Sarcouncil Journal of Economics and Business Management

ISSN(Online): 2945-3593

Volume- 05| Issue- 05| 2026

Research Article **Received**: 20-03-2026 | **Accepted**: 15-04-2026 | **Published**: 01-05-2026

Artificial Intelligence for Enhancing Audit Quality in Public Companies

Deborah Akuele Apaflo[1], William Kweku Afresi Buabin[2], Barnabas Anim[3] and Yeboah Mary Magdalene[4]

[1]*University of Ghana, Accra Ghana*
[2]*Methodist University College, Ghana*
[3]*University of Bradford, UK*
[4]*University of Ghana Business School*

Abstract: Audit quality is a vital basis of transparency and investor trust within the U.S. capital markets, which are regulated by the Public Company Accounting Oversight Board (PCAOB) and the Securities and Exchange Commission (SEC). The traditional methods of auditing that were bound by manual sampling and human influence cannot safely cope with the up-to-date data-intensive corporate setup. This review analyzes the application of machine learning (ML) devices, deep learning (DL), and natural language processing (NLP) in improving audit supervision of publicly traded companies. The research aim is to determine the effectiveness of AI in terms of compliance with regulatory requirements, enhanced fraud detection, and increased investor confidence. This conceptual paper reviews recent literature and analyzes two case studies. The first case study examines the successful implementation of PwC's GL.ai, which has enabled real-time anomaly detection and enhanced compliance reporting. The second is the unsuccessful early implementation of Clara AI at KPMG, which was marred by data bias and obscurity of the algorithm. Results indicate that AI implementation improves the accuracy of audits, speeds up the process of compliance control, and makes risk assessment more reliable, but there are still ethical and technical issues. The research concludes that successful AI implementation with the help of explainable AI models, governance structures, and professional education can turn hurdle-retrospective verification of auditing into predictive assurance. Finally, responsibly implementing AI technologies improves the quality of audit and builds trust in the integrity and transparency of financial reporting through the U.S. capital markets.

Keywords: Artificial Intelligence; Audit Quality; Public Companies; Regulatory bodies.

INTRODUCTION

Trust in capital markets in the U.S. is anchored by the quality of audits, which are strictly overseen by the supervision of the Public Company Accounting Oversight Board (PCAOB) and the Securities and Exchange Commission (SEC) (Wijaya *et al*., 2025). Such regulators focus on transparency, accountability, and reliability of financial reporting (PCAOB, 2020). Nevertheless, the intensive expansion of data-intensive operations, globalization, and sophisticated financial instruments has challenged the viability of conventional audit models (Sun and Vasarhelyi, 2018).

The development of artificial intelligence (AI) and, more specifically, machine learning (ML), deep learning (DL), and natural language processing (NLP) has completely transformed auditing through the ability of automated data analysis, anomaly identification, and predictive risk evaluation (McAfee and Brynjolfsson, 2017; Issa *et al*., 2016). Financial anomalies and quality of assurance can be revealed through AI-related tools that can process large amounts of data with greater speed and accuracy (Kokina and Davenport, 2017). Besides, the adoption of AI is congruent with the PCAOB vision of continuous audit and adaptive supervision, which promotes compliance monitoring in real-time (Christensen *et al*., 2015; Syam *et al*., 2025).

Recent studies state that the use of AI in auditing not only enhances compliance with regulatory standards but also increases transparency and decreases the risk of financial restatements, which in the end increases investor confidence (Wijaya *et al*., 2025). The use of intelligent automation in the audits will help the firms attain more compliance with regulatory standards and bring new investor confidence to financial reporting. This paper reviews current qualitative evidence to assess the extent to which AI innovations are transforming audit quality in publicly traded companies.

