MORFAI JOURNAL Multidiciplinary Output Research For Actual and International Issue
Multidisciplinary Output Research For Actual and International Issue (MORFAI Journal) ISSN (e): 2808-6635
Volumes 6 No. 2 (2026)

# EXPLORATION OF THE APPLICATION OF ARTIFICIAL INTELLIGENCE TECHNOLOGY IN AUDIT QUALITY – SYSTEMATIC LITERATURE REVIEW

**Putri Milenia Hadiwianti[1*], Syafrizal Ikram[2],**
Jurusan akuntansi, Fakultas ekonomi, Universitas Widyatama, Bandung
Jurusan akuntansi, Fakultas ekonomi, Universitas Widyatama, Bandung
E-mail: : putri.milenia@widyatama.ac.id*, syafrizal.ikram@widyatama.ac.id[2]

| | | | |
|---|---|---|---|
| Received | : 20 November 2025 | Published | : 05 January 2026 |
| Revised | : 01 December 2025 | DOI | : https://doi.org/ 10.54443/morfai.v6i2.4955 |
| Accepted | : 25 December 2025 | Publish Link | : https://radjapublika.com/index.php/MORFAI/article/view/4955 |

**Abstract**

The rapid evolution of digital technology has significantly transformed the landscape of the public accounting profession. One of the most disruptive innovations is the implementation of Artificial Intelligence (AI) within auditing processes. This study aims to explore how the integration of AI technology affects audit quality and to identify the opportunities and challenges arising from its implementation. The research methodology employed is a Systematic Literature Review (SLR) of reputable journal articles published over the last ten years. The literature selection process followed the PRISMA protocol to ensure transparency and objectivity of the findings. The analysis was conducted on various literatures discussing the use of machine learning, natural language processing, and robotic process automation in auditing procedures. The results of the literature review indicate that the application of AI contributes positively to the improvement of audit quality through more accurate anomaly detection, real-time processing of large data volumes, and the reduction of human error risks. AI enables auditors to shift from sample-based testing toward full population auditing, which directly increases the level of audit assurance. However, this study also identifies crucial challenges such as algorithmic ethics, the need for new digital competencies for auditors, and the high cost of technological infrastructure investment.

**Keywords:** *Artificial Intelligence*, Audit Quality, Systematic Literature Review, Digital Transformation, Auditor.

## INTRODUCTION

Despite ongoing efforts to improve global audit quality, investor and stakeholder concerns remain high because the achieved quality standards have not fully met expectations. The experience of the 2007/2008 global financial crisis emphasized the urgency of improving the reliability and timeliness of audit reporting (Adeoye et al., 2023). According to Wang et al. (2019), conventional financial reporting mechanisms have proven incapable of preventing declines in audit quality or the deterioration of auditor integrity that lead to major failures, despite the implementation of various regulations, enforcement of financial rules, and IFRS standards. Public trust in the reliability of financial information depends heavily on the quality of audits, which also reflect a company's accountability. The need for transparent and accurate financial data is increasingly pressing for investors and regulators amidst the dynamic growth of capital markets (Francis, 2004; Knechel et al., 2013). A quality audit provides assurance that financial statements are free from material errors, whether intentional or unintentional. According to DeFond & Zhang (2014) and Nelson (2009), this quality stems from a combination of technical expertise, moral integrity, and a high level of professional skepticism. Therefore, in a stressful business environment, the role of auditing is crucial as a safeguard of global market stability and credibility (DeAngelo, 1981; Francis, 2011). Digital transformation has positioned AI as a fundamental element, not just a supporting tool, in contemporary audit practice. Through big data processing and complex pattern recognition, AI helps auditors detect risks often missed by manual procedures (Issa et al., 2016; Kokina & Davenport, 2017). The implementation of AI platforms by major audit firms such as Deloitte and KPMG demonstrates that this technology has become a competitive strategy for achieving operational efficiency and delivering real-time predictive models (Seethamraju & Hecimovic, 2023). This creates a more measurable, rigorous, and risk-responsive audit paradigm in a digital format (Appelbaum et al., 2017).

Despite its significant potential, the adoption of AI poses the risk of technological dependency, which can undermine professional skepticism and auditor accountability if the underlying algorithmic logic is not fully understood (Commerford et al., 2022). Furthermore, there is the threat of algorithmic bias stemming from historical data, which risks reinforcing systemic inequalities (Mpofu, 2023; Raji & Buolamwini, 2019). Ethical dilemmas also arise regarding the protection of client data privacy and the limitations of legal liability in the event of system failures. Therefore, regulators need to play a role in developing digital audit governance that upholds transparency and data protection (Kokina & Davenport, 2017). Although the literature on AI in auditing continues to grow, existing research tends to be partial and overly focused on technical aspects. There is still a dearth of interdisciplinary studies exploring the impact of AI on ethical dimensions, independence, and stakeholder perceptions (Munoko et al., 2020; Almufadda & Almezeini, 2022). Furthermore, the synergy between auditors' AI systems and clients' information systems within an integrated digital ecosystem remains rarely discussed. This gap underlies the importance of a systematic literature review approach to build a more holistic conceptual framework (Munoko et al., 2020).

The integration of AI into the auditing world faces serious challenges related to the privacy and security of sensitive data. Auditors' reliance on AI to process massive amounts of data places the integrity and confidentiality of information as top priorities that must be guaranteed. Beyond technical aspects, ethical dimensions such as the risk of algorithmic bias and the degradation of human judgment in crucial decision-making are issues that require in-depth study. Successful AI adoption demands a paradigm shift in the auditor's professional expertise. As routine tasks are automated by machines, auditors are required to enhance their competency in validating and interpreting AI-based findings. Amid this changing professional landscape, the ability to maintain professional skepticism and navigate ethical regulations related to technology are inevitable new competency standards.

This study attempts to map the use of AI technology in the context of audit quality, which is currently a new area of study in the accounting literature. A comprehensive evaluation of the current state of the technology is needed to provide a foundation for future research. However, evidence from the literature indicates a gap; while AI is rapidly advancing in other business functions, its adoption in auditing tends to be slower. This is believed to be due to the unique characteristics and challenges auditing presents that are not found in other industry domains.Based on the phenomena described, this study aims to systematically explore how Artificial Intelligence technology impacts audit quality from a multidimensional perspective, entitled, "Exploration of the Application of Artificial Intelligence Technology in Audit Quality - Systematic Literature Review." This study examines not only efficiency and accuracy, but also professional integrity, ethical implications, and changes in the structure of auditor roles in the future. Through a systematic literature review approach, this study is expected to identify key trends, theoretical challenges, and practical opportunities relevant to building a technology-based audit conceptual framework. Furthermore, this study aims to provide strategic recommendations for audit firms, regulators, and accounting educational institutions in responding to technological disruption adaptively and responsibly.

