Bridging the Gap: Enhancing Traditional Auditing Techniques Using AI for Improved Audit Quality in the digital era

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Abstract

This paper explores how Artificial Intelligence can be integrated into and enhance traditional audit to improve audit quality in the digital era. The rapid digitalization of business environments has caused significant limitations in traditional audit techniques thereby creating the audit technology assurance gap (ATAG). In this study, critical audit procedures are reviewed including sampling, analytical procedures, substantive testing, test of controls and professional judgement, to assess how AI can augment these processes. Integrating AI into audit practice offers a promising path forward, bridging the assurance gap by enhancing analytical capacity, improving precision, efficiency, and enabling auditors to deliver deeper, more timely, and more reliable insights into organizational performance and risk. This study concludes that while AI cannot replace the traditional audit techniques and human element in the audit process, it can significantly strengthen the audit process and improve audit quality.

Key words: Artificial Intelligence, Machine Learning, Natural Language Processing, Predictive Analytics, Professional Judgement, Traditional Auditing, Audit Quality.

Conceptual background

In recent years, every facet of the business environment is experiencing a rapid technological mind shift, shedding the old ways of operations and embracing the new normal offered by fast evolving technology (Popkova & Sergi, 2021). Artificial Intelligence (AI) has come to stay, as it has now been infused into the operations of several businesses to optimize profit, increase revenue, and reduce costs (Almufadda & Almezeini, 2021). The reporting aspect of business is not left out as AI is revolutionizing the traditional accounting process. Natural language processing, machine learning, big data, predictive analysis, and advanced accounting software has transformed the way financial information is processed (Mwachikoka, 2024). This is done by automating data collection, analysis, report preparation, and presentation, thereby enhancing the accuracy, timeliness, and reliability of financial information while reducing human intervention.

In today's fast changing business environment, auditing remains essential in providing assurance and instilling trust in the financial statement (Vlaović-Begović & Tomašević, 2016; Fotoh & Lorentzon, 2023), as it tells how true and fair the financial statements are, as presented by the directors (IAASB 2024). For much of its history, auditing has relied on traditional methods such as sampling, substantive testing, test of controls, analytical procedures, and professional judgment — all of which rely heavily on the auditor's skill, expertise and intuition. These techniques have proven sufficient in traditional business environments. However, the world auditors operate in today has changed dramatically with technology. Organizations now generate and store vast amount of data across digital systems, and financial transactions occur in real time through complex, interconnected systems. This new digital reality exposes a fundamental tension between the constraints of traditional audit methods and the opportunities offered by emerging technologies (Usul & Alpay, 2024).

This article describes this issue as the *audit technology assurance gap (ATAG)*. There is a growing disconnect between the demands of the digital business environment and the capacity of traditional auditing techniques to meet these demands (Usul & Alpay, 2024). This gap emerges in several forms. There is a gap of scale, as manual audit procedures can no longer keep up with the sheer volume and velocity of digital transactions being processed across global systems (Celestin & Vanitha, 2019; Al-Ateeq et al., 2022). There is also a gap of perception, where even the most skilled human auditors may overlook complex misstatements or subtle anomalies hidden within massive datasets (Celestin & Vanitha, 2019; Rahman et al., 2021). In the same vein, there is a gap of time, as traditional audits provide assurance based on past events — a snapshot of financial health at a particular moment, while stakeholders nowadays seek real-time insights into financial performance, emerging risks and financial integrity.

Shareholders, regulators, lenders, and other stakeholders now expect assurance that is more comprehensive and continuous (Owolabi & Ajala, 2020; Elad Fotoh & Lorentzon, 2023). Investment has so evolved with the aid of technology that people are now able to make split second decisions with a single touch on a mobile device. As financial reporting has therefore had to be more timely and transparent, therefore audit and assurance services are expected to adapt and likewise, evolve (Sewpersadh, 2025). However, the traditional audit model, when used in its basic form, struggles to meet the evolving expectations of these stakeholders (Usul & Alpay, 2024). Consequently, the auditing profession is at a critical point, requiring a modification of its existing methodologies to remain in tune with the digital transformation influencing other areas of business (Sewpersadh, 2025).

This audit technology assurance gap (ATAG) is precisely what AI intends to fill. AI comes in as a powerful, practical tool for augmenting and enhancing the traditional audit framework. The conceptual shift required is for AI not to be viewed as a replacement for the auditor, but as an essential tool to extend and amplify their capabilities. AI, in its various forms such as Machine Learning (ML), Natural Language Processing (NLP), and Robotic Process Automation (RPA), has the potential to redefine audit in such a way that it overcomes the limitations of conventional methods of auditing in this digital era (Celestin & Vanitha, 2019; Rahman et al., 2021; Kokina et al., 2025). Knowing that in this digital era AI has come to stay, the focus has moved from whether to adopt technology to how to strategically integrate it in the audit process to resolve specific real-world challenges within auditing. This is not about discarding a proven model but about refining and advancing it, creating a new paradigm where human knowledge and capacity is amplified by artificial intelligence.