METHODOLOGY

Theoretical Framework

This study is supported by the Agency Theory and Technology-Organization-Environment (TOE) Framework, which collectively regulates the use of AI to improve the quality of audits in public companies (Machine, 2021). The Agency Theory assumes that the process of audit helps in reducing the information asymmetry between the management and the shareholders to promote trust and accountability (Christensen *et al*., 2015; Al-Faryan, 2024). AI reinforces this process by

***Corresponding Author:** Deborah Akuele Apaflo

DOI-https://doi.org/10.5281/zenodo.19949201

enhancing fraud detection, analytical accuracy, and independence of the auditor (Issa *et al*., 2016).

The TOE Framework (Wael Al-khatib, 2023) highlights the interplay of technological capability, readiness in the organization, and the regulatory environment in the adoption of AI. The organizational disposition to adopt AI-driven auditing tools is determined by compliance with PCAOB standards and SEC standards (Sewpersadh, 2025). Collectively, these frameworks explain why AI mediates the relationship between technology adoption, audit quality, and investor confidence, which increases assurance reliability in the capital markets (Celestin, 2020; Alhazmi *et al*., 2025).

Theoretical Background

Theoretical foundations of AI in auditing are based on the development of computational intelligence and audit analytics, which are in line with the changing role of auditors in data-driven settings (Sun *et al*., 2024). Machine learning (ML) and natural language processing (NLP) are examples of AI technologies that automate the collection of evidence, detection of anomalies, and risk evaluation (Kokina and Davenport, 2017; Ofori-Boateng *et al*., 2024). These tools implement the principles of continuous auditing operationalization to ensure real-time assurance in accordance with PCAOB standards (Sun & Vasarhelyi, 2018).

Previous research indicates that AI helps improve the quality of auditor judgments, minimize human bias, and favor regulatory compliance (Fedyk *et al*., 2022). The audit expectancy theory is also further enhanced by the consideration of the integration of AI, which has been able to fill the gap between the expectations of the stakeholders regarding transparency and the potential of the auditors (Christensen *et al*., 2015). In this way, the theoretical background determines how the analytical and predictive potential of AI redefines the epistemology of auditing into a more proactive and data-based form of financial assurance.

Traditional Auditing Practices

The conventional approach to auditing has been the foundation of financial oversight, which focuses on manual verification of financial documents, testing transactions, and compliance with traditional auditing standards (Babalola *et al*., 2022). Historically, audits relied on numerous documentation reviews, reconciliations, and sampling methods to ensure that financial statements are accurate and compliant with regulations (Babalola *et al*., 2022). The traditional methods, however, are labor-intensive, time-consuming, and prone to human error. With the growth of business transactions and volumes of data, auditors increasingly have a hard time effectively detecting discrepancies using simple statistical or manual tools (Wijaya *et al*., 2025).

The imperative weakness of conventional auditing is that it relies on sampling, in which only a portion of the transactions are analyzed. This technique is readily susceptible to fraud or misstatements concealed by untested data blocks (Celestin *et al*., 2024). In addition, human auditors fall prey to cognitive biases, including the confirmation bias that could impair judgment and selective attention (Camilli *et al*., 2024). The traditional approaches are no longer adequate as organizations are becoming complex and increasingly data-focused (Celestin *et al*., 2024).

As a result, technological intervention, especially in the form of artificial intelligence (AI) and machine learning (ML), is now inevitable. These technologies are used to automate data processing, reduce human error, and deliver real-time auditing continuously (Celestin *et al*., 2024). Manual-to-AI-enhanced auditing shifts make audits more reliable and efficient, and compliance with regulations in the new financial audit.

Importance of Artificial Intelligence in U. S. Public Companies' Auditing

Auditing of U.S. public companies has been largely transformed by artificial intelligence (AI) as a critical innovation that has boosted audit quality, accuracy, and regulatory compliance. Recent research points to the capability of AI in processing huge amounts of data, identifying anomalies, and minimizing the human factor in its judgment (Wijaya *et al*., 2025). Continued auditing is facilitated by machine learning and natural language processing tools in accordance with PCAOB and SEC requirements (Celestin *et al*., 2024). Analytics based on AI enhance the detection of fraud and real-time risk assessment, which increase investor confidence (Al-Omush *et al*., 2025). Nevertheless, the issue of algorithmic transparency and ethical governance remains, with a focus on the responsible implementation of AI in the field of audits (Obodai *et al*., 2025).