## LITERATURE REVIEW

1. Agency Theory
   Agency Theory, first proposed by Jensen and Meckling (1976), serves as an important foundation for understanding the relationship between shareholders as principals and management as agents. This relationship often gives rise to conflicts of interest because agents have access to more information than principals, creating the risk of agents acting inconsistently with the owners' interests. Audits serve as a control mechanism to mitigate these conflicts by providing independent assurance on the fairness of financial statements. From an Agency Theory perspective, audits serve to suppress opportunistic management behavior while simultaneously enhancing shareholder confidence. Audit quality is a key factor in the success of this mechanism, which, according to DeAngelo (1981), is determined by the auditor's ability to detect material misstatements and the courage to report them. AI is capable of detecting suspicious patterns and anomalies that are difficult for auditors to detect manually, thus resembling a digital assistant working tirelessly to trawl through massive amounts of data (Yoon, Hoogduin, & Zhang, 2015).
2. Audit Quality
   Audit quality is at the heart of the ability to obtain value for the audit fee and a strong value in building ongoing trust in the auditor's duties and functions. According to Abdollahi et al. (2020), audit quality is ensuring that the audited financial statements are free from error, and the primary objective of an audit is to obtain reasonable assurance that the financial statements are free from irregularities. Several studies have stated that audit quality is subjective and perceptual, for example, Agur, Peria, and Rochon (2020) and Akeem, Rufus, Abiodun, and Olawum (2020), while Alawaqleh and Almasria (2021) argue that audit quality

is significantly influenced by many factors, including audit fees, audit tenure, audit independence, and the size of the public accounting firm (KAP).

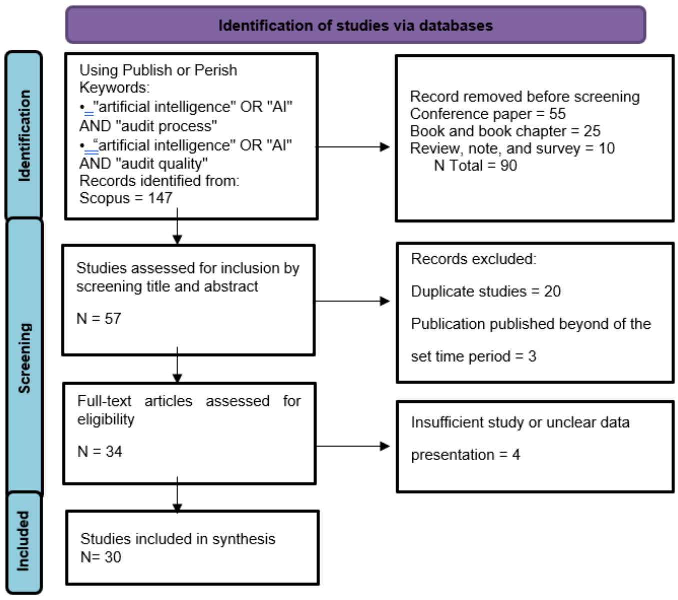
3. The Role of the Auditor
   Auditing is necessary because of its important role in examining the observable principal-agent relationships between companies and shareholders, managers, employees, and creditors (Eilifsen et al., 2006, p. 7f). According to Gramling et al. (2010, p. 7) financial statement auditing can be defined as "a systematic process of objectively obtaining and evaluating evidence regarding assertions about economic actions and events to ascertain the degree of correspondence between those assertions and established criteria, and communicating the results to interested users."
4. International audit standards
   Auditors must demonstrate professional skepticism due to the possibility of material misstatement. Furthermore, auditors should exercise professional judgment. Furthermore, auditors must gather sufficient audit evidence to reach reasonable assurance (IAASB, 2022). The IAASB defines professional judgment as "the application of relevant training, knowledge, and experience, within the context of auditing, accounting, and ethical standards, in making informed decisions about the appropriate course of action in the circumstances of the audit engagement" (IAASB, 2022, p. 23).
5. Technology Acceptance Model (TAM) Theory
   The Technology Acceptance Model (TAM) is a theory introduced by Davis in 1989, adapted from the Theory of Reasoned Action (TRA). TAM is designed to predict how individuals accept and use the latest information technology (Davis, 1989). The main objective of TAM is to explain and predict user acceptance of accounting information systems, by analyzing the relationship between perceived usefulness and ease of use and user interest in adopting information technology. TAM consists of four main factors that determine the acceptance of information technology use: perceived ease of use, perceived usefulness, behavioral intention to use, and actual system usage (Davis, 1989).
6. Artificial Intelligence Technology
   *Organization for European Economic Co-operation*(OECD) defines Artificial Intelligence (AI) as:
   "machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment" (OECD, 2019).
   Similarly, Fedyk et al. (2022) consider AI as a technical tool applied to interpret, organize, and develop large amounts of unstructured data with the aim of achieving more accurate insights and conclusions. Kommunuri (2022) demonstrates AI's ability to mirror, learn, and mimic human intelligence.

## METHOD

This study used the Systematic Literature Review (SLR) method, which is a rigorous approach to identifying, assessing, and synthesizing various evidence to answer research questions in an open and replicable manner (Tricco et al., 2018). The SLR research process consists of three stages: planning, conducting, and reporting. This study uses secondary data sources. Secondary data is data that is not directly taken from the field, but rather taken from previous research. The secondary data obtained comes from Scopus in the form of journal articles accessed using the PoP (Publish or Perish) application. A total of 30 articles were used for further analysis in this study. This research was conducted on June 14, 2025, with the following keywords: ("artificial intelligence" OR "AI") AND ("audit process" OR "audit quality").

The Systematic Literature Review (SLR) process used in this study. SLR is a systematic, transparent, and replicable approach to identifying, evaluating, and analyzing all relevant literature on a specific research topic (Kitchenham & Charters, 2007). This process ensures that the study's results are not based solely on subjectively selected literature, but are obtained through a structured selection procedure based on clear criteria. The literature selection method used in this study was PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses), which was conducted systematically and structured according to the stages of a good research protocol. Research conducted by (Shamseer et al., 2015) stated that the use of PRISMA can minimize the risk of bias and errors in literature reviews, thus resulting in more reliable and high-quality conclusions.

