EXTERNAL AUDITORS' PERCEPTIONS TOWARD THE USE OF ARTIFICIAL INTELLIGENCE IN THE AUDIT PROCESS AND ETHICAL CHALLENGES FACING ITS APPLICATION: EVIDENCE FROM AN EMERGING MARKET

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Abstract

The study explores the stages of the audit process to be improved through the implementation of artificial intelligence (AI) technology in an emerging setting. The study provides empirical evidence for the ethical challenges expected to arise from AI implementation. A survey method using structured questionnaires is employed. A questionnaire was administered to a sample of auditors working in international audit firms, including the Big 4, and 103 responses were collected. Using a t-test, the findings show that the client's acceptance phase and reporting phase are among the most audit phases to be improved. The findings provide empirical evidence of a prior projection that AI implementation in the audit field may negatively impact auditors' due professional care, competence level, and their professional judgment. However, the findings did not support the notion of prior studies that AI may impair auditors' independence, accountability, or even their commitment to their careers. The findings have implications for auditors, regulators, and standard setters, especially in environments that lack effective regulatory frameworks and sanction mechanisms.

Keywords: Artificial Intelligence, Egypt, Audit Process, Ethics

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1. INTRODUCTION

The increased complexity and nature of economic transactions nowadays, along with the recent developments in information technology (IT), have made it essential for auditors to adopt those technologies with cognitive abilities to enhance the credibility of the audited financial statements. The traditional human approach to analytics and decision-making became impossible with the emergence of an increased amount of data and the need for timely decisions (Kokina & Davenport, 2017). The development of different technologies used by the business client, such as enterprise resource planning and accounting information systems, created a necessity for audit firms to adopt audit technology tools in the audit process (Rosli et al., 2013). Traditional audit evidence is no longer sufficient in the current technologically developed environment that has changed the nature of audit evidence to be accumulated (Appelbaum, 2016). Moreover, many audit tasks are structured and repetitive, so they can be automated (Abdolmohammadi, 1999; Kokina & Davenport, 2017). Using feedback from various stakeholders such as regulators, audit firms, and academics, it has been argued that the technological adaptation within the audit field allows the data to be used differently than in the past audit and that auditing standards need revision to reflect the current technology (International Auditing and Assurance Standards Board [IAASB], 2018).

The perceived importance of implementing emerging technology in the audit profession aroused the curiosity of several studies to investigate such importance. Using emerging technology in the audit process could automate many repetitive, structured tasks and help in performing analytical review for a large amount of data, thereby improving audit quality and efficiency (Carpenter & McGregor, 2020). The implementation of emerging technology, such as Computer Assisted Audit Techniques (CAATS), increases audit quality and efficiency, improves data analysis reliability and audit evidence collection, and saves audit time (Correia et al., 2019; Ciprian-Costel, 2014). However, CAATS had been criticized for its inability to integrate non-financial data from sources such as social media platforms. The emergence of new technologies such as Big Data analytics and artificial intelligence (AI) helps auditors to overcome these limitations by analyzing more diverse large data sets (Brown-Liburd et al., 2015). Alrashidi et al. (2022) found that the use of Big Data analytics is perceived to influence different audit procedures, including client acceptance, audit planning, determining materiality levels and audit risks, and internal control evaluation. AI is perceived as a potential valuing tool for Big Data analytics (Najafabadi et al., 2015). Machine learning, which is a subset of AI, helps auditors to identify patterns from large data sets, then learn from such conclusions, and apply the same logic to similar cases with similar characteristics (Dickey et al., 2019). Other AI techniques that could be used in the audit process include deep learning that automatically analyzes unstructured data, natural language processing to identify discrepancies in a vast amount of text that may indicate fraud activities, and robots or drones to monitor inventory count. It is evident that the Big 4 audit firms started to extensively use those techniques, thus creating an intense competition among them (Boubaya, 2022).

Recent research studies have been conducted to examine the potential benefits and challenges that could arise from the implementation of AI in the audit profession (Kokina & Davenport, 2017; Henry & Rafique, 2021; Aljaaidi et al., 2023). Other limited studies focused more specifically on the impact of AI on the audit process (Issa et al., 2016; Ghanoum & Alaba, 2020). However, most of those studies are conducted in developed countries that have the skills and facilities to conduct such research. Little is known about the potential impact of the use of AI techniques on the audit process and the ethical challenges that could arise from its application in developing markets that suffer from a lack of proper regulatory frameworks and effective sanction mechanisms. Moreover, the rapid evolution and continuous development of AI tools necessitate continuous research on their implications for the audit profession (Munoko et al., 2020). The main objective of the current study is to provide insights into the use of AI in the audit process in an emerging market, Egypt, during an era of digital transformation and potential ethical challenges that the audit profession faces from such implementation. Using an online survey, the findings show that the implementation of AI in an emerging setting is highly perceived to improve the quality of the audit process through examining the full population of transactions and balances rather than relying on sampling techniques. The most agreed-upon phases perceived to be improved through AI technology are the audit client acceptance phase, the audit reporting phase, and the accumulation of sufficient appropriate audit evidence from unstructured data. Although the findings provide evidence that AI implementation in the audit field may negatively impact auditors' due professional care, competence level, and their professional judgment, it did not support the notion that AI will negatively affect auditor independence, accountability, or even their commitment to their career in a negative manner. The findings show that although AI has a positive impact on benefiting the audit process, it could significantly affect auditors' adherence to the ethical requirements of the audit profession.

The current study contributes to the auditing literature in a number of ways. First, most of the studies that address the impact of AI on the audit profession have been conducted in developed countries. This study is considered the first that examine the effect of AI implementation on different stages of the audit process and ethical challenges facing its implementation in the context of an emerging setting during an era of digital transformation. Second, it adds to the work of Issa et al. (2016) by empirically examining the proposed stages of the audit process that could be affected by the implementation of AI. Third, the study empirically examines the ethical implications of AI implementation in auditing projected by the bibliometric analysis of publications, which is conducted by Munoko et al. (2020). Finally, the study did not only focus on examining the positive side of AI, but it also explored its negative aspects and whether auditors perceive the associated ethical challenges and risks in the same manner as they perceive the benefits arising from its implementation.

The rest of the paper is organized as follows. Section 2 discusses the literature review and formulation of the research questions. Section 3 describes the research methodology. Section 4 presents the results analysis, and Section 5 provides a discussion of the results. Section 6 outlines the conclusion of the findings.

2. LITERATURE REVIEW

The emergence of innovative technologies, mainly AI, and their related abilities and benefits has motivated their application and implementation in different professions. AI is described as a computer program that is capable of making balanced decisions, imitating the cognitive functions of the human mind, observing its environment, and then taking actions toward goal achievement (Issa et al., 2016). However, Zhang et al. (2020) define AI as the use of both Big Data and machine learning technology to understand the past and forecast the future using large amounts of data. AI is based on technologies, such as machine learning and deep learning, which use algorithms to perform tasks such as classification and value prediction through statistically analyzing massive amounts of data (Institute of Chartered Accountants in England and Wales [ICAEW], 2018).