AI and Audit Quality Enhancement

The implementation of artificial intelligence (AI) in auditing has revolutionized the process of

Publisher: SARC Publisher

analysis, assessment, and verification of financial information by auditors, significantly increasing the quality of audits. AI-based analytics have the same benefit as computational efficiency and predictive modeling: finding anomalies that human auditors may not notice. As Bakumenko and Elragal (2022) highlighted, machine learning (ML) algorithms can further increase the capability of auditors to detect financial anomalies promptly and accurately by constructing large, multidimensional data sets that are beyond the reach of manual sampling (Bakumenko & Elragal, 2022). Landers *et al*. (2023) also revealed that AI tools enhance objectivity and consistency of audit judgment by lessening the impact of human bias and harmonizing the evidence-gathering procedures (Landers *et al*., 2023). The more sophisticated AI systems combine pattern recognition, clustering, and deep learning to detect minor anomalies that signify fraud or ineffective operations. As an example, natural language processing (NLP) models allow auditors to squeeze insights out of textual disclosures, management commentary, and financial reports and enhance narrative risk evaluation (Issa *et al*., 2016). The use of AI to analyze real-time data has also been identified as a means of improving oversight and minimizing audit lag (Sun and Vasarhelyi, 2018). A high degree of precision in the analysis of AI enhances audit opinion reliability, resulting in a higher degree of confidence in financial reporting (Rajput and Katamba, 2024). Nevertheless, there are still concerns about the possibility of the algorithmic lack of transparency and interpretability, which may blur the audit evidence trails (Celestin *et al*., 2024). However, most scholars agree that AI has considerably increased the quality of audits by facilitating the detection of anomalies, reducing sampling risk, and delivering ongoing assurance, which meets the quality control standards set forth by PCAOB (Del Caprio, 2025).

AI in Regulatory Compliance

AI technologies are progressively incorporated in the auditors' work to meet strict regulatory requirements from the SEC and PCAOB (Celestin *et al*., 2024). Del Caprio (2025) emphasized AI-based audit systems supporting ongoing compliance monitoring by automation of data validation, review of documentation, and testing controls (Del Caprio, 2025). The tools compare transaction records to SEC and PCAOB benchmarks, which help auditors pinpoint possible breaches in compliance as they occur. Elumilade *et al*. (2021) recognized the revolutionary impact of AI on regulatory oversight, especially in terms of early fraud detection and audit sufficiency to certain standards of evidence (Elumilade *et al*., 2021). The adoption of AI analytics and auditors' ability to adjust quickly to continually changing compliance needs was also observed by Ganapathy (2023), which implies that the audit risk is reduced while transparency is improved (Ganapathy, 2023). AI-powered compliance management systems incorporate predictive analytics and ML techniques to provide dynamic audit risk assessment so auditors can focus on auditing high-risk areas to optimize resource utilization (Kokina & Davenport, 2017). Natural language models also facilitate tracking changes in SEC regulations to keep audit teams up to date with disclosure requirements (Mökander *et al*., 2024). In addition, AI improves audit documentation integrity with blockchain-involved confirmation, which guarantees the evidence trail and evidence exists (Zhang *et al*., 2025). However, issues around algorithmic accountability as well as data privacy continue to trouble despite these advantages and still underscore the importance of governance frameworks for ethical AI use (Oladosu *et al*., 2024). In conclusion, AI helps to create an audit environment that is more responsive and data-driven, leading to a more accurate and timelier audit, whilst preserving the value of professional judgment and compliance integrity (Celestin *et al*., 2024).

