topic by examining the effect of artificial intelligence on audit quality in Nigeria and within the African region. In relation to the research limitations, the study encountered challenges considering that many of the respondents were economical with the truth. While our target respondents were practicing accountants, and those in any of the Big Four had good artificial intelligence knowledge, the truth of the responses could not be verified since the surveys were filled out online. Future studies could be extended to other areas beyond the scope covered in this study.

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Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Data Availability Statement: Upon a reasonable request, the supporting data of this study can be provided by the corresponding author.
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REFERENCES

Abdollahi, A., Rezaei, P., Yasser, & Safari, G., Mehdi. (2020). Auditor's report, auditor's size and value relevance of accounting information. *Journal of Applied Accounting Research, 21*(4), 721-739.

Aguguom, A. T., Dada, S. O., & Nwaobia, A. N. (2019). Earnings persistence and firm performance: Implications of Analysts' accurate forecast ability from the emerging market of Nigeria. *International Journal and Accounting Research, 7*(1), 17. https://doi.org/10.35248/2472-114x.19.7.197

Aguguom, T. A., & Ebun, O. (2021). Financial reporting quality and economic value added of listed companies in Nigeria. *Augustine University Journal of Social Sciences, 1*(1), 13-30.

Agur, I., Peria, S. M., & Rochon, C. (2020). Digital financial services and the pandemic: Opportunities and risks for emerging and developing economies. *International Monetary Fund Special Series on COVID-19, Transactions, 5*(2), 44-71.

Akeem, L. B., Rufus, A. I., Abiodun, S. W., & Olawum, L. B. (2020). Audit reporting lag and firm value in Nigerian food and beverage companies. *Market Forces, 15*(2), 25-36.

Akinyomi, O. J., & Joshua, A. A. (2022). Determinants of audit quality in Nigeria: Evidence from listed consumer goods sector in Nigeria. *Academy of Accounting and Financial Studies Journal, 26*, 1-14.

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

Al-Shatnawi, H. M. (2017). Measuring the quality of the interim financial reports using the qualitative characteristics of the accounting information and its effect on the investment decisions according to the IAS 34. *International Journal of Economics and Finance*, *5*(5), 159-170.

Alawaqleh, Q. A., & Almasria, N. A. (2021). The impact of audit committee performance and composition on financial reporting quality in Jordan. *International Journal of Financial Research*, *12*(3), 55-69. https://doi.org/10.5430/ijfr.v12n3p55

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

Albitar, K., Gerged, A. M., Kikhia, H., & Hussainey, K. (2020). Auditing in times of social distancing: The effect of COVID-19 on auditing quality. *International Journal of Accounting & Information Management*, *29*(1), 169-178. https://doi.org/10.1108/ijaim-08-2020-0128

Alfartoosi, A., & Jusoh, M. A. (2020). A conceptual model of e-accounting: Mediating effect of internal control system on the relationship between e-accounting and the performance in the small and medium enterprises. *Test Engineering and Management*, *83*(1), 733-750.

Alsharif, N. Z. (2019). The need for disruptive innovation in pharmacy. *American Journal of Pharmaceutical Education*, *83*(10), 1-10. https://doi.org/10.5688/ajpe837719

Alt, R., Beck, R., & Smits, M. T. (2018). FinTech and the transformation of the financial industry. *Electronic Markets*, *2*(8), 235-243.

Alwardat, Y. (2019). Disclosure quality and its impact on financial reporting quality, audit quality, and investors' perceptions of the quality of financial reporting: A literature review. *Accounting and Finance Research*, *8*(3), 201-218.

Amah, K. O., & Amauwa, B. C. (2019). Effect of financial reporting quality on financial performance of manufacturing firms in Nigeria. *Research Journal of Finance and Accounting*, *10*(11), 1-7.

Amani, F. A., & Fadlalla, A. M. (2017). Data mining applications in accounting: A review of the literature and organizing framework. *International Journal of Accounting Information Systems*, *24*, 32-58. https://doi.org/10.1016/j.accinf.2016.12.004

Aroyeun, T. F., Adefulu, A. D., & Asikhia, O. U. (2018). Effect of competitive aggressiveness on competitive advantage of selected small and medium scale enterprises in Ogun State Nigeria. *European Journal of Business and Management*, *10*(35), 125-135.