Although there is a growing body of literature exploring the relationship between AI and auditing, most of it remains conceptual, focusing on the technological advantages or potential of AI as it relates to auditing. That is, these articles focus on bridging the *audit expectation gap* by incorporating AI and other digital technologies in the audit process (Almufadda & Almezeini, 2021; Fotoh & Lorentzon, 2023; Mwachikoka, 2024). These studies focussed on how AI can automate audit tasks, detect anomalies, or enhance analytical precision. The practical aspect of examining how these technologies can be integrated to enhance the traditional auditing procedures remains underexplored. The gap, which this study seeks to address is the ATAG, which is understanding how AI can complement traditional auditing techniques in the current real-world settings. This gap is significant because discussions around AI-assisted audit has to shift from abstract theorization to applied, practical understanding. This article seeks to move the debate from “what AI can do” to “how AI can improve” the established audit framework to improve audit quality.

The aim of this article is to demonstrate how AI-assisted audit techniques could assist in bridging the audit technology assurance gap. The article will focus on practical terms, how transitioning from traditional auditing techniques to AI-assisted audit techniques can enhance audit quality by increasing efficiency, accuracy, and depth of analysis across the audit process. This discussion begins with a review of relevant theories to establish a strong theoretical background for understanding the subject matter. It will then explore the audit process from a practical point of view to identify how it can be enhanced by AI integration. Subsequently, the article will examine the challenges of AI adoption in auditing. Thereafter, the article will conclude and propose recommendations towards having improved audit quality through AI assisted audit techniques.

Theoretical background

This study has a theoretical foundation on the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Sociotechnical Systems Theory (SST), and the Adaptive Structuration Theory (AST). A good understanding of these theories should guide our appreciation of how AI could be integrated to traditional audit techniques for improved audit quality in the digital era.

The TAM, as developed by Davies (1989), provides a framework for understanding how auditors come to accept and use AI in the audit process. According to Davies, the motivation behind how new technology is accepted and used is determined by the Attitude Towards Using the system (Chuttur, 2009). This attitude of the user is influenced by two factors, which is Perceived Usefulness, and Perceived Ease of Use (Davis, 1989). This framework explains the psychological factors that influence the auditor's willingness to embrace audit assisted techniques.

In formulating the TAM, Davies (1989) drew inferences from extant studies looking at the relationship between innovation and its adoption. In the research work of Schultz and Slevin (1975) and Robey (1979), they argue that perceived usefulness is a reliable tool to predict if an individual will to use a decision-making system. Tornatzky and Klein (1982), in their study of the adoption of innovation, supported the theory of perceived ease of use. Their study found out that complexity is a major influential factor affecting a wide range of technological innovations. Bandura (1982), after considering both the perceived ease of use and perceived usefulness in predicting behaviour, concluded that technology users are motivated by both, which he described as self-efficacy and outcome judgements. Davies brings all these theories together, forming the TAM. The perceived usefulness is the degree to which the auditor believes that using AI would enhance their job performance, which is the audit quality. The perceived ease of use is the extent to which the auditor believes that using AI would be free from human effort.

A major limitation of TAM is its narrowness in scope. This stems from the myopic assumption that once a technology is perceived as useful and easy to use, adoption naturally flows. This has been proven flawed, as although it could apply for an individual use and adoption of technology, complex professional environments where rules and regulations, ethical considerations, and regulatory compliance play crucial roles, it may not hold water (Ajibade, 2018). However, the study of TAM is important as it gives a solid background for the understanding of subsequent models seeking to explain the psychology behind how technologies are accepted and used.

Overtime, other researchers have applied the TAM, building on its principles as a strong background for understanding the reason for acceptance of technology. The Unified Theory of Acceptance and Use of Technology (UTAUT) postulated by Venkatesh et al. (2003), as a more robust theory, expanded the TAM by incorporating 7 other models on use of technology such as Theory of Reasoned Action, Theory of Planned behaviour, Model of personal Computer Utilization, Motivational model, Innovation Diffusion Theory, Social Cognitive Theory, and Model of PC utilisation, (Rosli et al., 2012). Based on the commonalities of these models, the authors argues that the attitude of users towards the use of new technology as based on four constructs: Performance expectancy, similar to perceived usefulness, Effort expectancy, similar to perceived ease of use. Other factors are Social influence and facilitating conditions. These factors are further moderated by age, gender, experience and voluntariness of use (Venkatesh et al.,2003).

While the UTAUT seems comprehensive as it incorporates constructs of 8 different models on technological information, it is not without limitations. Its application is limited to organizational settings and use by employees, and its models largely irrelevant in explaining the use of technology by consumers (Marikyan & Papagiannidis, 2025). This is because the factors failed to consider the varied cost and benefits of behaviour (Marikyan & Papagiannidis, 2025). In fact, Venkatesh, the proponent of the UTAUT, identified its limitations leading to further studies captioned UTAUT 2. Venkatesh et al. (2012) identified other motivating factors, expanding the model by adding other factors for technology adoption such as hedonic motivation, price value, and habit. These additions acknowledge that technology use is also shaped by the fun or pleasure derived from use, perceived benefit when considering cost, and the extent to which people can us ethe technology subconsciously or instinctively (Venkatesh et al., 2012).