The audit sector presents a unique setting to study the impact of AI compared to other economic sectors as the audit process is exposed to rigid rules and standards and provide the scope to increase both the quality (by reducing the error rate) and the efficiency (by automating tasks such as fraud detection) of the auditing process (Fedyk et al., 2022).

2.1. Artificial intelligence and the audit profession: Benefits and challenges

AI in the audit profession is described as a hybrid set of technologies that supplement and change the audit (Issa et al., 2016). AI technology consists of different tools, including expert systems, natural language processing, artificial neural networks, machine learning, and deep learning (Almuffada & Almezzeni, 2022). Fedyk et al. (2022) document that the largest audit firms in the USA invest in AI, and this enables them to reduce the likelihood of material misstatements, especially those related to accruals and revenue recognition. The application of AI in auditing will enhance the audit profession as it reduces the risk of human fatigue that could result from the repetitive analysis of data. Although the use of AI in the audit profession is still in its early stages, some studies have been conducted to shed light on the importance and benefits as well as the expected risks associated with such technology in the accounting and audit professions.

2.2. Benefits of artificial intelligence on the audit process

Understanding the audit process is essential for identifying the role of AI in different phases of such process (Almuffada & Almezzeni, 2022). The audit process consists of four phases: preplanning, planning, execution, and reporting (Ghanoum & Alaba, 2020). AI applications are perceived by external auditors in Saudi Arabia as useful tools that improve the effectiveness and efficiency of planning the audit process, reduce the effort, cost, and time of the audit process, and carry out the continuous audit process better than traditional audit (Aljaaidi et al., 2023).

AI in each step of the audit process will enable auditors to avoid repetitive tasks in the process, analyze a large volume of data, and obtain a better understanding of the client's operations (Kokina & Davenport, 2017). Baldwin et al. (2006) summarize the earlier use of different AI tools in different audit tasks. Neural networks are used in the analytical review and risk assessment procedures, genetic algorithms help in the classification of debts and fraud detection, and expert systems are developed for going concern judgments, materiality assessment, and internal control evaluations. External auditors in the UAE perceive that AI could enable robust risk assessment through the analysis of the entire population rather than depending on audit sampling techniques (Noordin et al., 2022). This is supported by the view of Byrnes et al. (2018) and the study of Henry and Rafique (2021), who show that sampling techniques are characterized as more extensive and less efficient compared to examining the entire population.

When auditors analyze financial reports, the deep learning machine, as an AI tool, scans and identifies each account and balance and relates them to the supporting documents to identify any irregularities. It also helps to obtain supplementary evidence through analyzing unstructured data obtained from conference calls, emails, news, and social media platforms to support the traditional financial evidence (Issa et al., 2016). Ernst and Young (EY, 2018, as cited in Henry & Rafique, 2021) reports that machine learning tools allow auditors to analyze a large number of contracts, such as lease contracts, in a shorter time compared to manual review. AI could help analyze board meeting minutes and process large amounts of data (such as reading bank statements and legal contracts) and reconcile accounts in a timely manner and with fewer errors compared to humans (American Institute of Certified Public Accountants [AICPA], & Chartered Professional Accountants of Canada [CPA Canada], 2020). This is possible through training the system on a collection of sample documents to identify and extract key terms (Greenman, 2017). AI tools could facilitate the accumulation of evidence related to inventory checks through, for example, images taken by drones or videos captured by surveillance cameras (Issa et al., 2016). Lombardi and Dull (2016) provide evidence that AudEx, an audit expert data assessment system, supports the auditor fraud risk assessment task through the decomposition of financial and nonfinancial cues. Moreover, image and speech recognition of deep learning can help detect fraud through, for example, detecting nervousness or significant delays in answering questions (Dickey et al., 2019; Munoko et al., 2020).

A research study conducted by Ghanoum and Alaba (2020) demonstrates through semi-structured interviews with a limited number of auditors in Sweden audit firms that AI is useful during the different stages of the audit process. AI improves the pre-engagement phase/client acceptance phase through analyzing historical information and thereby predicting future risks and activities. During the planning phase, AI helps in identifying materiality levels, risk assessment, and pattern recognition (Ghanoum & Alaba, 2020). AI also helps in substantive tests and tests of controls through observation, inspection, and recalculations. The benefit of AI in the reporting stage depends on the accuracy and timeliness of the previous stages (Ghanoum & Alaba, 2020). Rodrigues et al. (2023) provide additional evidence that AI tools are perceived as important toward assessing audit risks, estimating hours of work required, and increasing the possibility of issuing an audit opinion in a more timely manner. Moreover, Ghanoum and Alaba (2020) provide that AI could transfer the audit process from a reactive to a proactive process. It increases auditors' responsibilities by interpreting data produced by AI and adding value to the business of their clients (Brennan et al., 2017, as cited in Kokina & Davenport, 2017).

The importance of utilizing different AI technologies in the audit process is evident by their use by the Big 4 audit firms in developed countries. For example, KPMG used International Business Machines Corporation's (IBM's) Watson system, which has a wide variety of program interfaces that carry out different tasks from document extraction to facial recognition. It also analyzes a high volume of data to detect anomalies (KPMG, 2016). Deloitte employs Kira systems, a contract analysis system, to extract important and relevant information and terms from contracts, leases, invoices, and other legal documents (Issa et al., 2016). PricewaterhouseCoopers (PwC) employs Halo for analyzing accounting journals, identifying problem areas, and making reliable risk assessments, while EY relies on Big Data analytics (Kokina & Davenport, 2017). EY also uses natural language processing to review lease agreements to ensure its compliance with lease accounting standards (Zhou, 2017). Most of the Big 4 audit firms use drones to perform inventory count and inspection (Munoko et al., 2020).

In the context of emerging markets, the use of emerging technology in the Egyptian audit environment has been perceived as underutilized. The lack of experience of IT in the audit field represents a constraint toward its implementation in such markets (Abou-El-Sood et al., 2015). The national council for AI recommends promoting AI research in Egypt to realize tangible benefits from AI and prove its value and challenges facing its application in different sectors (Radwan, 2021). Limited research studies have been conducted to explore the importance of AI in the audit process in emerging markets that are characterized by a minimal level of use of such technologies. Those studies expect that AI implementation will positively affect the audit profession. Egyptian auditors perceive the importance of technology in risk assessment and sampling (Abou-El-Sood et al., 2015). Academics in Nigeria expect that AI will present changes in the audit process, mainly materiality and risk analysis, audit planning, internal control evaluation, evidence evaluation, and audit opinion issuance (Ukpong et al., 2019). A recent study by Ali et al. (2022) shows that AI is perceived as important toward enhancing remote internal audit activities through reducing cost and saving time. Deaf et al. (2023) provide evidence that those digital transformation techniques, including blockchain, Big Data, cloud computing, and AI, are perceived to have a significant impact on audit quality. Adeoeye et al. (2023) provide evidence that AI using natural language processing, robotics, neural networks, and genetic algorithms has a significant positive impact on audit quality. A more recent study by Shazly et al. (2024) found that AI helps to carry out complex audits more efficiently and effectively than humans, which may lower the need for human auditors in the future. They concluded that AI could improve audit quality by finding misstatements in the financial statements.