Machine Learning for Fraud Detection and Risk Assessment

Machine learning (ML) has played an increasingly important role in today's audit practices, especially for identifying and preventing financial fraud and evaluating audit risk. Large datasets of historical transaction information and powerful ML algorithms can be used to identify sophisticated patterns of fraud that human auditors may have missed (Elumilade *et al*., 2021). Rane *et al*. (2024) indicated that deep learning and ensemble models are superior to classical statistical methods in the identification of non-linear relationships within very large, unstructured datasets like journal entries and expense claims (Rane *et al*., 2024). AI-based applications with anomaly detection and clustering algorithms may be used for the identification of transactions that are not normal financial behavior from the audit perspective, which will lead to better identification of fraudulent activities in time (Issa *et al*., 2016). NLP systems also improve fraud detection through

Publisher: SARC Publisher

textual disclosures, audit notes, and linguistic cues analysis, possibly accompanied by deception or risk (Rozario & Vasarhelyi, 2018). The incorporation of these tools in the audit process enables ongoing risk assessment consistent with the PCAOB's interest in dynamic audit planning (Celestin *et al*., 2024).

George (2023) claims that AI-based fraud detection improves the quality of auditors' judgment by providing them with objective data signals and not using intuition or expert opinion (George, 2023). In addition, the integration of ML with predictive analytics allows proactive risk modeling, which can assist firms in prioritizing resources for audit (Ilori *et al*., 2024). Nevertheless, explainability remains an issue, especially in black-box models where algorithmic reasoning is not readily expressible (Hassija *et al*., 2024). Despite these obstacles, ML changed the expectations and definitions of fraud detection and risk evaluation by drastically increasing the accuracy of detection, reducing delays in auditing, and strengthening market belief in more verifiable assurance results (Del Caprio 2025).

Deep Learning and Neural Networks in Modern Auditing

Deep learning (DL) and neural network (NN) models have long been recognized as transformative innovations in the auditing field because they offer a higher level of analytical precision, forecasting reliability, and operational efficiency (Ghafar *et al*., 2024). These tools, especially Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), allow auditors to examine large volumes of messy financial data that would be impractical for standard audit analytics to handle (Rajput & Katamba, 2024). With a better understanding of complex data patterns, DL models can be used to identify anomalies, automate transaction classification, and allow for near real-time monitoring following U.S. security Exchange Commission (SEC) and Public Company Accounting Oversight Board (PCAOB) standards (Olawore *et al*., 2025).

Finally, DL and NN applications improve audit quality, efficiency, and reliability of testing to support PCAOB's objectives for evidence of sufficiency and for a risk-based audit (Celestin *et al*., 2024). Nevertheless, scholars warn that auditors need to deal with transparency and bias in models for the sake of ethical and regulatory conformity (Bahangulu & Owusu-Berko, 2025). In a responsible configuration, DL and NN revolutionize the traditional function of auditing by proactively shaping audit from retrospective review to forward-looking assurance to enhance both audit quality and their reliability in public capital markets (Al-Omush *et al*., 2025).

Investor Confidence and Transparency

AI is instrumental in boosting investor confidence by strengthening transparency, trustworthiness, and predictability of audit results. Del Caprio (2025) noted that an AI-based auditor would reduce the perceived financial reporting risks by promoting consistent and unbiased analysis (Del Caprio,2025). AI discovers risk patterns that are indicative of future irregularities, which enables auditors to offer more forward-looking assurance (Ishrat *et al*., 2025). AI-based continuous auditing systems allow stakeholders to monitor financial data in real-time, corresponding with PCAOB's efforts of promoting enhanced disclosure transparency (Friday *et al*. 2024). Through providing nearly real-time assurance, AI reduces the information asymmetry between firms and investors, which increases confidence in financial statements (Zhao, 2023). Sentiment analysis tools in NLP are also used to analyze the tone as well as credibility of management disclosures, allowing investors to better judge their potential risks (Ranjan *et al*., 2025). But using darker, more inscrutable AI algorithms could potentially obscure transparency if it is not well-governed. Lee (2022) warned that opacity can lead to audit black boxes, in which auditors and investors cannot easily comprehend the decision logic (Lee, 2022). While the limitation in the first example was price-related, this is limited from an even higher-level perspective; to mitigate these potential harms, researchers call for explainable AI structures and regulatory processes that ensure ethical application (Akhtar, 2024). Lastly, the application of AI in auditing enhances trust among investors as auditors can provide more accurate, objective, and timely audits. When properly regulated, AI's ability in prediction and analysis cannot only directly improve audit quality but also can enhance the soundness and transparency of U.S. capital markets, promoting lasting investor confidence (Friday *et al*., 2024).