Particularly important in this research is the Socio-technical Systems Theory (SST). This theory posits that optimal performance is achieved when both the social and technical sub-systems are jointly optimized (Mumford, 2000). In other words, technology does not operate in isolation, it interacts with people, structures, cultures, and workflows. SST emphasizes that for technological implementation to be successful, there must be an alignment between the technical/technological elements and the human environment in which it is introduced (Eason, 2014). With AI representing the technical subsystem, this implies that integrating AI into the audit process cannot focus solely on the technical capabilities of the AI systems. Equally essential are the social factors such as auditor competence, organisational culture, communication patterns, regulatory expectations, and established professional norms. These must be fully taken into consideration as neglecting them undermines the effectiveness and acceptance of the technology.

The Adaptive Structural Theory (AST) complements the SST. Developed by Desanctis and Poole (1994) as an extension to the Structural Theory by Giddens (1984), the AST explores the relationship between the use of advanced information technology and existing organizational structures. AST posits that advanced technology could be infused into these structures, making them imbibe technological capabilities that mirror, adapt, or improve upon traditional non-technological processes (Lethbridge, 2003). In some cases, these technologies may blend with manual procedures, creating new, dynamic structures that reshape how the work is done within the organization (Desanctis and Poole, 1994). It therefore means that if we are to understand how AI can improve audit quality, we need to uncover the relationship between AI structures and the structures offered in traditional audits. Even as AI improves audit quality by automating routine tasks, it does not negate the essential human input required from the auditor established by traditional audit techniques. The need for collaboration between human auditors and artificial intelligence systems becomes more essential to ensure that even when we consider the outcomes from the use of technology, we do not undermine the critical role of professional judgement, professional scepticism, strategic decision making, and a consideration of the unique requirement of each audit engagement (Sewpersadh, 2025).

Mapping AI Integration to Traditional Techniques – shift from traditional auditing to AI-assisted audit

Bridging the audit technology assurance gap using AI does not mean a complete replacement of the established traditional methodologies, this article proposes a strategic amalgamation of both. It involves taking advantage of the analytical depth, processing speed, and predictive capabilities of AI, without discarding professional scepticism, professional judgement, ethical reasoning that traditional auditing is known for, all these within the context of strict adherence to the regulatory framework. This article therefore seeks to explain how the enhancement of key aspects of the audit process using AI could enhance the overall audit quality:

- From Sampling Transactions to Full Population Testing with Machine Learning (ML)

Sampling involves applying an audit procedure on a representative of items from a population, thereby allowing auditors draw a conclusion on the population without examining every detail. Although traditional auditing practices involves a high dependence on sample-based testing, its limitations in the digital era have become more profound. Indeed, sampling works with the assumption that the sample is a perfect representative of the population (Carmichael & Whittington, 2001). However, due to the large volume and variety of data generated in modern businesses, it is increasingly difficult in getting a sample that accurately reflects the characteristics of the population (Santoso et al., 2023).

Sampling risks is the possibility that auditors may reach a different conclusion if they test the full population rather than rely on a sample of items. Usually, the smaller the sample in relation to the population, the higher the sampling risk. Transactions containing material misstatements are inherently rare, therefore the probability of such transactions being selected as part of the sample is relatively low. For example, Chen, Wu & Yan, (2022) in their study, applied algorithms to all accounting records and successfully identified abnormal transactions and entries that traditional sampling would most likely miss. Consequently, this questions the efficiency of sampling as an audit technique, faulting the reliability of audit evidence obtained from a small portion of a population (Huang et al., 2022).

Researchers have proposed the shift from sample testing to full population testing, also highlighting its limitations in practice, such as cost of implementation, documentation, and the excessive liability burden on auditors. This can be achieved through machine learning, a branch of AI that enables computers to learn from data, identify patterns, and make decisions with minimal human intervention. ML relies on algorithms that improve automatically through experience, thus allowing systems to analyse large datasets and detect anomalies more effectively than traditional methods (Mitchell, 1997). Through machine learning, small misstatements can be detected in bigdata. This overcomes the constraints ...by risk-based audit, which tends to focus primarily on areas of major misstatements and promotes full population testing (Chen et al., 2022; Huang et al., 2022, Huang et al., 2024).

Although AI-driven audit tools (AATs) can reduce the audit risk by processing and analysing large volume of data accurately and in detail, the importance of the human element of professional judgement and professional scepticism, essential skills of an auditor, cannot be overemphasized. This is vital for interpreting the results, managing false positives, dealing with complex regulatory frameworks, and ensuring that the audit maintain the right ethical standards (Sewpersadh, 2025).

- From Analytical Procedures to Predictive Analytics and Anomaly Detection

Analytical procedures, as used in traditional audit, gives an overall assessment of the reasonableness of the financial statement, and of the balances therein (Önder, 2020). Traditional analytical procedures, such as ratio analysis and trend analysis, have overtime served as essential tools in the audit process, providing a structured means of identifying inconsistencies that could warrant further investigation (IAASB, 2021). The expectation is that the relationships among financial and non-financial date remain constant and consistent over time, with deviations signifying potential misstatement. Analytical procedures have traditionally been a cornerstone of the audit process, used at the planning stage for formulating the audit strategy to pinpoint areas of possible material misstatement, as a substantive test of the balances in the financial statement, and an overall test of the reasonableness of the numbers in the financial statement (Glover et al., 2000).