Audit process consists of different phases, including client acceptance, planning, audit evidence accumulation, and reporting phases (Ghanom & Alaba, 2020). Auditors need to understand which phase of the audit process they can rely more on AI, so they can properly plan their audit engagement and identify the skills needed in each phase. Previous studies (Kokina & Davenport, 2017; Noordin et al., 2022; Deaf et al., 2023; Shazly et al., 2024) examined the impact of AI on audit quality in general, but without examining in a more specific manner the different phases of the audit process that are expected to be mostly affected by such technology. Issa et al. (2016) theoretically introduce the proposed phases of the audit process expected to be affected by AI technology without empirical evidence. Most of the prior studies had been conducted in developed countries where AI technology is extensively emerging, and this affects the generalizability of their results in developing countries. Little is known about the usage of AI during the audit process in emerging markets that are still in early stages of their implementation. This leads to the following research question:

RQ1: What are the phases of the audit process that will be mostly affected by the implementation of artificial intelligence technology in an emerging market?

2.3. Ethical implications and challenges of using artificial intelligence in the audit profession

The fundamental principles of ethics for professional accountants include integrity, objectivity, professional competence and due care, confidentiality, and independence. Those principles establish the standard of behavior expected of a professional accountant (International Ethics Standards Board for Accountants [IESBA], 2018). There are potential ethical challenges that could result from AI implementation. The current code of ethics does not take into consideration the use of emerging technologies and AI tools (Munoko et al., 2020).

Henry and Rafique (2021) conclude that potential job loss, inherent bias in data, data security, and overreliance on AI are ethical implications of AI. Qadir (2017) raises concerns that the use of AI could result in significant job losses in the future as AI becomes more efficient than humans at recognizing errors and anomalies. One of the Big 4 audit firms (EY) expects that the number of new hires will fall by half each year due to the emergence of AI (Agnew, 2016). Fedyk et al. (2022) document that an increase in the recruitment of AI employees in audit firms in the USA might reduce audit fees through cutting down the labor force (accounting employees). However, Kokina and Davenport (2017) argue that AI technologies may replace specific tasks rather than entire jobs. It is also argued that the expectation of financial statement users of the quality of audit, due to the use of AI in the audit process, will be increased, leading to a higher audit expectation gap (AICPA & CPA Canada, 2020). Moreover, a lack of proper experience and training in audit software and different technologies by auditors could represent a significant challenge to the application of AI in the auditing field (Abou-El-Sood et al., 2015). Education systems in many accounting programs do not prepare students for such dramatic changes in the auditing field (Tschakert et al., 2016). High initial and maintenance costs of AI systems, limited knowledge of such technology among graduate auditors, inaccuracies in input data, potential human bias, and concerns over data security are all viewed as constraints toward the implementation of AI tools (Seethamraju & Hecimovic, 2020; Issa et al., 2016). Moreover, the use of AI in auditing has no standards that regulate its use and an inherent lack of transparency (Ghanoum & Alaba, 2020). Supporting such a view is the study of Torroba et al. (2025), who conclude that the lack of regulations and absence of a regulatory framework are among the challenges that face AI adoption in the audit field. They also argue that a lack of knowledge and trust in such technology represents another barrier to its adaptation. Those factors could affect the implementation of the code of professional conduct among auditors.

Munoko et al. (2020) conduct a bibliometric analysis of publications that address technology and ethics. It is argued that the complexity of AI and limited understanding of its core could hinder it from being effectively regulated (Kirkpatrick, 2016). The complexity of algorithms embedded in AI tools could result in a lack of transparency regarding the data input being used and the rationale behind specific decisions (Munoko et al., 2020). Accountability is also questionable when responsibility is distributed between technology and humans (Wright, 2011). In their systematic review, Murikah et al. (2024) conclude that both a lack of trust and transparency in AI systems and reduced human capability could erode social accountability of auditors over time. Since AI algorithms make automated decisions with difficulty in understanding the rationale behind the outcome, concerns about auditor accountability could arise (Vidya, 2024). Moreover, the increased reliance on technology tools in performing routine audit tasks may lead to less developed professional judgment (Arnold & Sutton, 1998). Auditors may also focus on factors identified by the system and ignore those not identified by the system, and this affects auditors' professional skepticism and judgment (Seow, 2011). On the other hand, Ashir and Mekonen (2024) conclude that auditors must view AI as a supplementary tool and the use of AI requires a higher level of professional judgment to reach an audit decision. Moreover, it has been argued that AI can perform audit tasks that require a low level of judgment, such as extracting relevant information from documents, thereby allowing auditors to devote more time to areas requiring higher-level judgment (Kokina & Davenport, 2017; Henry & Rafique, 2021). Moreover, viewing AI as a black box system that can produce unexplained results necessitates an increased level of auditor professional skepticism (Ashir & Mekonen, 2024).

Auditor's independence is another potential ethical implication of AI and could be impaired in case of increased reliance on the client's AI systems (Munoko et al., 2020). On the contrary, Libby and Witz (2024) conclude that the use of AI can reinforce perceived objectivity and trust in the audit process when independence concerns arise, and this mitigates auditor legal liability. Another ethical implication of AI technology is data integrity and confidentiality. Possible cyber attacks are a significant reputational risk that must be taken into consideration; otherwise, data confidentiality and integrity would be questionable (Boillet, 2018). Westermann et al. (2015) observe that technology leads to decreased interaction between auditors and client personnel and among engagement team members as auditors focus more on computer interfaces. This could have unintended effects on the appropriate supervision required by the code of ethics.

The growth of sophisticated technology motivates academic research to shed light on its ethical implications (Munoko et al., 2020). It is also argued that the manner in which auditors respond to audit policy depends on the effectiveness of regulations that motivate auditors' ethical behavior (Samsonova-Taddei & Siddique, 2016). Most developing countries suffer from corruption, weak governments, and unethical practices (Adekoya et al., 2023). The ethical implications of using sophisticated technology could be more evident in emerging markets such as Egypt, which suffers from a lack of effective regulations and sanction mechanisms (Elbayoumi et al., 2019). The audit practitioners in Egypt are not required to follow any modern code of ethics that is consistent with the IESBA's (2018) Code of Ethics for Professional Accountants. In practice, there is little awareness among many practicing auditors of international best practices concerning conflicts of interest and auditor independence (Rahman et al., 2002). Even with the recent establishment of an oversight body over audit firms (the Audit Oversight Board — AOB) in Egypt, Eldaly and Abdel-Kader (2017) showed that the AOB faces several challenges (e.g., the legal framework) that hinder its ability to achieve its objectives. This provides a motivating setting to explore the ethical implications of using AI in the audit profession in an emerging market, such as Egypt, that could hinder auditors' compliance with professional ethical standards.