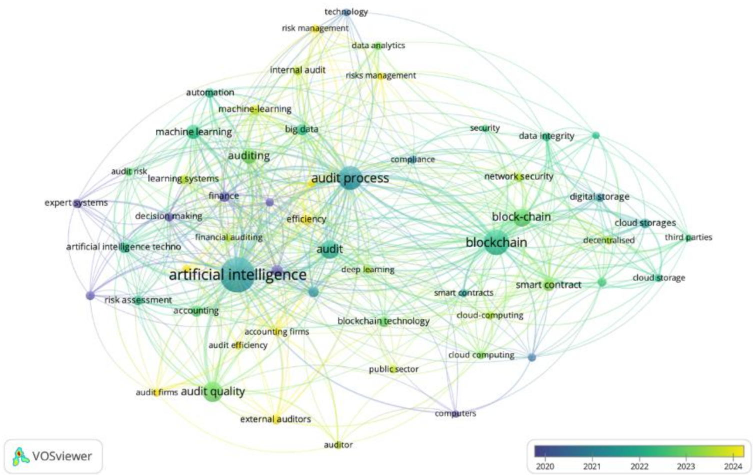
**PRISMA Flow Diagram**




*Sumber: Analisis Penelitian*

## RESULTS AND DISCUSSION

The results of the research conducted by this author will be presented in the form of data as follows:




Based on the VOSviewer overlay visualization, Figure 4 displays a temporal map of the results of the overlay visualization analysis using VOSviewer for the period 2020–2024. This map shows the evolution of research focus from the application of Artificial Intelligence (AI) and machine learning in the early stages to the integration of audit processes and data analytics in the middle phase, to strengthening blockchain assurance and data integrity in the most recent period. Blue indicates legacy topics, green marks transitional topics, and yellow represents current topics. This color shift shows a shift in the research paradigm from audit efficiency to transparency and reliability of blockchain-based audits. This finding is consistent with the results of the thematic synthesis (Section 4.3.3) which underscores the synergy of AI–Blockchain in improving audit quality (Manita et al., 2020; Kokina & Davenport, 2017; Dai & Vasarhelyi, 2017).

1. Implementation of Artificial Intelligence Technology in Improving Audit Quality (RQ1)

The results of the Synthesis and Discussion of the Systematic Literature Review (SLR) analysis in this study confirm that the integration of Artificial Intelligence (AI) has brought significant transformations to the effectiveness and efficiency of the audit process. The use of this technology has been proven to strengthen various crucial aspects, from the sharpness of error detection, the depth of risk analysis, to the overall reliability of audit results. Strong empirical evidence was found in the study by Musa & Lefkir (2024), which showed that even in the context of developing countries, AI has a highly significant positive correlation with improved audit quality ($\beta$=0.800; $p$<0.001). This finding aligns with research conducted by Üçoğlu (2022) and Manuel & Arumugam (2024), which highlighted how the use of machine learning and data analytics accelerates the risk identification process. This ultimately helps auditors work with a higher level of precision when evaluating financial statements. Thematically, this literature positions AI as a key catalyst in improving audit quality, particularly in the dimensions of strengthening professional skepticism, optimizing processing time, and accuracy in strategic decision-making. However, the effectiveness of this technology is not a stand-alone measure. Numerous literature critically notes that the success of AI is highly dependent on the quality of input data and the extent to which digital systems have been integrated. This dependency factor often hinders the uniform adoption of AI across diverse audit environments.

Several recent studies conducted by Adeoye et al. (2023), Hilario et al. (2024), and Hidayat & Lindrianasari (2025) provide a solid empirical foundation for the vital role of Artificial Intelligence (AI) in transforming audit effectiveness and efficiency. Adeoye et al. (2023) specifically highlight that the synergy between robotics, neural networks, genetic algorithms, and natural language processing has a positive impact on various audit quality parameters, including aspects of accuracy, independence, and report reliability. The presence of this technology has proven capable of assisting auditors in conducting more objective risk assessments while minimizing the risk of subjectivity or human bias in the audit process. Complementing this perspective, Hilario et al. (2024) present quantitative data showing that the use of Artificial Neural Networks (ANN) and Support Vector Machines (SVM) can boost audit accuracy by up to 93%. At this level, AI has evolved into an intelligent system capable of performing predictive analysis of anomalous patterns and errors in financial data that are difficult to detect using conventional methods.

From a local context, research by Hidayat & Lindrianasari (2025) reinforces these findings in the Indonesian context, where AI implementation has been shown to significantly improve work efficiency while simultaneously enhancing fraud detection. With a very strong correlation coefficient of $r = 0.801$ ($p < 0.001$), this study confirms that the use of AI not only accelerates the audit process to be more precise but is also a crucial instrument in reducing the number of auditors' professional negligence. Through systematic reviews, studies conducted by Aljaaidi et al. (2023) and Musa (2024) serve as primary references in validating the effectiveness of Artificial Intelligence (AI) in improving audit quality. Both studies agree that AI integration has a significant positive impact on the accuracy, speed, and efficiency of the audit process, both within the internal and external audit scopes. Aljaaidi et al. (2023) emphasize that AI's contribution to audit firm performance is realized through workflow automation, expanding the scope of data analysis, and strengthening auditors' capacity to identify material misstatements. More specifically, Musa (2024) offers an interesting perspective by categorizing AI implementation into three levels: assisted, augmented, and autonomous. Within this classification, augmented AI was found to be the most effective level in supporting auditors in making sharper and higher-quality decisions. Lehner et al. (2022) explored the dynamics of AI challenges and opportunities in depth, further supported by empirical evidence from Musa (2024), Aljaaidi et al. (2023), and Torroba et al. (2025). Lehner et al.'s (2022) work provides a crucial conceptual foundation, highlighting the issues of ethics and human accountability amidst the mechanization of audits. They formulated five key challenges that must be addressed:

1. Objectivity
2. Privacy
3. Transparency
4. Accountability
5. Trustworthiness

One crucial point emphasized is that AI lacks moral agency; meaning, despite the technology's ability to process data at incredible speeds, the final responsibility for every audit decision remains solely with the human auditor. However, despite these risks, there is a significant opportunity to transform the reliability of financial reporting through more precise and responsive data-driven decision-making. Despite AI's enormous potential, its implementation in practice still faces significant obstacles. Musa (2024) and Aljaaidi et al. (2023) highlight that regulatory limitations, high investment costs, and a lack of technical training are key obstacles for audit firms. However, these obstacles are outweighed by the transformational opportunities it offers, such as the transition to continuous auditing, real-time risk analysis, and cost and time efficiencies. Torroba et al. (2025) add that these dynamics are heavily influenced by market pressures and regulatory policies, which can act as both accelerators and inhibitors of technology adoption. Essentially, the challenges of AI center on ethics and trustworthiness, while the opportunities lie in predictive capabilities and the expansion of audit services toward strategic analytics. One of the biggest revolutions brought by AI is Technological Process Reframing (TPR). According to Issa, Sun, and Vasarhelyi (2016), AI enables auditors to shift from traditional sample-based testing to examining the entire population of transactions (full population testing) through deep learning. This results in audit evidence that is far more representative and reliable. Validation of this theory was found in a large-scale study by Tan et al. (2025) of 25,000 observations in China, which showed that client companies that adopted AI internally actually helped improve the quality of external audits. This synergy strengthens internal control and transparency, which directly reduces the risk of misstatements and late reporting (audit lag). This effectiveness is further optimized when auditors have a strong background in information technology.

The effectiveness of AI also lies in the paradigm shift from a retrospective (backward-looking) approach to a proactive one through real-time monitoring (Leocádio et al., 2024). In the banking sector, Alassuli (2025) demonstrated that Robotic Process Automation Systems (RPAS) can minimize human error and reduce operational costs. Even simple AI applications, such as Optical Character Recognition (OCR), have been shown to accelerate data extraction without increasing auditor workload (Kokina et al., 2025). A new concept has emerged: AI co-piloted auditing. Gu et al. (2024) describe collaboration between human auditors and large language models (foundation models such as GPT-4). Using Chain-of-Thought prompting, AI does not replace auditors but rather enhances their cognitive capacity to generate deeper and more accurate insights. However, Li and Goel (2025) caution that this success depends heavily on the system's auditability and the auditor's expertise in technically and ethically evaluating algorithms.

The future of auditing also points to the integration of blockchain technology to ensure transparency through real-time verification and triple-entry accounting (Han et al., 2023). AI's predictive capabilities are also becoming increasingly sophisticated; Muñoz-Izquierdo et al. (2019) demonstrated that machine learning models were able to predict bankruptcy risk with 80% accuracy based on simple audit report variables. In developing countries, the use of cloud computing and data mining has increased positive perceptions of the effectiveness of digital audits (Almaqtari et al., 2024). However, to achieve optimal audit quality, organizations must prioritize AI strategy and governance (Hu et al., 2023). In closing, Schiff et al. (2024) remind us that ultimately, audit quality is determined not only by technical sophistication but also by adherence to the principles of transparency, accountability, and independence within an AI ethics framework.

The implementation of AI opens up significant opportunities for transforming audit methodology. Alassuli (2025) emphasized that AI facilitates the creation of continuous auditing and real-time risk monitoring systems, shifting the traditional audit paradigm toward a more proactive model. This opportunity is further expanded by Gu et al. (2024) through the concept of co-piloted auditing. In this model, AI not only functions as an automation tool but also becomes a collaborative partner for auditors in the reasoning and decision-making process, thereby boosting productivity and generating sharper analytical insights. Despite this potential, AI optimization still faces significant challenges. Li and Goel (2025) highlight the issue of auditability, namely the low transparency in the documentation of algorithmic processes, which makes it difficult to verify the performance of the AI system itself. Kokina et al. (2025) warn of the risks of algorithmic bias, limited data quality, privacy issues, and concerns about auditor overreliance on technology. Furthermore, Han et al. (2023) noted that synchronization between AI systems and blockchain technology requires high interoperability standards and organizational cultural readiness to adapt.

Addressing the question of AI's effectiveness on audit quality, Fedyk et al. (2022) provided empirical evidence from AI investments at 36 large audit firms in the United States. The results showed a significant improvement in quality, marked by a 5% reduction in restatement rates and audit cost savings of between 0.9% and 2.1%. This confirms that AI enhances auditors' anomaly detection, increases professional skepticism, and enables data-driven audits on a massive scale. Kokina and Davenport (2017) complemented these findings by explaining that through machine learning, audit coverage has expanded to encompass the full population of transactions, rather than simply sample-based testing. This change creates transparency and provides real-time assurance. Similarly, Frey and Osborne (2017) stated that although the audit profession has been significantly impacted by automation, AI plays a strategic role in taking over routine tasks. Consequently, auditors can shift to a more analytical and strategic role, where the effectiveness of AI is measured not only by the final results but also by the transformation of auditors' work methods, becoming more technology-based. AI's Contribution to Audit Effectiveness and Credibility A current literature synthesis confirms that the implementation of Artificial Intelligence (AI) plays a crucial role in revolutionizing audit effectiveness and quality across the board. Using the Technology–Organization–Environment (TOE) framework, Seethamraju and Hecimovic (2020) explain that AI adoption goes beyond technical automation, accelerating data analysis and sharpening auditors' capacity to identify material misstatements. This ongoing digital transformation adds value to audit firms by enhancing deeper professional judgment processes. In line with this perspective, Austin et al. (2020) highlighted that the integration of data analytics within an AI ecosystem can expand the scope of audits and increase transparency. This innovation effectively minimizes subjective human bias and creates a new, more constructive dynamic in the interaction between auditors and clients. Similarly, Mpofu (2023) reinforced these findings by emphasizing AI's significant potential in optimizing accuracy, time efficiency, and audit risk management. Interestingly, AI's contribution also extends to the psychological dimension by strengthening perceptions of objectivity and independence (Libby and Witz, 2023). Through an experimental approach, this research demonstrated that the involvement of AI in the audit process can reduce public concerns about potential conflicts of interest. Consequently, public trust in audit reports increases because technology is perceived as a more neutral guarantor of independence. Collectively, the findings from these studies indicate that the impact of AI is multidimensional. AI not only offers technical advantages in terms of efficiency and accuracy, but also serves as a strategic tool for building credibility and public trust in the integrity of audit results.