Indeed, while analytical procedures have overtime proven to be an important and necessary in the audit process, its limitations in today's data driven environment have become more apparent. These procedures depend on aggregated historical data and simple correlations, which may necessarily not capture the complexity and dynamic nature of business transactions in this digital era.

The emergence of predictive analytics has proven to be a significant evolution of the basic traditional analytical procedures. Predictive analytics involve the use of statistical modelling, machine learning algorithms, and large datasets to forecast expected outcomes and identify irregular patterns with precision. It involves procedures such as data mining to extract and analyze valuable insights from large data, decision support system which help users make informed decision by providing information from complex dataset, and also the use of cognitive computing to simulate the human cognitive process like applied reasoning, perception and learning (Alotaibi, 2023)

Anomaly detection techniques include procedures such as clustering, neural networks and unsupervised learning. With anomaly testing, it becomes possible to identify unusual transactions even when they appear reasonable on the surface or fall within traditional materiality threshold (Thiprungsri & Vasarhelyi, 2011). The beauty of anomaly detection is that unlike traditional auditing procedures, it does not depend on predefined relationships. Instead, it learns patterns from the data itself and flags unexpected behaviour.

Together, Predictive analytics and anomaly detection reduces auditor bias, ensuring that risk assessment is informed, based on rigorous data driven algorithms rather than the auditor's subjective expectations based on minor calculations. Consequently, the audit evidence is more reliable, timely, and shows more depth which are critical expectations in this digital era and encourages a data-driven approach to the audit planning and risk assessment process.

- From Periodic Control Testing to Continuous Monitoring

A critical aspect of the audit process is the test of controls. Here, auditors evaluate the internal controls put in by management to ascertain if they are designed appropriately and functioning effectively at specific points in time (IAASB, 2021). These assessments are carried out annually, bi-annually, or other agreed intervals. Not only does test of controls highlight areas of possible risk of material misstatement, but it also helps determine whether the control environment provides reasonable assurance over financial reporting reliability.

Scholars have argued that the periodic nature of controls testing is a major limitation of traditional auditing (Rezaee et al., 2001). Control testing becomes merely a snapshot of control performance and cannot be used to judge the control behaviour throughout the financial year (Rezaee et al., 2001). As a result, by the time a control failure is detected, significant damage may already have been done.

With AI through machine learning and analytics, monitoring transactions and processes in real time becomes possible. In this digital era where from the initiation of transactions, approvals, reviews, all the way to final reporting are computerized, it becomes easy for control measures to be embedded into the applications. Control rules become part of the process, and deviation from the rules are immediately flagged. Vasarhelyi and Halper (1991) proposes “audit-by-exception”, an automatic Continuous Process Auditing Monitoring (CPAM). They argue that auditors should establish a structured set of rules and using automatic systems, monitor any breaches of those rules in real time. These rules are grounded on the internal control framework, informed by professional judgement and experience of seasoned auditors. When transactions breach these rules, the system flags these transactions, issues an alert thereby prompting the auditor to investigate further. If the system is constantly monitored using control measures inputted by the auditor, then tests which would normally be performed once a year, are repeated daily (Vasarhelyi and Halper, 1991; Huang et al., 2024).

- From Manual Substantive Testing to Automated Document Analysis with NLP

Substantive testing is a core audit procedure. This is used to gather evidence about the accuracy, completeness and validity of financial statement assertions (IAASB, 2021). Typically, it involves examining supporting evidence of transactions such as invoice, contracts, bank statements, waybills, confirmations, and other transaction records with the aim of verifying whether the numbers as reported by management can be relied on. Auditors performed these tests manually by selecting a sample of transactions and reviewing each in detail to confirm that they occurred, were genuine, properly authorized, went through the right process, and properly recorded.

Traditionally, substantive testing has been the most labour-intensive part of an audit. Auditors manually reviewed each transaction, tracing it through each process by examining the relevant documentation. While this worked in smaller paper-based environments, the digital age brought about changes that made it more difficult because as organizations grew, transactions volume multiplied and the workflow became digital. It became

AI offers a transformative alternative, which is augmenting the traditional methods with automated document analysis powered by Natural Language Processing (NLP). NLP can is an aspect of AI that enables computers understand and interpret written and spoken human language. NLP can scan large documents, confirm values, check accuracy and consistency, and give a summary report of its findings (PWC 2019, Venkatasubramanian, 2023). The manual aspect of substantive testing can be taken off the auditor and done by AI, as NLP can be relied on to flip through multitude of documents in seconds, identify key themes, extract relevant information, find relationships between documents, and flag irregularities (Qatawneh, 2024). There is also the advantage of being able to review the whole population, that is all contracts, invoices, bills, agreements, rather than a sample of documents.

- From Isolated Professional Judgement to AI-Informed Decision Making

Professional judgement is the key to a successful audit (Puthukulam et al., 2021). This is the discernment of an auditor, shaping his decision making. Here, auditors have to rely on their experience, training, and ethical reasoning to form an opinion and take a decision after careful review of audit evidence. Professional judgement is hand-in-hand with professional skepticism, which is having a critical questioning mindset rather than accepting evidence at face value (Nelson, 2009). Professional judgement and professional skepticism ensure that the audit stays grounded in human expertise.