Most of the prior literature focuses on the benefits of AI in the audit field, with little focus on the challenges and threats related to its implementation. Munoko et al. (2020) conduct a bibliometric analysis of publications and project a set of ethical challenges to arise from AI without empirical investigation. Few studies (Kokina & Davenport, 2017; Henry & Rafique, 2021; Libby & Witz, 2024) that explored the ethical threats of AI have been conducted in developed markets and provide inconsistent and mixed results. For instance, Henry and Rafique (2021) argue that AI could lead to significant job losses, while Kokina and Davenport (2017) conclude that AI could replace specific tasks rather than entire jobs. In addition, Munoko et al. (2020) believe that AI could impair auditor independence, while Libby and Witz (2024) conclude that AI increases auditors' perceived objectivity. More research is needed to extensively examine those ethical challenges, and this could be more evident in emerging markets that suffer from a lack of regulatory frameworks and effective sanction mechanisms. This raises the following research question:

RQ2: What are the ethical implications of using artificial intelligence technology in the auditing field in an emerging market?

3. RESEARCH METHODOLOGY

3.1. Research method

The research method is a qualitative method that is based on an online survey. A Google form is designed as a questionnaire to collect data in 2024. The participants are auditors working in either a Big 4 audit firm or an audit firm with international affiliation in Egypt. The selection of the sample is judgmental, as those international audit firms are expected to be more aware of the usage of AI and its different tools in the audit field and its implications during an era of digital transformation worldwide. The questionnaire was pilot tested to ensure the clarity of the questions by refining the wording of some questions. There was a statement explaining the purpose of the study and a brief explanation of the AI technology and its different tools.

The questionnaire consists of three sections. The first section was on the background information of the participants (job position at the firm/type of audit firm/experience level). It also asks the participants if they use AI in their audit process and the type of AI tools they use. The next two consecutive (second and third) sections of the questionnaire consist of two sets of questions on a five-point Likert scale with 1 = strongly disagree and 5 = strongly agree. The second section consists of ten questions that ask the participants about the different phases of the audit process they perceive to be improved through the use of AI technology. The third section consists of eight questions that ask the participants about their perceptions of the ethical challenges and implications that could result from the use of AI in the audit field. The items of the questionnaire are extracted from a systematic review of some literature (Ghanom & Alaba, 2020; Rodrigues et al., 2023) and from the bibliometric analysis of publications conducted by Munoko et al. (2020). The response rate is 51.5% as 103 responses were collected from a targeted sample of 200 participants. Table 1 shows the demographic data of the participants and their background experience.

Table 1. Demographic data of the participants

Characteristic	*No*	*Percentage (%)*
Job position		
Junior	48	46.6
Senior	20	19.4
Vice audit manager	12	11.7
Audit manager	17	16.5
Audit partner	6	5.8
Type of international audit firm		
Big 4	24	23.3
Non-Big 4	79	76.7
Experience level (in years)		
1–5	52	50.5
6–9	20	19.4
10–15	12	11.7
> 15	19	18.4
Use of AI in the audit process		
Yes	29	28.2
No	74	71.8

3.2. Reliability and validity of the questionnaire

Cronbach's alpha test is conducted to measure the reliability and internal consistency of the two constructs of the research. The reliability coefficient of the first construct, which measures the perceived benefits of AI on different stages of the audit process, is 0.924. The reliability coefficient of the second construct, which measures the ethical challenges resulting from the use of AI in the audit field, is 0.813. It is shown that reliability coefficients are high and greater than the limits of the appropriate value (0.60–70) at least (Hair et al., 2017).

Confirmatory factor analysis (CFA) is also conducted to test how well the measured variables represent the constructs. The construct validity is the extent to which a set of measured items actually measures the construct. The standardized regression weights are greater than 0.5 (or approximately near 0.5, such as for *X2.3*), which means that all measured variables represent the construct. The composite reliability (CR) shows results that are greater than 0.70, which means that the variables did converge at some point (Hair et al., 2017). As a result of squared multiple correlations, the average variance extracted (AVE) for the first construct (after excluding the variable *X1.1*) and the second construct (after excluding variable *X2.1*, *X2.7*, and *X2.8*) are 0.467 (near to the cutoff point of 0.5) and 0.596, respectively (> 0.5) which means that the variables had a convergent validity. The heterotrait-monotrait ratio of the correlations (HTMT) approach to assess discriminant validity is 0.84 for the first construct and 0.93 for the second construct. Since this ratio is near to the threshold of 0.9, it means that the variables had high discriminant validity (Teo et al., 2008).

The model goodness of fit is assessed in terms of ten indices with a Chi-square of 92.427, degree of freedom (DF) of 55, and level of significance 0.001. Those ten indices are normed Chi-square (1.680), root mean square residual (RMSR) (0.057), goodness of fit index (GFI) (0.898), adjusted goodness of fit index (AGFI), normed fit index (NFI) (0.916), relative fit index (RFI) (0.862), incremental fit index (IFI) (0.9640), Tucker Lewis index (TLI) (0.939), comparative fit index (CFI) (0.963) and root mean square residual approximation (RMSEA) (0.082). A model is considered to be satisfactory if CFI > 0.95, GFI > 0.90, and RMSEA is less than or near 0.08 (Hair et al., 2017).

The goodness of fit measures of the model showed a significant fit of the results, i.e., the majority of the indicators at acceptable limits or identical to cut-off values, GFI, AGFI, NFI, RFI, IFI, TLI, and CFI near 0.90 and normed Chi-square with cut-off values less than 5. Moreover, the values of RMSR and RMSEA are approximately less than 0.08, which indicates a close fit of the model in relation to the DF. Overall, the evidence of a good model fit, reliability, convergent validity, and discriminant validity indicates that the measurement model was appropriate for exploring the perceived benefits of AI on the audit process and the ethical challenges resulting from its application.

4. RESEARCH RESULTS

4.1. Main analyses

Descriptive statistics, as shown in Table 2, are conducted to determine the level of agreement among the participants in the survey about the benefits of AI usage on the different stages of the audit process and related ethical implications. Since the data is normally distributed according to the one-sample Kolmogorov-Smirnov test, the one-sample t-test, which is a parametric test, is conducted. The one-sample t-test in Table 3 compares the sample mean against a hypothetical value to determine if they are significantly different.

According to Panel A of Table 3, it can be concluded that there is a significant difference between the sample mean and population parameter (3.4) at a significance level less than 0.05. This means that there is general agreement among the respondents regarding the benefits of AI on the different stages of the audit process, with varying levels of agreement as shown by descriptive statistics in Table 2, and the mean responses on each benefit are greater than the test value of 3.4. Since the CV is expressed as the ratio of standard deviation to the mean, the statements with the lowest CV are assumed to have the highest level of agreement among the respondents.