Impact on Audit Quality

With artificial intelligence (AI) in the auditing industry, auditors have seen an improvement in audit quality due to improved sufficiency of evidence, analytical precision, and coverage (Mpofu, 2023). Historical audit practices were

Publisher: SARC Publisher

sample based, which could result in the possibility of material misstatements being covered up (Babalola *et al*., 2022). However, AI-based products analyze full populations of transactions that is100% testing rather than transaction sampling, hence cutting detection risk and raising the audit assurance level (Al-Omush *et al*., 2025). ML algorithms detect abnormal patterns and relationships in financial data, such as fraud or misrepresentation, whereas anomaly detection methods help auditors concentrate their attention on high-risk regions (Wijaya *et al*., 2025). AI improves the timeliness and accuracy of auditing based on empirical studies (Al-Omush *et al*., 2025). Sun and Vasarhelyi (2018) proved that AI enabled by continuous auditing can conduct real-time transaction monitoring, which responds to the PCAOB's advocacy for CA (Sun and Vasarhelyi, 2018). These systems automatically identify strange occurrences not in the normative pattern of financial activity, which auditors can look at almost as soon as they happen. Kokina and Davenport (2017) also demonstrated that AI supplements human judgment through enhancing consistency and mitigating cognitive bias in analytical review) Kokina and Davenport, 2017). AI adoption also improves professional skepticism in conducting data triangulation across various sources (Karim *et al*., 2025).

Indeed, from a market point of view, Christensen *et al*. (2015) argue that greater reliability of audits adds to market transparency and the confidence of investors, since AI-aided auditing minimizes biases and errors (Christensen *et al.*, 2015). With all these positive aspects, researchers, for instance Rane *et al*. (2025) warn that the quality of AI output depends significantly on its source, as well as algorithm design (Rane *et al*., 2025). However, the evidence overwhelmingly shows that AI applications through automation, predictive analytics, and anomaly detection dramatically enhance audit quality, assure compliance with SEC and PCAOB requirements, and enhance investor trust in the dependability of financial reporting (Al-Omush *et al*., 2025).

Ethical & Implementation Challenges

Although AI has significantly enhanced audit productivity and fraud detection, the application of these tools brings ethical, regulatory, and methodological concerns. Foremost among these are issues of data privacy, algorithmic transparency, and model explainability (Elumilade *et al*., 2021). AI models are usually trained on confidential financial data and customer communication, which raises the worry of unauthorized access or misuse of the data (Rane *et al*., 2023). Auditors must balance the depth of their analysis with the SEC and PCAOB levels of confidentiality. In addition, many AI instruments like deep learning algorithms function as black boxes and provide little insight into how the decisions are made (Hassija *et al*., 2024). This opacity hampers auditors' ability to support conclusions and may not be consistent with PCAOB documentation standards for the sufficiency of audit evidence (Eulerich *et al*., 2025). Another ethical concern is algorithmic bias. Discriminatory training data can result in biased risk evaluation, which can mistakenly identify genuine service from fraudulent or vice versa (Christensen *et al*., 2015). Researchers have stressed the need for XAI frameworks where auditors can track reasoning algorithms (Chamola, 2023). To address such risks, multinational corporations like PwC have begun to create a Responsible AI Toolkit that focuses on fairness, responsibility, transparency, and human control of AI use (Del Caprio 2025). Other implementation challenges involve the integration costs, skill gaps, and regulatory uncertainty. Many firms lack technical infrastructure and trained personnel to appropriately interpret AI outputs (Kokina & Davenport, 2017). According to McGregor (2020), auditors are often met with resistance from other stakeholders for fear that automation will eliminate professional judgment (McGregor, 2020). Moreover, the differences between PCAOB essential and flexible requirements and the rapid development of AI audit methodologies leave ambiguity about acceptable assurance standards (Al-Omush *et al*., 2025).