1. Challenges and Opportunities in the Application of Artificial Intelligence Technology to Audit Quality (RQ2)

The Balance Between Opportunities and Challenges of AI Implementation The results of the SLR synthesis demonstrate a complex dynamic between the opportunities for improving audit quality through AI and the various accompanying implementation barriers. As emphasized by Üçoğlu (2022) and Nogueira et al. (2024), the main advantage of AI lies in its ability to precisely identify transaction anomalies and facilitate continuous auditing. However, this potential is overshadowed by crucial challenges such as the auditor digital competency gap, the lack of ethical regulations, and the risk of eroding professional independence due to excessive reliance on algorithms. On a slightly different spectrum, Musa & Lefkir (2024) provide an optimistic note through a study of SMEs in Saudi Arabia, which shows that AI can strengthen the reliability of audit reports, although the study does not explore the obstacles to its implementation in depth.

Broader analyses by Chávez-Díaz et al. (2024), Kakwani & Naidu (2024), and Hilario et al. (2024) confirm that the sustainability of AI in auditing is highly dependent on systemic readiness. Using a bibliometric approach, Chávez-Díaz et al. (2024) uncovered a wide research gap; AI research still dominates in developed countries, while its development in developing countries remains very limited. The authors identified three main obstacles: human resource readiness, limited technological infrastructure, and ethical dilemmas. However, this phenomenon remains viewed as a significant opportunity to accelerate the digitalization of the accounting profession and stimulate audit innovation based on big data analytics that is more adaptive to future challenges. Kakwani & Naidu's (2024) research highlights the practical challenges facing the banking sector, particularly related to high investment costs, internal resistance to change, and the urgency of continuous training. Nevertheless, the adoption of AI and digitalization has been shown to have a significant positive impact on transparency, operational efficiency, and compliance with banking regulations, thus the prospects for its implementation remain highly promising. Similarly, Hilario et al. (2024) caution that privacy, ethics, and data security risks are fundamental issues that must be mitigated, although AI opens up significant opportunities for the automation of internal oversight and continuous auditing systems.

One of the main obstacles to the use of AI is the lack of algorithmic transparency, often referred to as the black-box problem. Zhang, Cho, and Vasarhelyi (2022) emphasized that the opacity of machine logic can hinder auditor performance. As a solution, they introduced the concept of Explainable Artificial Intelligence (XAI) through techniques such as LIME and SHAP. This XAI approach allows auditors to understand the reasons behind anomaly detection, thereby strengthening professional skepticism while ensuring compliance with international audit documentation standards (such as PCAOB AS 1105 & AS 1215). In a more integrative context, Qader and Cek (2024) see the synergy between AI and blockchain as a key innovation to ensure the integrity of audit data. Based on an empirical study in Turkey, the combination of these two technologies has been shown to accelerate fraud detection and increase investor confidence in the validity of financial statements. However, the success of this integration still depends on the organization's readiness to face new challenges, ranging from auditor training needs to privacy protection and professional independence. Hu et al. (2023) highlighted that the implementation of AI in auditing involves a complex relationship between governance, data quality, and human factors, which often trigger feedback loops and systemic dependencies. From an organizational perspective, although initial investment and infrastructure pose significant challenges, Almaqtari et al. (2024) emphasized that the opportunities are very promising because AI can accelerate processes and maintain the consistency of audit results. Normatively, Schiff et al. (2024) see the lack of global standards as a barrier, but this actually opens up a strategic opportunity to develop an AI ethics audit framework that integrates technological advancements with social responsibility.

The low adoption of AI in various countries is often rooted in auditor competency gaps. Wassie and Lakatos (2024) proposed the CACS (Commitment, Access, Capability, Skills) framework as a solution to optimize the internal audit function. Similarly, Fedyk et al. (2022) identified that the main obstacle is not only technical skills, but also the need for organizational restructuring to support technology integration. Kokina and Davenport (2017) warned of the risks of algorithmic bias and data security, which require auditors to deeply understand system integrity. However, these challenges are leading audits towards a major transformation: from merely verifying the past (retrospective) to a more proactive, predictive auditing system (Carvalho & Esteban-Navarro, 2014). Furthermore, auditing the intelligence system itself provides added value in the form of organizational legitimacy and the sustainability of modern audit practices (Izquierdo Triana et al., 2017).

The adoption of AI also faces external resistance. Seethamraju and Hecimovic (2020) identified conservative attitudes from regulators and legal and reputational risks resulting from algorithmic misinterpretation as real obstacles. These changes have even sparked new negotiations regarding the division of roles, boundaries of responsibility, and the determination of audit fees between auditors, managers, and regulators (Austin et al., 2020). While Mpofu (2023) highlighted the risk of bias and resistance to change among practitioners, Libby and Witz (2023) offer a more optimistic perspective. They found that AI actually has the potential to improve public perception of auditor independence. With more transparent and objective processes, this technology strengthens the profession's credibility and mitigates litigation risk by increasing the reliability of audit results.

1. Driving Factors for External Auditors to Explore and Adopt Artificial Intelligence Technology to Improve Audit Quality (RQ3)

The results of the SLR synthesis highlight that external auditors' intentions to adopt AI are influenced by various complex motivational dimensions. Using the Unified Theory of Acceptance and Use of Technology (UTAUT) theoretical framework, Musa & Lefkir (2024) identified four main pillars: performance expectancy, effort expectancy, and motivation. AI adoption is not solely dependent on the technology itself but is the result of the interaction between individual competencies, organizational readiness, and environmental pressures. Hidayat & Lindrianasari (2025) emphasized that educational background and digital experience significantly influence auditor adaptability, with millennials tending to integrate AI systems more quickly than previous generations. Furthermore, the drive to maintain professional reputation and credibility serves as a moral motivation for auditors to switch to more accurate technology (Adeoye et al., 2023). From an external perspective, Kakwani & Naidu (2024) highlight the role of regulation and efficiency demands in the banking sector as strategic drivers. Compliance with supervisory policies forces organizations to quickly implement digital audits to maintain competitive operational standards. The most comprehensive determinants of AI adoption are explained through the Technological–Organizational–Environmental (TOE) and Innovation Diffusion Theory (IDT) approaches by Torroba et al. (2025). The success of this technology integration is influenced by three crucial dimensions:

1. Technology Dimension: Includes technical knowledge and perception of the tangible benefits of AI.
2. Organizational Dimension: Includes internal infrastructure readiness, auditor confidence in the system, and commitment to support from management.
3. Environmental Dimension: Related to government regulations, market competition, and client demand for technology-based audits.