The importance of AI in substantive tests through examining full population of transactions and balances on a continuous basis, thus helping in decreasing the likelihood of abnormal records (*X1.7*), is the most audit phase in the audit process that gained agreement among the participants as an expected benefit of AI with mean of 4.17 and CV of 17.48 as shown in Table 2. With a mean of 4.20 and a CV of 17.76, participants agree that AI can improve the client acceptance phase through analyzing the client's historical information and reviewing trends in financial data (*X1.1*). This supports the study of Ghanoum and Alaba (2020) on Sweden audit firms that AI improves the client acceptance phase through analyzing historical information and thereby predicting future risks and activities. Enhancing the quality of audit reports (*X1.10*) is also recognized as the third most agreed upon audit process phase that is perceived as an important benefit of AI implementation, with a mean of 4.05 and a CV of 19.68. Participants could believe that enhancing the accuracy and timeliness of the initial stages of the audit process drives this result. This is consistent with Ghanoum and Alaba

(2020). The fourth agreed upon audit phase that is being perceived as a positive influence of AI implementation is the accumulation of sufficient appropriate audit evidence of unstructured data (*X1.8*), with a mean of 4.05 and a CV of 20.57. Approximately 78% of the respondents agree that AI technology could help collect and analyze unstructured data, such as that collected from social media platforms or emails, to support the financial data included in the financial statements of the client. AI is also perceived as an important tool to assist in the preplanning phase of the audit process (*X1.2*), with a CV of 20.72 and a mean of 4.17, through collecting and analyzing Big Data of clients' organizational structure, operational methods, and accounting systems to estimate their initial risks. There is also a high agreement among the participants that the AI technology will enable auditors to continuously assess control risk through identifying and reporting any violations through AI-based continuous control monitoring system (*X1.5*), assess fraud risk through identifying patterns of transactions, comparing trends and identifying outliers (*X1.6*), and to understand internal control systems and related risks through text mining and visualization methods (*X1.4*) with means of 3.92, 3.91, and 3.84, respectively, and p-values less than 0.001.

Table 2. Descriptive statistics

Construct	*Statement*	*Descriptive statistics*					
		Strongly agree-Agree (%)	*Neutral (%)*	*Strongly disagree-Disagree (%)*	*Mean*	*Std. dev.*	*Coefficient of variation (CV)*
Panel A: Benefits of AI on the audit process							
X1.1	AI can improve client acceptance decisions through its capability to check and analyze historical information, review trends in financial data, and assess integrity and potential threats.	84.5	13.6	1.9	4.20	0.746	17.76
X1.2	AI can assist in the preplanning phase as AI can collect and analyze Big Data related to the client's organizational structure, operational methods, and accounting systems to estimate the initial risks related to the client.	81.6	12.6	5.8	4.17	0.864	20.72
X1.3	AI estimates the number of hours and calculates audit fees and analyzes previous auditor-client contracts, and consequently generates a client-specific engagement letter.	63.1	29.1	7.8	3.87	0.957	24.73
X1.4	Using text mining and visualization methods, AI helps in understanding internal controls and identifying risk factors by identifying any anomalies.	62.2	32	5.8	3.84	0.905	23.57
X1.5	An AI-based continuous control monitoring system helps in continuous risk assessment through identifying any violations, prioritizing them based on their level of riskiness, and reporting them.	67	30.1	2.9	3.92	0.837	21.35
X1.6	AI helps in better risk assessment and fraud detection through identifying patterns of transactions, comparing trends, and identifying outliers.	67	29.1	3.9	3.91	0.853	21.82
X1.7	AI can help in substantive tests by examining the full population of transactions and balances on a continuous basis, thus helping to decrease the likelihood of abnormal records being undetected.	80.6	19.4	-	4.17	0.729	17.48
X1.8	AI helps in better accumulation of sufficient appropriate audit evidence through collecting and analyzing unstructured data (e.g., social media platforms, newspaper articles, and e-mails) to support financial data.	77.7	20.4	1.9	4.05	0.833	20.57
X1.9	AI helps in better accumulation of sufficient appropriate audit evidence through vouching, tracing, recalculation, reperformance, and electronic confirmations by third parties.	66	27.2	6.8	3.80	0.911	23.97
X1.10	AI enhances the quality of audit reports produced by enhancing the accuracy and timeliness of the initial stages of the audit process.	78.6	17.5	3.9	4.05	0.797	19.68
Panel B: Ethical challenges facing the implementation of AI							
X2.1	Difficulty in understanding the rationales behind AI outcomes may impair auditors' due professional care.	70.8	24.3	4.9	3.92	0.837	21.35
X2.2	Inherent bias in data due to insufficient or less diverse data used in the system may affect data integrity and objectivity.	71.9	17.5	10.6	3.82	0.947	24.79
X2.3	Auditor's increased involvement with client companies' AI systems (e.g., continuous monitoring control systems) may negatively impact the auditor's independence.	49.5	27.2	23.3	3.40	1.079	31.74
X2.4	Job loss threats may decrease auditors' commitment and career satisfaction.	57.2	17.5	25.3	3.50	1.244	35.54
X2.5	Shared responsibility between auditors and technology reduces auditors' accountability.	40.8	24.3	34.9	3.09	1.172	37.93
X2.6	Overreliance on AI tools in performing routine audit tasks may negatively impact the development of an auditor's professional judgment.	66	16.5	17.5	3.76	1.098	29.20
X2.7	Difficulty in ensuring the confidentiality and security of client data used in AI systems, especially those provided by third-party platforms.	69.9	21.4	8.7	3.83	0.876	22.87
X2.8	Lack of sufficient knowledge and skills in AI tools may affect the competence level required to perform audit tasks in accordance with professional auditing standards.	71.9	13.6	14.5	3.88	1.013	26.11

Table 3. One-sample t-test

Construct	*t-test*	*p-value*
Panel A: Benefits of AI on the audit process		
X1.1	10.941	0.000
X1.2	8.984	0.000
X1.3	5.026	0.000
X1.4	4.987	0.000
X1.5	6.337	0.000
X1.6	6.099	0.000
X1.7	10.652	0.000
X1.8	7.903	0.000
X1.9	4.411	0.000
X1.10	8.261	0.000
Panel B: Ethical challenges of AI		
X2.1	6.337	0.000
X2.2	4.453	0.000
X2.3	-0.018	0.985
X2.4	0.856	0.394
X2.5	-2.706	0.008
X2.6	3.303	0.001
X2.7	5.042	0.000
X2.8	4.846	0.000

However, among the audit procedures that gained the lowest agreement among the participants to be improved through AI implementation is the better accumulation of audit evidence through vouching, tracing, re-performance, recalculation, and electronic confirmations (*X1.9*), with a mean of 3.8 and a CV of 23.97. This could indicate that the accumulation of those types of audit evidence may not be greatly affected by the occurrence of AI technology compared to other audit procedures. Moreover, the generation of client client-specific engagement letter through estimating the number of audit hours and calculating audit fees and analyzing previous auditor client contracts (*X1.3*) is the least agreed upon audit procedure as being positively affected by the implementation of AI technology with a CV of 24.73.