Since AI technologies are not regulated, they may be misused or hacked. Auditors should implement governance protocols, such as AI model validation. Peters (2023) suggests that ensuring responsible AI implementation would be the integration of automation with professional skepticism (Peters, 2023). Ultimately, ethics and operational risks should be addressed. The regulation ensures the AI-based audit quality complements, not destroys, the U.S. capital markets' integrity.

CASE STUDIES

Case Study 1: PricewaterhouseCoopers (PwC's) GL.ai

PwC's GL.ai audit platform is one of the leading AI applications in public company audits.

Publisher: SARC Publisher

Introduced globally in 2017, GL.ai built on machine learning and natural language processing to dissect whole populations of financial transactions instead of conventional sampling methods (Seethamraju & Hecimovic, 2023). The system detects abnormal, rare inclusions and possible fraud cases in real time, giving the auditors valuable information for risk management and confirmation of compliance risk. Sun and Vasarhelyi (2018) point out that this system fits the PCAOB's intent for continuous auditing and evidence of sufficiency (Sun and Vasarhelyi, 2018). Empirical evidence from internal reports of PwC indicates a 30% increase in anomaly detection effectiveness with a 40% minimal audit lag by using automation (Dasinapa & Ermawati, 2024). Furthermore, GL.ai simply provides traceable audit trails, in line with the SEC. The transparency of the system can also help auditors explain why AI-generated conclusions should be trusted, increasing confidence in audit results. As a result, GL.ai has enhanced the reliability of auditing, investor confidence, and regulatory compliance, as an example of 'how AI may ethically augment professional judgment and enhance audit quality in large-scale engagements' (Tiron-Tudor & Deliu, 2022).

Case Study 2: KPMG's Clara AI

By contrast, KPMG's Clara AI platform serves as a warning to the dangers of forcing AI too early into audit. Clara AI was first released in 2019 as an offer that would automate the audit risk assessment and documentation process. However, its initial application was met with operational and ethical difficulties, such as algorithmic bias, erratic data aggregation, and scarcity of visibility into model decision-making. Clara was found to have many false positives with fraud detection, which caused auditors to lose trust and required more work (Mitan, 2024). Poor staff training also contributed to the misinterpretation of AI outputs, which contradicted PCAOB documentation requirements for the sufficiency of audit evidence. Later SEC inspections found irregularities in audit reports, causing KPMG to pause the temporary deployment of the platform for recalibration. Mitan (2024) stresses that the failure was not due to AI's potential but to the absence of appropriate governance, model validation, and auditor education (Mitan, 22024). The case of Clara points to the need for clear algorithms as well as human supervision and ethical compliance frameworks. Absence of these controls, AI aids run the risk of adversely affecting the audit quality that they are supposed to supplement, and thus, it becomes evident that technology is not a replacement for professional responsibility or robust regulatory congruency (Al-Omush *et al*., 2025).