However, researchers argue that professional judgement is not without its limitations. When the auditor does not have the right information, he is susceptible to misjudgements, and his assessment could be flawed. Without evidence on which to base decisions, judgements can vary significantly among individuals, leading to inconsistency in audit quality (Puthukulam et al., 2021). In the digital era, where business models have evolved and financial reporting has become more intricate, reliance on the auditor's isolated professional judgement would certainly not provide the depth or accuracy needed make a credible audit opinion.

AI-informed decision making enhances the human element of the traditional professional judgement. AI tools such Neutrosophic CRITIC–CODAS, SURF–PROSAC, and Explainable AI can improve the credibility of the audit evidence gathering process by processing entire populations rather than a sample, identifying hidden patterns, and highlight inconsistencies (Abdullah et al., 2025). AI has the ability to identify and analyse information of utmost importance and relevance to the auditor, aiding the auditor's ability to exercise informed judgement. It can also extract important information from large datasets, thereby improving the auditor's decision-making capacity (Kokina & Davenport, 2017; Puthukulam et al., 2021). Furthermore, this is presented with visualisations that are clear and understandable, making decision making easy.

Admittedly, it is highly unlikely that AI will replace professional judgement and professional skepticism because it requires the human element. However, informed decision-making is key, and this is how AI aids this aspect of the audit process. Without the right audit evidence generated with reliable, comprehensive and technology-enhanced procedures in this digital era, professional judgement may merely be "professional guesswork".

Challenges to the integration of AI in auditing

Undoubtedly, the integration of AI into different sectors has brought about improvement in efficiency, accuracy, and cut costs tremendously. In auditing, these strengths are especially useful. With the use of AI, auditors can analyse populations instead of samples as they are able to process vast amounts of data in a very short time, identify patterns that humans might miss, and provide insights that enhance the auditor's professional judgement. However, despite these strengths, there exist challenges as regards the integration of AI to the traditional methods of auditing for optimal efficiency.

A major challenge facing the integration of AI in auditing is the cultural and organizational resistance within the auditing profession (Anomah et al., 2024). This is the reluctance to consider that the traditional methods of auditing can be enhanced using AI. Traditional auditing relies on established protocols, depending heavily on the expertise and intuition of the auditor, thereby making professional scepticism and professional judgement a key skill. Consequently, the introduction of advanced technology to the audit process can therefore appear threatening (Krayyem Al-Hajaya et al., 2025). For some auditors, AI is coming to take their jobs, and would ultimately leave them redundant. Some auditors, who have gotten overly used to the traditional processes, perceive AI as either unnecessarily complicated, or taking up tasks that are traditionally the domain of the auditor's personal expertise. This challenge exposes the need for fostering a culture that views AI as a support tool not as a competition threat. This is done by continuously exposing auditors to technology, encouraging discussions about how technology improves the quality of the audit while making the job faster and easier.

Another strong challenge opposing the integration of AI in the audit process to complement the traditional methods, is the skill gap that characterises the audit profession (Kokina & Davenport, 2017). AI-assisted audit requires the auditor to have a blend of both good accounting and auditing knowledge, and technological competences such as data analytics, machine learning, and the ability to interpret the output generated by complex AI algorithms (Chen et al., 2022). The older generation workforce, especially those in the senior management and partner levels, were trained in an era dominated by the traditional methods of auditing. Although they are seasoned professionals in the field of accounting and auditing, they may not be tech savvy to have good understanding of AI-driven processes. On the other hand, there are the young graduates often bring strong digital skills and a natural familiarity with emerging technologies but may not have adequate knowledge and practical experience to properly exercise professional judgement and professional scepticism necessary to interpret, evaluate, and draw conclusions from the output of AI systems.

Addressing this skills gap begins with continuous training. The need for mentorship, upskilling programmes, and encouraging collaboration between professional accountants and tech enthusiasts cannot be overemphasized. With this, technical skills and professional judgement can be strengthened.

There is also the challenge of high costs associated with implementing AI-assisted audit techniques, especially for smaller firms with limited budget (Venkatasubramanian, 2023). This cost includes the cost of acquiring the specialized AI powered audit software, investment in the necessary IT infrastructure, licensing fees, cybersecurity enhancements, then initial and continuous staff training (Mohammad Zoynul Abedin et al., 2021). While large multinational audit firms may have the financial capacity to comfortably bear these costs and experiment with advanced technologies, smaller firms will struggle. Consequently, the integration of AI into auditing is backed by financial capacity, rather than professional need or public interest considerations. This further widens the existing gap between larger firms who continue to maintain market dominance through technological advancements which they can afford, and smaller firms who have no choice but continue to rely on traditional audit methods alone.

Regulation, standard setting, and governance is another major obstacle to the adoption of AI assisted auditing. Auditing is a highly regulated field, and as a very important aspect of corporate governance, must operate within clear, well-defined standards to ensure accountability, consistency, and public trust. However, the current auditing standards, such as the International Auditing Standards (IAS) by the International Auditing and Assurance Standards Board (IAASB), and the Public Accounting Oversight Board in the United States, were largely written as a guide for the traditional methods of auditing and does not cover the use of emerging technologies like AI (Kokina et al., 2025). As a highly regulated profession with strong values, firms are afraid of non-compliance, litigation risk or reputational issues. This is because firms do not know the extent to which they can rely on evidence generated through AI, or how they could justify their opinion based on AI-generated evidence without legal or regulatory backing.