Regarding the ethical implication that could result from use of AI in the audit field, the descriptive statistics in Panel B of Table 2 and the one sample t-test in Panel B of Table 3 shows that there are five statements (*X2.1, X2.2, X2.6, X2.7,* and *X2.8*) that gained strong agreement as expected ethical implications arising from AI usage in the audit field with p value less than 0.05 and with mean values ranging from 3.92 to 3.76. Auditors perceive that impairment of their due professional care due to difficulty in understanding the rationale behind AI outcomes (*X2.1*) is the most negative ethical impact on auditors, with a mean of 3.92 and a CV of 21.35, as shown in Table 2. They also perceive that difficulty in ensuring confidentiality and security of client data used in AI systems is the second most agreed upon ethical implication, with a CV of 22.87. This could be due to possible cyberattacks on AI systems that affect data confidentiality, as indicated by Boillet (2018). They also believe that inherent bias in data due to insufficient or less diverse data could be another ethical implication affecting audit quality, with a mean of 3.82 and a CV of 24.79. Moreover, auditors' competence level due to lack of sufficient skills in AI tools and auditors' professional judgment due to overreliance on AI tools in performing routine audit tasks are perceived by the participants as negative ethical implications affecting audit quality with mean values of 3.88 and 3.76 and coefficients of variation of 26.11 and 29.20 respectively.

Using the one sample t-test, it is also shown in Panel B of Table 3 that there is a significant difference between sample mean and population parameter (3.4) at a significant level less than 0.05 except for AI negative impact for auditor independence (*X2.3*) or its impact on job loss threats, career commitment and satisfaction (*X2.4*) with mean value of 3.4 and 3.5, respectively.

Moreover, there is a significant difference between the sample mean and population parameter (3.4) at a significant level of 0.008 for the ethical implication related to the reduction of auditor accountability due to shared responsibility between auditors and technology (*X1.5*). However, such a significant difference arises due to little agreement among the participants regarding such ethical impact, as the mean value is only 3.09, and this is significantly different from the test value of 3.4.

To sum up, participants don't perceive that AI will significantly affect auditor independence, accountability, or even their commitment to their career in a negative manner. However, they strongly agree that AI implementation in the audit field may negatively impact auditors' due professional care, competence level, and their professional judgment. It could also have significant implications for data integrity and confidentiality.

The path analysis (see Table 4) explains the relative importance of the two factors or constructs (F1 = Benefits and F2 = Ethical challenges) while examining the effect of AI on them. The first construct (benefits of AI on audit process) explains approximately 27.7% of the total variation of AI, while the second construct (ethical challenges of AI in audit field) explains approximately 27.1 of the total variation of AI, as shown in Table 4 and Figure 1. The remaining percentage could be due to either random error in the regression model or variables excluded from the model. This means that AI technology has approximately equal importance and effect on both audit process improvement and related ethical challenges.

Table 4. Structural equation modeling — Path analysis

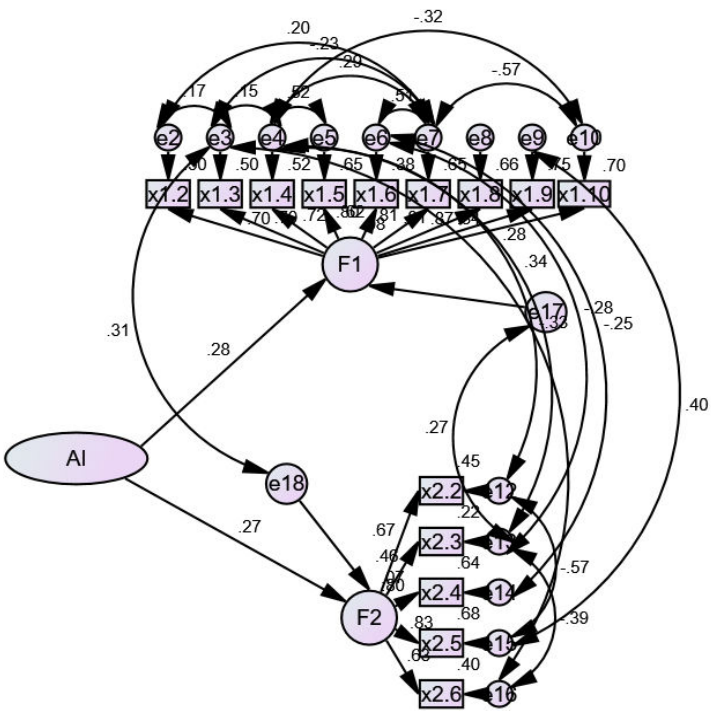
Construct	*Standardized estimate*	*Standard error*	*CR*	*p-value (Sig.)*
First construct (Audit process benefits)	0.277			
Second construct (Ethical implications)	0.271			
X1.2	0.704			
X1.3	0.705	0.144	7.660	***
X1.4	0.724	0.148	7.035	***
X1.5	0.804	0.143	7.752	***
X1.6	0.618	0.137	6.050	***
X1.7	0.808	0.111	8.612	***
X1.8	0.814	0.142	7.843	***
X1.9	0.865	0.154	8.380	***
X1.10	0.838	0.137	8.004	***
X2.2	0.668			
X2.3	0.465	0.183	4.472	***
X2.4	0.798	0.234	6.886	***
X2.5	0.825	0.261	5.960	***
X2.6	0.629	0.201	5.524	***

*Note: *** Significant at a level less than 0.001.*

The p-value, shown in Table 4, indicates that there is a significant positive effect of the AI on the audit process in terms of *X1.2* to *X1.10* at a significant level less than 0.001. There is also a significant positive effect of the AI on ethical challenges facing the audit field in terms of *X2.2* to *X2.6* at a significant level less than 0.001.

The goodness of fit measures of the structural model indicate that all measures are at acceptable limits. The GFI (0.882), AGFI (0.782), NFI (0.902), RFI (0.844), IFI (0.952), TLI (0.920), and CFI (0.950) are close to one. The normed Chi-square (1.891) has a cut-off value less than 5. Both RMSR (0.059) and RMSEA (0.089) are less than or near 0.08.

Figure 1. Path analysis



4.2. Additional analysis

Independent sample t test is conducted to determine if there is a significant difference in responses among the participants who are currently using some of AI tools such as ChatGPT, data analytics and machine learning in their audit process and those who have not yet applied any of those tools (see Panel A of Table 5). It also tests if there is significant difference in responses among participants who work in a Big 4 audit firm who are assumed to start to invest heavily in AI technology (Issa et al., 2016; Boubaya, 2022) or those who work in an international audit firm other than those Big 4 firms (see Panel B of Table 5).