Askary, S., Nasser, A., & Yasean, T. (2018). Artificial intelligence and reliability of accounting information. *Lecture Notes in Computer Science*, *11195*, 315–324. https://doi.org/10.1007/978-3-030-73057-4_24

Avram, V., Calu, D. A., Dumitru, V. F., & Dănescu, T. (2019). The clarity of the information regarding the bioeconomy: An analysis of the reports published by the organizations. *Amfiteatru Economic*, *21*(50), 41-59. https://doi.org/10.24818/ea/2019/50/41

Balios, D., Kotsilaras, P., Eriotis, N., & Vasiliou, D. (2020). Big data, data analytics and external auditing. *Journal of Modern Accounting and Auditing*, *16*(5), 211-219. https://doi.org/10.17265/1548-6583/2020.05.002

Brodny, J., & Tutak, M. (2021). Assessing the level of digitalization and robotization in the enterprises of the European Union Member States. *PloS One*, *16*(7), e0254993. https://doi.org/10.1371/journal.pone.0254993

Carlin, T. (2019). Blockchain and the journey beyond double entry. *Australian Accounting Review*, *29*(2), 305-311. https://doi.org/10.1111/auar.12273

Castelo-Branco, I., Cruz-Jesus, F., & Oliveira, T. (2019). Assessing industry 4.0 readiness in manufacturing: Evidence for the European Union. *Computers in Industry*, *107*, 22-32. https://doi.org/10.1016/j.compind.2019.01.007

Christensen, C. M. (1990). Meeting the challenge of disruptive change. *Harvard Business Review*, *1*(2), 1-5.

Chukwuani, V. N., & Egiyi, M. A. (2020). Automation of accounting processes: Impact of artificial intelligence. *International Journal of Research and Innovation in Social Science*, *4*(8), 444-449.

Dagiliene, L., & Kloviene, L. (2019). Motivation to use big data and big data analytics in external auditing. *Managerial Auditing Journal, 34*(7), 750-782. https://doi.org/10.1108/maj-01-2018-1773

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

Deng, S., & Yeh, T.-H. (2011). Using least squares support vector machines for the airframe structures manufacturing cost estimation. *International Journal of Production Economics, 131*(2), 701-708. https://doi.org/10.1016/j.ijpe.2011.02.019

Deniz, A., & Jeffery, S. (2022). *Artificial intelligence and the auditor: Are you ready?* Retrieved from https://idea.caseware.com/ai-auditor-are-you-ready/

Dessureault, S., & Benito, R. (2012). Data mining and activity based costing for equipment replacement decisions part 1–establishing the information infrastructure. *Mining Technology, 121*(2), 73-82. https://doi.org/10.1179/1743286312y.0000000003

García-Nicolás, O., V'kovski, P., Zettl, F., Zimmer, G., Thiel, V., & Summerfield, A. (2021). No evidence for human monocyte-derived macrophage infection and antibody-mediated enhancement of SARS-CoV-2 infection. *Frontiers in Cellular and Infection Microbiology, 11*, 644574. https://doi.org/10.3389/fcimb.2021.644574

Gentner, D., Stelzer, B., Ramosaj, B., & Brecht, L. (2018). Strategic foresight of future b2b customer opportunities through machine learning. *Technology Innovation Management Review, 8*(10), 5-17. https://doi.org/10.22215/timreview/1189

Giehl, J., Göcke, H., Grosse, B., Kochems, J., & Müller-Kirchenbauer, J. (2020). Survey and classification of business models for the energy transformation. *Energies, 13*(11), 2981. https://doi.org/10.3390/en13112981

Gielen, D., Boshell, F., Saygin, D., Bazilian, M. D., Wagner, N., & Gorini, R. (2019). The role of renewable energy in the global energy transformation. *Energy Strategy Reviews, 24*, 38-50. https://doi.org/10.1016/j.esr.2019.01.006

Greenman, C. (2017). Exploring the impact of artificial intelligence on the accounting profession. *Journal of Research in Business, Economics and Management, 8*(3), 1451-1454.

Griffin, O. (2019). *How artificial intelligence will impact accounting. Economia.* Retrieved from https://www.icaew.com/technical/technology/artificial-intelligence/artificial-intelligence-articles/how-artificial-intelligence-will-impact-accounting

Hasan, A. R. (2021). Artificial intelligence (AI) in accounting & auditing: A literature review. *Open Journal of Business and Management, 10*(1), 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. *Journal of Clean Production, 45*(4), 1-21.

Jariwala, B. (2015). Exploring AI and the accountancy profession: Opportunity, threat, both, neither? Retrieved October 9, 2019.