There have been increased calls for the development of ethical guidelines, increased regulatory oversight, and an update of the auditing standards to cover the integration of AI in auditing (Fotoh & Lorentzon, 2023; Ashir & Mekonen, 2024). There is a need for the regulatory authorities to update the auditing standards to cover AI and other technology enabled procedures, and provide criteria for the level of dependence on AI generated evidence (Kokina et al., 2025).

Another significant challenge to the adoption of AI in auditing is the risk of bias and discrimination embedded within AI systems affecting the audit outcome. This is when the results produced by an algorithm are systematically prejudiced (Kokina et al., 2025). Although AI is often promoted as being objective, neutral, and capable of eliminating human error, the evidence shows that AI can reproduce, and even amplify the very biases present in its training data (Venkatasubramanian, 2023). When such biases are translated into auditing, the consequences are enormous. Audit AI tools trained on historical client data, past audit files, or industry-specific patterns may over-flag certain transactions, entities, or sectors, while under-flagging others. This can lead to errors in risk assessment, distorted anomaly detection, and potentially unfair audit attention. Moreover, auditors may place undue trust in algorithmic outputs because they appear mathematically precise, masking the underlying biased logic that produced them (Bailey & Schmidt, 2025).

Mitigating this challenge requires adopting strong AI governance practices, including auditing the AI itself. Firms must evaluate training data for possible inherent biases, ensure transparency in model design, and ensure that the human element in the process is not ignored to safeguard professional judgement. Auditors also need to apply professional skepticism, recognising that AI outputs may be biased. By combining ethical oversight with technical controls, the profession can ensure that AI enhances—rather than undermines—fairness and audit quality.

Conclusion and recommendations

This academic research paper has examined how artificial intelligence can meaningfully complement traditional auditing techniques to enhance audit quality in the digital era. By integrating insights from emerging AI driven tools and current established audit methods, the study advocates for enhanced audit quality achieved by a more efficient, rigorous, and data informed audit process. The idea propagated by this study is that AI should not be seen as a substitute to human professional judgement, but rather as a strategic support that allows auditors to navigate the current digital financial environment with greater precision. This research concludes that, to bridge the audit technology assurance gap, auditors must be willing to embrace a balanced approach that acknowledges the current shortcomings of traditional audit techniques, embeds responsible AI use while preserving the fundamental principles of professional scepticism and professional judgement.

Although this study contributes to the ongoing discourse on technology adoption in the audit process, it is not without its limitations. To begin with, researching on the incorporation of AI into audit practice requires a multi-disciplinary understanding beyond the conventional accounting knowledge and audit methods. Developing the technical competences to work with AI tools such as machine learning models, data analytics platforms, natural language processing, and algorithmic assurance tools is inherently time consuming, especially for researchers and practitioners trained primarily in traditional audit frameworks. Furthermore, the reliability of these AI models heavily depends on both the training data, and the quality and volume of data for analysis. Poorly curated or biased training dataset can undermine the accuracy and interpretability of AI outputs, creating the risk of the audit evidence being flawed, thereby weakening the assurance process.

Based on the insights presented in this research, several recommendations are made. In this digital age, technology has advanced and undoubtedly, AI has come to stay. Audit firms should invest in ongoing training to build digital competencies across all levels considering that technology is constantly evolving. It is constantly being integrated into financial reporting process thus audit should not be left behind. Regulators and standard setters should prioritize the development of clear guidelines on the use of AI in auditing. This would give it a structure, encouraging consistency and accountability.

Further research should continue to test, refine and validate AI-driven audit techniques to ensure that as technology evolves, new innovations enhance rather than compromise audit quality by not ignoring the human elements in the process. By embracing collaboration, transparency and responsible innovation, the auditing profession can successfully bridge the audit technology assurance gap in ways that strengthen audit quality in the digital age.

References

Abdullah, F., Olilingo, F. Z., Hinelo, R., & Amaliah, T. H. (2025). AI-Based Audit Judgment: A Systematic Analysis of the Integration Between Algorithmic Rationality and Auditor Professional Intuition. *International Journal of Economics Studies*, *2*(3). https://ijes.seevalue.org/index.php/ijes

Ajibade, P. (2018). Technology Acceptance Model Limitations and Criticisms: Exploring the Practical Applicationsand Use in Technology-related Studies, Mixed-method, and Qualitative Researches. *Library Philosophy and Practice*, *9*.

Al-Ateeq, B., Sawan, N., Al-Hajaya, K., Altarawneh, M., & Al-Makhadmeh, A. (2022). Big data analytics in auditing and the consequences for audit quality: A study using the technology acceptance model (TAM). *Corporate Governance and Organizational Behavior Review*, *6*(1), 64–78.

https://doi.org/10.22495/cgobrv6i1p5

Almufadda, G., & Almezeini, N. (2021). Artificial Intelligence Applications in the Auditing Profession: A Literature Review. *Journal of Emerging Technologies in Accounting*, *19*(2). https://doi.org/10.2308/jeta-2020-083

Alotaibi, E. M. (2023). Risk assessment using predictive analytics. *International Journal of Professional Business Review*, *8*(5).