This theoretical finding is empirically reinforced by Aljaaidi et al. (2023), who demonstrated that digital competence and firm support are key prerequisites. Complementing this perspective, Syamsuddin et al. (2023) remind us that technological advancements must remain grounded in non-technical foundations, namely personal integrity and auditor competence as the most fundamental safeguards of audit quality.

Although AI significantly improves audit performance, Zhang, Cho, and Vasarhelyi (2022) caution against the "black-box problem" or lack of algorithmic transparency. As a solution, they introduce Explainable Artificial Intelligence (XAI) through the LIME and SHAP techniques. This approach enables auditors to understand the logic behind anomaly identification, thereby maintaining professional skepticism and ensuring compliance with audit documentation standards (such as PCAOB AS 1105 & AS 1215). Thematically, the effectiveness of AI adoption is largely determined by individual readiness, institutional support, and clarity of the technology's benefits. Tan et al. (2025) identify four key catalysts: auditor technological literacy, auditor-client geographic proximity, corporate governance quality, and the client's high-tech industry characteristics. Complementing this view, Leocádio et al. (2024) propose a four-dimensional framework encompassing digital transformation, technological advancement, innovation development, and ethical considerations as prerequisites for organizational success in managing the digital transition.

The push for AI adoption also comes from regulatory and competitive perspectives. Li and Goel (2025) highlight the influence of international standards such as the EU AI Act and the IIA Framework, which require auditors to ensure the ethical conduct of AI systems. Meanwhile, Big Four firms are encouraged to adopt AI to maintain competitive advantage and operational efficiency in the global market (Kokina et al., 2025). The potential of new technologies, such as foundation models (e.g., GPT-4), is also attractive due to their ability to expand analytical power and productivity (Gu et al., 2024). A crucial factor determining ultimate success is support from top management. Hu et al. (2023) found that senior executives' AI cognition was the most influential factor. This aligns with Wassie and Lakatos' (2024) CACS framework, which places organizational commitment and data access as key pillars. In addition to digital infrastructure, external pressures, such as market expectations for audit accuracy and reputational pressures to adhere to technology ethics, are strong drivers for public accounting firms to continue investing in AI (Almaqtari et al., 2024; Schiff et al., 2024). Based on a literature synthesis, the impetus for audit firms to adopt Artificial Intelligence (AI) technology can be classified into four main pillars. First, competitiveness and cost efficiency, where audit firms invest in technology to maintain a competitive advantage in the global market (Fedyk et al., 2022). Second, the rapid development of technological innovations, such as machine learning and

Auditors' decisions to integrate AI are heavily influenced by the Technology–Organization–Environment (TOE) framework. Seethamraju and Hecimovic (2020) emphasize that infrastructure readiness, top management commitment, and pressure from regulators and clients are crucial determinants of audit practice. These dynamics are reinforced by social interactions; Austin et al. (2020) highlight that collaboration between auditors and managers in understanding technology accelerates the diffusion of innovation and strengthens trust in machine-based audit results. Beyond technical aspects, audit firms' motivations are also driven by non-technical and psychological factors. Financial statement users' expectations of auditor competence and professional skepticism are key drivers for firms to improve their service quality through AI (Kilgore et al., 2014). From a public perspective, Libby and Witz (2023) show that the use of AI significantly improves public perceptions of the objectivity and fairness of the audit process. This provides stronger social legitimacy for the auditing profession in the eyes of the public.

## CONCLUSION

The results of the Systematic Literature Review (SLR) concluded that the implementation of Artificial Intelligence (AI) plays a crucial role as a digital transformation agent that improves audit quality through automation, full population data analysis, and real-time monitoring that can significantly mitigate the risk of material misstatement (Issa et al., 2016; Hilario et al., 2024; Aljaaidi et al., 2023). This effectiveness is driven by multidimensional factors that include technological readiness, auditor digital competence, managerial support, and regulatory pressure summarized in the Technology-Organization-Environment (TOE) framework (Torroba et al., 2025; Hidayat & Lindrianasari, 2025). However, for opportunities such as continuous auditing and predictive auditing to be achieved sustainably, the profession must address critical challenges related to the "black-box" problem through Explainable AI (XAI), the risk of algorithmic bias, data security, and the lack of moral agency in machines, which emphasizes that ethical and professional responsibility remains entirely in the hands of human auditors (Zhang et al., 2022; Lehner et al., 2022; Syamsuddin et al., 2023).

## REFERENCES

Adeoye, IO, Akintoye, R.I., Aguguom, T.A., & Olagunju, O.A. (2023). Artificial intelligence and audit quality: Implications for practicing accountants. Asian Economic and Financial Review, 13(11), 756–772.https://doi.org/10.55493/5002.v13i11.4861

Adhiputra, MW (2015). Analysis of factors influencing the acceptance of information technology using the Technology Acceptance Model (TAM). Journal of Computer Science and Information Systems, 3(2), 45–56.

Alassuli, A. (2025). Impact of artificial intelligence using the robotic process automation system on the efficiency of internal audit operations at Jordanian commercial banks. Banks and Bank Systems, 20(1), 122–135.https://doi.org/10.21511/bbs.20(1).2025.11

Aljaaidi, KS, Alwadani, NF, & Adow, AH (2023). The impact of artificial intelligence applications on the performance of accountants and audit firms in Saudi Arabia. International Journal of Data and Network Science, 7(3), 1165–1178.https://doi.org/10.5267/j.ijdns.2023.5.007

Alles, M. G. (2015). Drivers of the use and facilitators and obstacles of the evolution of Big Data by the audit profession. Accounting Horizons, 29(2), 439–449.https://doi.org/10.2308/acch-51067

Almaqtari, F.A., Farhan, NHS, Al-Hattami, HM, Elsheikh, T., & Al-dalaien, BOA (2024). The impact of artificial intelligence on information audit usage: Evidence from developing countries. Journal of Open Innovation: Technology, Markets, and Complexity, 10(2), 100298.https://doi.org/10.1016/j.joitmc.2024.100298

Almufadda, S., & Almezeini, N. (2022). A review of AI adoption in the auditing profession: Trends and implications. Journal of Accounting and Organizational Change, 18(4), 533–551.https://doi.org/10.1108/JAOC-03-2022-0032

Austin, A.A., Carpenter, T.D., Christ, M.H., & Nielson, C.S. (2021). The data analytics journey: Interactions among auditors, managers, regulation, and technology. Contemporary Accounting Research, 38(3), 1888–1924.https://doi.org/10.1111/1911-3846.12680