According to Panel A of Table 5, it is shown that as an overall result, there is significant difference between those who started to implement some of AI tools during the audit process and those who have not yet applied any of those tools regarding the improvements in audit procedures and process with a p-value 0f 0.011. This significant difference is mainly due to the responses related to *X1.5, X1.7, X1.9*, with p-values of 0.012, 0.031, 0.001, respectively. It appears that those who have not yet applied AI tools have higher mean values of agreement regarding the benefits of AI on the audit tasks related to continuous assessment of control risk (*X1.5*), better risk assessment and fraud detection (*X1.7*) and better accumulation of audit evidence through tracing, recalculation and reperformance (*X1.9*). This indicates that those who have not yet used AI tools are more optimistic regarding the expected benefits of AI technology on the audit process than those who are in the early stages of its application. Moreover, it is shown that there is no significant difference between those two groups of participants regarding the expected ethical implications of AI implementation in the audit field, with a p-value > 0.05, except for *X2.1* and *X2.6* with p-values of 0.010 and 0.029, respectively. Those who have not yet applied AI tools have higher mean values and agree more that AI could lead to difficulty in understanding the rationales behind AI outcomes, with a mean of 4.03, and it could negatively impact auditor professional judgment improvement through overreliance on AI tools in performing routine audit tasks with mean value of 3.82.

Table 5. Independent sample t-test

Construct	No.	Independent sample t-test								
		Panel A: Auditor's use of AI				Panel B: Type of audit firm				
		Mean	Std. dev.	T-test	Sig.	No.	Mean	Std. dev.	T-test	Sig.
X1.1	1*	4.28	0.751	0.611	0.468	1*	4.29	0.859	0.594	0.028
	2**	4.18	0.747			2**	4.18	0.712		
X1.2	1	3.97	0.981	-1.475	0.454	1	4.17	0.963	0.010	0.887
	2	4.24	0.808			2	4.16	0.839		
X1.3	1	3.28	0.960	-4.297	0.489	1	3.79	1.021	-0.478	0.637
	2	4.11	0.853			2	3.90	0.942		
X1.4	1	3.59	0.867	-1.836	0.901	1	3.96	0.806	0.701	0.196
	2	3.95	0.905			2	3.81	0.935		
X1.5	1	3.86	0.639	-0.529	0.012	1	3.96	0.806	0.240	0.753
	2	3.95	0.905			2	3.91	0.850		
X1.6	1	3.79	0.726	-0.889	0.361	1	3.75	0.794	-1.067	0.831
	2	3.96	0.898			2	3.96	0.869		
X1.7	1	4.07	0.651	-0.894	0.031	1	4.08	0.717	-0.625	0.404
	2	4.20	0.758			2	4.19	0.735		
X1.8	1	3.90	0.772	-1.161	0.899	1	4.21	0.588	1.074	0.203
	2	4.11	0.853			2	4.00	0.892		
X1.9	1	3.79	0.559	-0.027	0.001	1	3.88	0.741	0.482	0.187
	2	3.80	1.020			2	3.77	0.960		
X1.10	1	4.17	0.711	0.988	0.979	1	4.29	0.690	1.885	0.026
	2	4.00	0.828			2	3.97	0.816		
X2.1	1	3.66	1.010	-1.083	0.010	1	4.13	0.741	1.361	0.461
	2	4.03	0.740			2	3.86	0.858		
X2.2	1	3.62	0.903	-1.312	0.815	1	4.21	0.415	3.569	0.000
	2	3.89	0.959			2	3.70	1.030		
X2.3	1	3.14	1.156	-1.542	0.902	1	3.71	0.690	2.108	0.001
	2	3.50	1.037			2	3.30	1.159		
X2.4	1	3.28	1.192	-1.172	0.845	1	3.46	0.833	-0.266	0.001
	2	3.59	1.260			2	3.52	1.348		
X2.5	1	2.52	0.986	-3.229	0.240	1	2.71	1.042	-1.829	0.692
	2	3.31	1.170			2	3.20	1.192		
X2.6	1	3.59	1.296	-0.889	0.029	1	3.96	0.999	1.025	0.145
	2	3.82	1.012			2	3.70	1.125		
X2.7	1	3.62	0.622	-1.566	0.070	1	4.08	0.282	2.610	0.000
	2	3.92	0.947			2	3.76	0.977		
X2.8	1	3.83	1.002	-0.349	0.984	1	3.88	1.191	-0.47	0.060
	2	3.91	1.023			2	3.89	0.961		
X1.1–X.10	1	3.86	0.500	-1.456	0.011	1	4.03	0.620	0.337	0.954
	2	4.04	0.699			2	3.98	0.665		
X2.1–X2.8	1	3.40	0.710	-2.321	0.513	1	3.76	0.350	1.350	0.009
	2	3.74	0.655			2	3.61	0.757		

Note: For Panel A: 1 = participants who use AI in the audit process, n = 29; 2** = participants who do not use AI in the audit process, n = 74. For Panel B: 1* = participants who work in a Big 4 firm, n = 24; 2** = participants who work in an international audit firm other than the Big 4, n = 79.*

According to Panel B of Table 5, the type of audit firm does not significantly affect auditors' responses regarding the expected benefits of AI on different stages of the audit process, with a p-value of 0.954. However, the responses between the two groups of audit firms significantly differ only regarding the improvement of the client acceptance phase (*X1.1*) and the reporting phase, with p-values of 0.028 and 0.026, respectively. Auditors working in Big 4 audit firms give higher levels of agreement than those working in non-Big 4 firms regarding the expected benefit of AI technology on the improvement of those two phases, with mean values of 4.29. On the other hand, there is a significant difference among the responses of those working in Big 4 audit firms and those working in non-Big 4 firms regarding the expected ethical implications of AI on the audit field, with a p-value of 0.009. Such a significant difference is due to their responses related to *X2.2, X2.3, X2.4,* and *X2.7,* with p-values less than 0.05. Auditors working in Big 4 audit firms provide a higher level of agreement than those working in non-Big 4 audit firms, that AI implementation could negatively affect data integrity due to inherent bias in data used in the system (*X2.2*), with a mean value of 4.21. They also believe that threatening auditor independence due to increased involvement with clients' AI systems, and difficulty in ensuring confidentiality and security of client data, are important ethical implications expected to arise from AI implementation. Maintaining an audit firm's reputation, especially for Big 4 audit firms, is an essential matter and could be a probable justification behind this result. However, auditors working in non-Big 4 firms have higher levels of agreement than the other group that job loss threats in an important ethical implication of AI technology. A possible justification is that non-Big 4 firms may not provide their employees with the required resources and training related to emerging technologies compared to those provided to auditors working in Big 4 firms, and consequently, this could threaten employees' jobs, commitment, and satisfaction.