Anomah, S., Ayeboafo, B., Owusu, A., & Aduamoah, M. (2024). Adapting to AI: exploring the implications of AI integration in shaping the accounting and auditing profession for developing economies. *EDPACS*, *69*(11), 28–52. https://doi.org/10.1080/07366981.2024.2388412

Ashir , F., & Mekonen, K. (2024). The Impact of Artificial Intelligence on Auditing: Navigating Ethical challenges. *Graduate School, School of Business, Economics and Law, University of Gothenburg, Sweden*.

Bailey, K., & Schmidt, J. (2025). *The Ethics of AI in Finance: How to Detect and Prevent Bias*. Corporate Finance Institute. https://corporatefinanceinstitute.com/resources/data-science/ai-ethics-in-finance-detect-prevent-bias/

Bandura, A. (1982a). Self-efficacy mechanism in human agency. *American Psychologist*, *37*(2), 122–147. https://doi.org/10.1037/0003-066X.37.2.122

Bandura, A. (1982b). Self-efficacy mechanism in human agency. *American Psychologist*, *37*(2), 122–147. https://doi.org/10.1037//0003-066x.37.2.122

Carmichael, D. R., & Whittington, O. R. (2001). Audit Sampling: An Introduction to Statistical Sampling in Auditing. In *Medical Entomology and Zoology*. Japan Society of Medical Entomology and Zoology.

Celestin, M., & Vanitha, N. (2019). Artificial Intelligence in fraud detection: Are traditional auditing methods outdated? *2nd International Conference on Recent Trends in Arts, Science, Engineering & Technology*, *3*(2), 180–186.

Chen, Y., Wu, Z., & Yan, H. (2022). A Full Population Auditing Method Based on Machine Learning. *Sustainability*, *14*(24), 17008. https://doi.org/10.3390/su142417008

Chuttur, M. (2009). Overview of the Technology Acceptance Model: Origins, Developments and Future Directions. *Sprouts: Working Papers on Information Systems*, *9*(37). http://sprouts.aisnet.org/9-37

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

DeSanctis, G., & Poole, M. S. (1994). Capturing the Complexity in Advanced Technology Use: Adaptive Structuration Theory. *Organization Science*, *5*(2), 121–147. https://doi.org/10.1287/orsc.5.2.121

Eason, K. (2014). Afterword: The past, present and future of sociotechnical systems theory. *Applied Ergonomics*, *45*(2), 213–220. https://doi.org/10.1016/j.apergo.2013.09.017

Fotoh, E. L., & Lorentzon, J. I. (2023). Audit digitalization and its consequences on the audit expectation gap: A critical perspective. *Accounting Horizons*, *37*(1). https://doi.org/10.2308/horizons-2021-027

Giddens, A. (1984). *The Constitution of Society: Outline of the Theory of Structuration*. Polity Press.

Glover, S. M., Jiambalvo, J., & Kennedy, J. (2000). Analytical Procedures and Audit-Planning Decisions. *AUDITING: A Journal of Practice & Theory*, *19*(2), 27–45.

https://doi.org/10.2308/aud.2000.19.2.27

Huang, F., Cho, S., Lee, K., & No, W. G. (2024). Examining the Effectiveness and Efficiency of Full Population Testing versus Traditional Sampling. *Accounting Horizons*, 1–19. https://doi.org/10.2308/horizons-2022-177

Huang, F., No, W. G., Vasarhelyi, M. A., & Yan, Z. (2022). Audit data analytics, machine learning, and full population testing. *The Journal of Finance and Data Science*, *8*(8), 138–144. https://doi.org/10.1016/j.jfds.2022.05.002

International Auditing and Assurance Standards Board, (2025). International Standards on Auditing (ISA).

Kokina, J., Blanchette, S., Davenport, T. H., & Pachamanova, D. (2025). Challenges and opportunities for artificial intelligence in auditing: Evidence from the field. *International Journal of Accounting Information Systems*, *56*(1), 100734. https://doi.org/10.1016/j.accinf.2025.100734

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

Krayyem Al-Hajaya, Ruba Taleb Alma'aitah, Rami, & Khaled Hutaibat. (2025). Understanding challenges of conventional remote auditing and AI-enabled remote IT auditing: audit professionals' perspectives from an emerging economy. *Journal of Accounting & Organizational Change*, 1–29. https://doi.org/10.1108/jaoc-12-2024-0395

Kuenkaikaew, S. (2013). Predictive Audit Analytics: Evolving to a New Era. *Graduate School – Newark Rutgers, the State University of New Jersey*.

Lethbridge, N. (2003). *Adaptive Structuration Theory: Relevant Structures for Web*

Technologies. https://aisel.aisnet.org/acis2003/26

Marikyan, D., & Papagiannidis, S. (2025). Unified Theory of Acceptance and Use of Technology: A review. *TheoryHub Book*. https://open.ncl.ac.uk

Mitchell, T. M. (1997). Does Machine Learning Really Work. *AI Magazine*, *18*(3). https://doi.org/10.1609/aimag.v18i3.1303

Mohammad Zoynul Abedin, Hassan, K., Hajek, P., & Uddin, M. M. (2021). *The Essentials of Machine Learning in Finance and Accounting*. Routledge.