Bell, T. B., Peecher, M. E., & Solomon, I. (2005). The 21st century public company audit: Conceptual elements of KPMG's global audit methodology. Auditing: A Journal of Practice & Theory, 24(1), 151–165.https://doi.org/10.2308/aud.2005.24.1.151

Carcello, J. V., & Nagy, A. L. (2004). Audit firm tenure and fraudulent financial reporting. Auditing: A Journal of Practice & Theory, 23(2), 55–69.https://doi.org/10.2308/aud.2004.23.2.55

Carvalho, A. V., & Esteban-Navarro, M. (2016). Intelligence audit: Planning and assessment of organizational intelligence systems. Journal of Librarianship and Information Science, 48(1), 47–59.https://doi.org/10.1177/0961000614536198

Chávez-Díaz, J.M., Aquiño-Perales, L., De-Velazco-Borda, J.L., Villagómez-Chinchay, J.A., & Flores-Sotelo, W.S. (2024). Artificial intelligence in accounting and auditing: Bibliometric analysis in Scopus 2020–2023. Indonesian Journal of Electrical Engineering and Computer Science, 36(2), 1319–1328.https://doi.org/10.11591/ijeecs.v36.i2.pp1319-1328

Commerford, B. P., Dennis, S. A., Joe, J. R., & Wang, K. (2022). Man versus machine: Complex estimates and auditor reliance on artificial intelligence. The Accounting Review, 97(1), 117–140.https://doi.org/10.2308/TAR-2019-0485

Dai, X., & Zhu, W. (2022). Intelligent financial auditing model based on deep learning. Computational Intelligence and Neuroscience, 2022, 8282854.https://doi.org/10.1155/2022/8282854

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108–116.

Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.

DeAngelo, L. E. (1981). Auditor size and audit quality. Journal of Accounting and Economics, 3(3), 183–199.https://doi.org/10.1016/0165-4101(81)90002-1

DeFond, M. L., & Zhang, J. (2014). A review of archival auditing research. Journal of Accounting and Economics, 58(2–3), 275–326.https://doi.org/10.1016/j.jacceco.2014.09.002

Dillon, A. (1997). User acceptance of information technology. In M. Helander, T. K. Landauer, & P. Prabhu (Eds.), Handbook of human-computer interaction (pp. 877–889). Elsevier.

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. Journal of Business Research, 133, 285–296.https://doi.org/10.1016/j.jbusres.2021.04.070

Fedyk, A., Hodson, J., Khimich, N., & Fedyk, T. (2022). Is artificial intelligence improving the audit process? Review of Accounting Studies, 27(3), 938–985.https://doi.org/10.1007/s11142-022-09697-x

Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention and behavior: An introduction to theory and research. Reading, MA: Addison-Wesley.

Francis, J. (2004). What do we know about audit quality? The British Accounting Review, 36(4), 345–368.https://doi.org/10.1016/j.bar.2004.09.003

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254–280.https://doi.org/10.1016/j.techfore.2016.08.019

Gu, H., Schreyer, M., Moffitt, K., & Vasarhelyi, M. (2024). Artificial intelligence co-piloted auditing. International Journal of Accounting Information Systems, 54, 100698.https://doi.org/10.1016/j.accinf.2024.100698

Han, H., Shiwakoti, R.K., Jarvis, R., Mordi, C., & Botchie, D. (2023). Accounting and auditing with blockchain technology and artificial intelligence: A literature review. International Journal of Accounting Information Systems, 48, 100598.https://doi.org/10.1016/j.accinf.2022.100598

Hidayat, NU, & Lindrianasari, L. (2025). Evaluating financial audit efficiency: The role of artificial intelligence in proactive negligence mitigation. Edelweiss Applied Science and Technology, 9(4), 1437–1446.https://doi.org/10.55214/25768484.v9i4.6311

Hilario, M., Paredes, P., Mayhuasca, J., Liendo, M., & Martínez, S. (2024). Evaluation of the impact of artificial intelligence on the systems audit process. Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 15(3), 184–202.https://doi.org/10.58346/JOWUA.2024.I3.013

Hu, K.-H., Chen, F.-H., Hsu, M.-F., & Tzeng, G.-H. (2023). Governance of artificial intelligence applications in a business audit via a fuzzy fusion multiple rule-based decision-making model. Financial Innovation, 9(1), 117.https://doi.org/10.1186/s40854-022-00436-4

IAASB. (2014). A framework for audit quality: Key elements that create an environment for audit quality. International Auditing and Assurance Standards Board.https://www.ifac.org/publications-resources/framework-audit-quality

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

Izquierdo Triana, H., Fernández, J. L., & Ballesté, E. (2017). Audit of a competitive intelligence unit. The International Journal of Intelligence, Security, and Public Affairs, 19(3), 214–241.https://doi.org/10.1080/23800992.2017.1384679

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. Journal of Financial Economics, 3(4), 305–360.https://doi.org/10.1016/0304-405X(76)90026-X

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. Science, 349(6245), 255–260. https://doi.org/10.1126/science.aaa8415

Kilgore, A., Harrison, G., & Radich, R. (2014). Audit quality: What's important to users of audit services. Managerial Auditing Journal, 29(9), 776–799.https://doi.org/10.1108/MAJ-08-2014-1062

Knechel, W.R., Krishnan, G.V., Pevzner, M., Shefchik, L.B., & Velury, U.K. (2013). Audit quality: Insights from the academic literature. Auditing: A Journal of Practice & Theory, 32(Supplement 1), 385–421.https://doi.org/10.2308/ajpt-50350

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

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, 100734.https://doi.org/10.1016/j.accinf.2025.100734

Kusumawati, R., & Wibowo, A. (2021). Audit failure and public trust: Lessons from Indonesia. Indonesian Journal of Accounting and Auditing, 25(2), 115–127.