5. DISCUSSION

The main findings of the study reveal that AI technology has approximately equal importance and effect on both audit process improvement and related ethical challenges. The findings of the study allow the identification of phases of the audit process that are perceived to be mostly improved by AI technology in an emerging market. The results reveal that examining the full population of transactions and balances on a continuous basis is the most improved audit procedure. This result is consistent with Fedyk et al. (2022) and Noordin et al. (2022) that AI is capable of processing and analyzing large amounts of data. The results also emphasize the importance of AI in enhancing the client acceptance phase and audit reporting phase. This indicates that AI can analyze clients' historical information and thereby predict future risks and activities. This also indicates that enhancing the accuracy and timeliness of the initial stages of the audit process could improve the audit reporting phase. Moreover, the accumulation of sufficient appropriate audit evidence of unstructured data is perceived to be enhanced through AI tools. This result supports studies of Issa et al. (2016) and Boubaya (2022) that AI automatically analyzes unstructured data to support the traditional financial evidence and determine any anomalies among them. The results also show that audit risk assessment, mainly assessment of control risk and fraud risk, is expected to be improved by AI technology. This is supported by Boubaya (2022) that natural language processing as an AI tool helps to identify discrepancies in a vast amount of texts that may indicate fraudulent activities. Moreover, the analysis of the entire population rather than a sampling technique could help in a better risk assessment, as indicated by Noordin et al. (2022).

However, the results show that the importance of AI implementation didn't appear greatly in other phases of the audit process, such as the accumulation of audit evidence through vouching, tracing, re-performance, recalculation, and electronic confirmations or the generation of client-specific engagements. This could indicate that the novelty of AI technology is associated with less developed technical skills of auditors in AI, especially in emerging markets, which have not yet allowed full utilization of AI in all audit process phases. This necessitates the need to continue examining the effect of such technology over time, at which point auditors may gain more knowledge and expertise with such technology.

The results also show that AI implementation in the audit field may negatively impact auditors' due professional care, competence level, and their professional judgment. This is not consistent with Kokina and Davenport (2017) and Henry and Rafique (2021), who perceived that AI can perform routine audit, thereby allowing auditors to devote more time to areas requiring a higher level of judgment. The results show that AI could also have a significant implication on data integrity and confidentiality. However, the findings did not support the notion that AI will negatively affect auditor independence, accountability, or even their commitment to their career in a negative manner. This indicates that auditor independence is perceived as an essential ethical matter that maintains public confidence in the audit service and should be maintained by auditors, regardless of the type of technology being used. This is not consistent with Munoko et al. (2020), who projected that auditor independence may be impaired due to increased reliance on client systems. However, it could support the findings of Libby and Witz (2024) that the use of AI increases perceived auditor objectivity when independence concerns arise. The results didn't support the results of the systematic review made by Murikah et al. (2024) that the opaqueness of AI systems may reduce auditors' social accountability. The result is also not consistent with Qadir (2017) and Henry and Rafique (2021), who raised concerns that the use of AI could result in significant job losses in the future. However, it is consistent with the arguments raised by Kokina and Davenport (2017) that AI technologies may replace specific tasks rather than entire jobs. A possible interpretation is that the emergence of new technologies and related job threats may create pressure on auditors to improve their technical capabilities to secure their job positions. In addition, it could be argued that AI cannot replace human judgment, which is an essential part of the audit profession. Such inconsistencies between some of the results of this study and those of prior studies could motivate more research studies in this area.

6. CONCLUSION

While the auditing literature provide evidence on the impact of different AI tools on audit quality, most of the studies are conducted in developed countries and little is known about the potential impact of the use of AI techniques on the different phases of audit process in developing markets that are still at the early stages of such technology implementation. Although AI could benefit the audit field, it is also important to assess the risks and challenges, mainly the ethical challenges, associated with its implementation. The findings of the current study provide evidence that the implementation of AI in an emerging setting is highly perceived to improve the quality of the audit process through examining the full population of transactions and balances rather than relying on sampling techniques. The most agreed-upon phases perceived to be improved through AI technology are the audit client acceptance phase, the audit reporting phase, and the accumulation of sufficient appropriate audit evidence from unstructured data. However, audit procedures related to better accumulation of audit evidence through vouching, tracing, re-performance, recalculation, and electronic confirmations, and the generation of client engagement letters are not highly perceived to be affected by AI technology compared to the other audit procedures. The current study also provides evidence that AI implementation in the audit field may negatively impact auditors' due professional care, competence level, and their professional judgment. It could also have significant implications for data integrity and confidentiality. However, the findings did not support the notion that AI will negatively affect auditor independence, accountability, or even their commitment to their career in a negative manner. Some of the results are consistent with Issa et al. (2016), Ghanoum and Alaba (2020), Fedyk et al. (2022), and Noordin et al. (2022), but not in line with Munoko et al. (2020), Henry and Rafique (2021), and Murikah et al. (2024). The findings support the notion that although AI has a positive impact on benefiting the audit process, it could significantly affect auditors' adherence to the ethical requirements of the audit profession in the same manner.

As an additional analysis, the results show that auditors working in Big 4 firms are more optimistic than those working in non-Big 4 firms in their perception regarding the expected benefit of AI on both the audit client acceptance phase and audit reporting phase. They also believe more that AI could negatively impact data integrity, auditor independence, and client data confidentiality compared to auditors of non-Big 4 firms. Moreover, those who have not yet dealt with any of the AI tools show higher agreement than those who have already used some of those tools regarding the expected benefit of AI toward control and fraud risk assessment, and the accumulation of sufficient appropriate audit evidence.

The current study is considered the first that examine the effect of AI implementation on both different stages of the audit process and ethical challenges facing its implementation in the context of an emerging setting during an era of digital transformation. It also adds to the work of Issa et al. (2016) by empirically examining the proposed stages of the audit process that could be affected by the implementation of AI. Findings of the study will help auditors to anticipate the phases of the audit process at which AI implementation could be effective. Moreover, the study empirically examines the ethical implications of AI implementation in auditing projected by the bibliometric analysis of publications, which is conducted by Munoko et al. (2020). This could help standard setters and regulatory bodies review the current auditing standards and code of professional conduct and suggest ways to fully utilize the benefits of such technology while adhering to the required professional ethics. Finally, through examining both the benefits and challenges of AI and whether the benefits outweigh the costs, audit firms could decide if it is worth adopting this type of technology.

The current study has some limitations. The adoption of AI technology is still in its early stages, and many of the participants in the study are not currently using it. Thus, participants are not fully aware of the different AI tools that can be used in the audit field, which could affect the generalizability of the results of the study. Thus, future research could be conducted at some future time when AI tools are expected to be extensively used in developing countries. The current study focused on examining the effect of AI technology in general without being exposed to examining the effect of each tool (e.g., machine learning, deep learning, or natural language processing) in a separate manner. Future research could examine the role of each AI tool in a more extensive manner.

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