Mumford, E. (2000). A Socio-Technical Approach to Systems Design. *Requirements Engineering*, *5*(2), 125–133. https://doi.org/10.1007/pl00010345

Mwachikoka, F. (2024). Effects of artificial intelligence on financial reporting accuracy. *World Journal of Advanced Research and Reviews*, *23*(3), 1751–1767. https://doi.org/10.30574/wjarr.2024.23.3.2791

Nelson, M. W. (2009). A model and literature review of professional skepticism in auditing. *AUDITING: A Journal of Practice & Theory*, *28*(2), 1–34. https://doi.org/10.2308/aud.2009.28.2.1

Önder, T. (2020). Analytical Procedures in an Audit: Review and Application by Cases. *Öneri Dergisi*, 99–106. https://doi.org/10.14783/maruoneri.710692

Owolabi, S. A., & Ajala, M. O. O. (2020). Auditing Concepts and Stakeholders' Expectations. *Indian-Pacific Journal of Accounting and Finance*, *4*(2), 46–60. https://doi.org/10.52962/ipjaf.2020.4.2.105

Popkova, E. G., & Sergi, B. S. (2021). *"Smart Technologies" for Society, State and Economy*. Springer International Publishing, Imprint Springer.

PricewaterhouseCoopers. (2019). *Re-inventing Internal Controls in the Digital Age*. PwC. https://www.pwc.com/sg/en/publications/

Puthukulam, G., Ravikumar, A., Sharma, R. V. K., & Meesaala, K. M. (2021). Auditors' Perception on the Impact of Artificial Intelligence on Professional Skepticism and Judgment in Oman. *Universal Journal of Accounting and Finance*, *9*(5), 1184–1190. https://doi.org/10.13189/ujaf.2021.090527

Qatawneh, A. M. (2024). The role of artificial intelligence in auditing and fraud detection in accounting information systems: moderating role of natural language processing. *International Journal of Organizational Analysis*, *33*(6), 1391–1409. https://doi.org/10.1108/IJOA-03-2024-4389

Rahman, F., Putri, G., Wulandari, D., Pratama, D., & Permadi, E. (2021). Auditing in the Digital Era: Challenges and Opportunities for Auditors. *Golden Ratio of Auditing Research*, *1*(2), 86–98. https://doi.org/10.52970/grar.v1i2.367

Rezaee, Z., Elam, R., & Sharbatoghlie, A. (2001). Continuous auditing: the audit of the future. *Managerial Auditing Journal*, *16*(3), 150–158. https://doi.org/10.1108/02686900110385605

Robey, D. (1979). User Attitudes and Management Information System Use. *Academy of Management Journal*, *22*(3), 527–538. https://doi.org/10.5465/255742

Rosli, K., Yeow, P., & Siew, E.-G. (2012). Factors Influencing Audit Technology Acceptance by Audit Firms: A New I-TOE Adoption Framework. *Journal of Accounting and Auditing: Research & Practice*, *2012*(1), 1–11. https://doi.org/10.5171/2012.876814

Santoso, F., Wulandari, I., & Pratiwi, D. (2023). Evaluation of Sampling Techniques in Audit: A Qualitative Approach. *Golden Ratio of Auditing Research*, *3*(1), 11–20. https://doi.org/10.52970/grar.v3i1.373

Sewpersadh, N. S. (2025). Adaptive structural audit processes as shaped by emerging technologies. *International Journal of Accounting Information Systems*, *56*, 100735. https://doi.org/10.1016/j.accinf.2025.100735

Shultz, R. L. , & Slevin, D. P. (1975). *Implementation and organizational validity: An empirical investigation in implementing operations research and management science*.

Thiprungsri, S., & Vasarhelyi, M. (2011). Cluster Analysis for Anomaly Detection in Accounting Data: An Audit Approach. *The International Journal of Digital Accounting Research*, *11*. https://doi.org/10.4192/1577-8517-v11_4

Tornatzky, L. G., & Klein, K. J. (1982). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. *IEEE Transactions on Engineering Management*, *EM-29*(1), 28–45. https://doi.org/10.1109/tem.1982.6447463

Usul, H., & Alpay, M. F. (2024). From traditional auditing to information technology auditing: a paradigm shift in practices. *European Journal of Digital Economy Research*, *5*(1), 3–9.

Vasarhelyi, M. A., & Halper, F. B. (1991). The continuous audit of online systems. *Auditing: A Journal of Practice & Theory*, *10*(1), 110.

Venkatasubramanian, G. (2023). AI in Auditing: A Comprehensive Review of Applications, Benefits and Challenges. *International Council for Education Research and Training*, *2*(04), 328–343. https://doi.org/10.59231/SARI7643

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information technology: toward a Unified View. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of

Information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–178. https://doi.org/10.2307/41410412

Vlaović-Begović, S., & Tomašević, S. (2016). Responsibility of an auditor for accounting fraud detection. *Skola Biznisa*, *1*, 89–101. https://doi.org/10.5937/skolbiz1-11730