Jerneck, A., Olsson, L., Ness, B., & Anderberg, S. (2021). Structuring sustainability science. *Sustainability Science, 6*(1), 69-82. https://doi.org/10.1007/s11625-010-0117-x

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*(1), 15-25. https://doi.org/10.1016/j.bushor.2018.08.004

Knauer, T., Nikiforow, N., & Wagener, S. (2020). Determinants of information system quality and data quality in management accounting. *Journal of Management Control, 31*(1-2), 97-121. https://doi.org/10.1007/s00187-020-00296-y

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

Laudon, K., Laudon, J., & Elragal, A. (2020). *Management information systems: Managing the digital firm* (16th ed.). New Jersey: Pearson.

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*(1), 213-240. https://doi.org/10.22452/ajba.vol13no1.8

Liu, G., Yin, X., Pengue, W., Benetto, E., Huisingh, D., Schnitzer, H., . . . Casazza, M. (2018). Environmental accounting: In between raw data and information use for management practices. *Journal of Cleaner Production, 197*, 1056-1068. https://doi.org/10.1016/j.jclepro.2018.06.194

Lombardo, L., Bakka, H., Tanyas, H., van Westen, C., Mai, P. M., & Huser, R. (2019). Geostatistical modeling to capture seismic-shaking patterns from earthquake-induced landslides. *Journal of Geophysical Research: Earth Surface, 124*(7), 1958-1980. https://doi.org/10.1029/2019jf005056

Moll, J., & Yigitbasioglu, O. (2019). The role of internet-related technologies in shaping the work of accountants: New directions for accounting research. *The British Accounting Review, 51*(6), 100833. https://doi.org/10.1016/j.bar.2019.04.002

Neofytou, H., Nikas, A., & Doukas, H. (2020). Sustainable energy transition readiness: A multicriteria assessment index. *Renewable and Sustainable Energy Reviews, 131*, 109988. https://doi.org/10.1016/j.rser.2020.109988

Noordin, N. A., Hussainey, K., & Hayek, A. F. (2022). The use of artificial intelligence and audit quality: An analysis from the perspectives of external auditors in the UAE. *Journal of Risk and Financial Management, 15*(8), 339. https://doi.org/10.3390/jrfm15080339

Nwakaego, D. A., & Ikechukwu, O. E. (2015). The effect of accounts payable ratio on the financial performance of food and beverages manufacturing companies in Nigeria. *Journal of Research in Business and Management, 3*(9), 15–21.

Odoh, L. C., Echefu, S. C., Ugwuanyi, U. B., & Chukwuani, N. V. (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*(2), 1-11. https://doi.org/10.9734/ajeba/2018/41641

Puce, A., & Hämäläinen, M. S. (2017). A review of issues related to data acquisition and analysis in EEG/MEG studies. *Brain Sciences, 7*(6), 58. https://doi.org/10.3390/brainsci7060058

Samadi, S. (2017). The social costs of electricity generation—Categorising different types of costs and evaluating their respective relevance. *Energies, 10*(3), 356. https://doi.org/10.3390/en10030356

Schulenberg, J. L. (2007). Analysing police decision-making: Assessing the application of a mixed-method/mixed-model research design. *International Journal of Social Research Methodology, 10*(2), 99–119. https://doi.org/10.1080/13645570701334050

Sullivan, S., & Hannis, M. (2017). "Mathematics maybe, but not money": On balance sheets, numbers and nature in ecological accounting. *Accounting, Auditing & Accountability Journal, 30*(7), 1459-1480. https://doi.org/10.1108/aaaj-06-2017-2963

Wang, S., Ouyang, L., Yuan, Y., Ni, X., Han, X., & Wang, F.-Y. (2019). Blockchain-enabled smart contracts: Architecture, applications, and future trends. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 49*(11), 2266-2277. https://doi.org/10.1109/tsmc.2019.2895123

Wu, X., Xu, Y., Lou, Y., & Chen, Y. (2018). Low carbon transition in a distributed energy system regulated by localized energy markets. *Energy Policy, 122*, 474-485. https://doi.org/10.1016/j.enpol.2018.08.008

Yadav, A., Gupta, V., Sahu, H., & Shrimal, S. (2017). Artificial intelligence-new era. *International Journal of New Technology and Research, 3*(3), 263339.

Yeh, T.-H., & Deng, S. (2012). Application of machine learning methods to cost estimation of product life cycle. *International Journal of Computer Integrated Manufacturing, 25*(4-5), 340-352. https://doi.org/10.1080/0951192x.2011.645381

Zhang, Y., Xiong, F., Xie, Y., Fan, X., & Gu, H. (2020). The impact of artificial intelligence and blockchain on the accounting profession. *IEEE Access, 8*, 110461-110477. https://doi.org/10.1109/access.2020.3000505