Lehner, O.M., Ittonen, K., Silvola, H., Ström, E., & Wührleitner, A. (2022). Artificial intelligence based decision-making in accounting and auditing: Ethical challenges and normative thinking. Accounting, Auditing & Accountability Journal, 35(9), 109–135.https://doi.org/10.1108/AAAJ-09-2020-4934

Leocádio, D., Malheiro, L., & Reis, J. (2024). Artificial intelligence in auditing: A conceptual framework for auditing practices. Administrative Sciences, 14(10), 238.https://doi.org/10.3390/admsci14100238

Li, Y., & Goel, S. (2025). Artificial intelligence auditability and auditor readiness for auditing artificial intelligence systems. International Journal of Accounting Information Systems, 56, 100739.https://doi.org/10.1016/j.accinf.2025.100739

Libby, R., & Witz, P. D. (2024). Can artificial intelligence reduce the effect of independence conflicts on audit firm liability? Contemporary Accounting Research, 41(2), 1346–1375.https://doi.org/10.1111/1911-3846.12941

Mpofu, FY (2023). The application of artificial intelligence in external auditing and its implications on audit quality? A review of the ongoing debates. International Journal of Research in Business and Social Science, 12(9), 496–512.https://doi.org/10.20525/ijrbs.v12i9.2737

Munoko, I., Brown-Liburd, H.L., & Vasarhelyi, M. (2020). The ethical implications of using artificial intelligence in auditing. Journal of Business Ethics, 167(2), 209–234.https://doi.org/10.1007/s10551-019-04407-1

Muñoz-Izquierdo, N., Camacho-Miñano, M.-d.-M., Segovia-Vargas, M.-J., & Pascual-Ezama, D. (2019). Is the external audit report useful for bankruptcy prediction? Evidence using artificial intelligence. International Journal of Financial Studies, 7(2), 20.https://doi.org/10.3390/ijfs7020020

Murikah, W., Nthenge, J. K., & Musyoka, F. M. (2024). Bias and ethics of AI systems applied in auditing - A systematic review. Scientific African, 25, e02281.https://doi.org/10.1016/j.sciaf.2024.e02281

Moses, AMH (2024). Detecting the effect of artificial intelligence on internal audit performance: Empirical study in Saudi Arabia. Decision Science Letters, 13(4), 967–976.https://doi.org/10.5267/j.dsl.2024.7.003

Musa, AMH, & Lefkir, H. (2024). The role of artificial intelligence in achieving auditing quality for small and medium enterprises in the Kingdom of Saudi Arabia. International Journal of Data and Network Science, 8(2), 835–844.https://doi.org/10.5267/j.ijdns.2023.12.021

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

Olusegun, J. (nd). The impact of artificial intelligence on financial audits: Enhancing accuracy and efficiency.

Organization for Economic Co-operation and Development (OECD). (2023). About the OECD. OECD. https://www.oecd.org/about/

Palmrose, Z.-V. (1988). An analysis of auditor litigation and audit service quality. The Accounting Review, 63(1), 55–73.https://www.jstor.org/stable/247685

Phan, H.-T., Nguyen, P.-H., Nguyen, C.-T., Vo, T.-TT, & Nguyen, T.-T. (2021). Effect of emotional intelligence on auditors' judgment and audit sustainability: Empirical evidence from Vietnam. Problems and Perspectives in Management, 19(2), 333–345.https://doi.org/10.21511/ppm.19(2).2021.27

Power, M. (1997). The audit society: Rituals of verification. Oxford University Press.

Qader, K.S., & Cek, K. (2024). Influence of blockchain and artificial intelligence on audit quality: Evidence from Turkey. Heliyon, 10(9), e30166.https://doi.org/10.1016/j.heliyon.2024.e30166

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. Academy of Management Review, 46(1), 192–210.https://doi.org/10.5465/amr.2018.0072

Saad, R. (2021). The role of artificial intelligence techniques in achieving audit quality. [Journal name missing], 25(5).

Schiff, D.S., Kelley, S., & Camacho Ibáñez, J. (2024). The emergence of artificial intelligence ethics auditing. Big Data & Society, 11(4), 20539517241299732.https://doi.org/10.1177/20539517241299732

Seethamraju, R., & Hecimovic, A. (2023). Adoption of artificial intelligence in auditing: An exploratory study. Australian Journal of Management, 48(4), 780–800.https://doi.org/10.1177/03128962221108440

Sikka, P. (2009). Financial crisis and the silence of the auditors. Accounting, Organizations and Society, 34(6-7), 868–873

Syamsuddin, R., Indrijawati, A., & Bandang, A. (2023). Effect of competence, whistleblower, and audit probability on. International Journal of Professional Business Review, 8(4), e01525.https://doi.org/10.26668/businessreview/2023.v8i4.1525

Tan, J., Chang, S., Zheng, Y., & Chan, K. C. (2025). Effects of artificial intelligence in the modern business: Client artificial intelligence applications and audit quality. International Review of Financial Analysis, 104, 104271.https://doi.org/10.1016/j.irfa.2025.104271

Tepalagul, N., & Lin, L. (2015). Auditor independence and audit quality: A literature review. Journal of Accounting, Auditing & Finance, 30(1), 101–121.https://doi.org/10.1177/0148558X14544505

Tornatzky, L. G., & Fleischer, M. (1990). The processes of technological innovation. Lexington Books.

Torroba, M., Sánchez, J.R., López, L., & Callejón, Á. (2025). Investigating the impacting factors for audit professionals to adopt data analysis and artificial intelligence: Empirical evidence for Spain. International Journal of Accounting Information Systems, 56, 100738.https://doi.org/10.1016/j.accinf.2025.100738

van Eck, N.J., & Waltman, L. (2010). Survey software: VOSviewer, a computer program for bibliometric mapping. Scientometrics, 84(2), 523–538.https://doi.org/10.1007/s11192-009-0146-3

Wassie, F. A., & Lakatos, L. P. (2024). Artificial intelligence and the future of the internal audit function. Humanities and Social Sciences Communications, 11(1), 386.https://doi.org/10.1057/s41599-024-02905-w

Wilks, T. J., & Zimbelman, M. F. (2004). Decomposition of fraud-risk assessments and auditors' sensitivity to fraud cues. Contemporary Accounting Research, 21(3), 719–745.https://doi.org/10.1506/V3Y6-9TML-0T4T-GC4J

Yuniarti, R., Novriela, BC, & Rahmadona, F. (2021). The Effect of Audit Fees and Audit Tenure on Audit Quality. PSYCHOLOGY AND EDUCATION.

Zhang, C., Cho, S., & Vasarhelyi, M. (2022). Explainable artificial intelligence (XAI) in auditing. International Journal of Accounting Information Systems, 46, 100572.https://doi.org/10.1016/j.accinf.2022.100572

Zhao, M., Li, Y., & Lu, J. (2022). The effect of audit team's emotional intelligence on reduced audit quality behavior in audit firms: Considering the mediating effect of team trust and the moderating effect of knowledge sharing. Frontiers in Psychology, 13, 1082889.https://doi.org/10.3389/fpsyg.2022.1082889