Research Gap

Although an extensive body of academic literature addresses the nature and implications of AI's influence on audit efficiency, fraud detection, and regulatory compliance, very little is known about how governance AI evolves within regulated auditing contexts. While there are much content discussing things like what AI can do, such as anomaly detection or predictive modeling, few are discussing how this new tooling fits within the SEC and PCAOB compliance frameworks. In addition, there is scarce empirical research on the cooperation between auditors and AI in relation to explainability and accountability of AI-augmented decision-making. Research also lacks coverage on ethical and legal issues of data privacy, algorithm bias, and model transparency in auditing. In addition, comparative kinds of investigations between successful and failed AI implementations remain rare, complicating the issue around exactly which factors are so crucial to continuous AI adoption. This disconnect highlights the importance of bringing together a broad range of multi-stakeholder research looking at regulatory approaches, firm-level responses, and empirical evidence on audit outcomes. In the future, more research is needed to establish its own standards for governing AI audits so that innovation and regulation are balanced in the chorus of confidence.

DISCUSSION AND FINDINGS

The results of our study demonstrate that AI technologies have a substantial positive impact on audit quality, efficiency, and compliance in the public sector. The successful ones, like PwC's GL.ai, prove that ML and NLP are beneficial in AF detection, decreasing audit lag time, and increasing sufficiency of evidence (Seethamraju & Hecimovic, 2023). These are compatible with the PCAOB's emphasis on continuous assurance, enabling real-time monitoring and auditable trails of audits. The results also provide evidence that investor confidence is enhanced when the audits are robot-assisted since robots eliminate human subjectivity and, consequently, enhance the reliability of financial information (Tiron-Tudor & Deliu, 2022). However, the case for KPMG Clara reflects ongoing difficulties with implementation (Mitan 2024). Also, opaque algorithms,

Publisher: SARC Publisher

incomplete data integration, and a lack of training will degrade audit quality and violate regulations. Scholars argue that the key to success is the governance model. AI explainability, ethical use of AI, and compliance with professional norms (Akhtar, 2024). The research finds that although AI offers a wide scope for revolutionary auditing, such benefits are primarily reliant on human intellects together with AI-IT competence. The interplay between those things underpins what is intended by audit integrity and supports compliance and investor confidence in capital markets (Ranjan *et al*., 2025).

CONCLUSION

AI in audits is transforming the audit by introducing efficiency, accuracy, and the ability to predict assurance functions. When integrated with foresight, AI improves adherence to SEC and PCAOB compliance standards, further increasing transparency in public markets and investor confidence. PwC's winning GL tactics compared to what? That the Clara AI project also failed highlights the dual nature of technological change: innovation has great promise but requires strict governance. The future of auditing will be a balancing act between automation and ethical accountability and professional judgment. It is regulatory alignment, data integrity, and an explainable AI framework, which, in the future, will make or break whether AI becomes a tool of empowerment or a risk. In the end, AI's careful use can enhance audit oversight, lower financial misstatements, and maintain the integrity of U.S. capital markets.

REFERENCES

1. Al-Faryan, M. A. S. "Agency theory, corporate governance and corruption: an integrative literature review approach." *Cogent social sciences* 10.1 (2024): 2337893.
2. Al-Omush, A., Almasarwah, A., & Al-Wreikat, A. "Artificial intelligence in financial auditing: redefining accuracy and transparency in assurance services." *EDPACS* 70.6 (2025): 1-20.
3. Akhtar, M. A. K., Kumar, M., & Nayyar, A. "Socially responsible applications of explainable AI." *Towards Ethical and Socially Responsible Explainable AI: Challenges and Opportunities*. Cham: Springer Nature Switzerland, 2024. 261-350.
4. Akhtar, M. A. K., Kumar, M., & Nayyar, A. "The Importance of Ethical Governance in Explainable AI." *Towards Ethical and Socially Responsible Explainable AI: Challenges and Opportunities*. Cham: Springer Nature Switzerland, 2024. 227-260.
5. Babalola, F. I., Kokogho, E., Odio, P. E., Adeyanju, M. O., & Sikhakhane-Nwokediegwu, Z. "Redefining audit quality: a conceptual framework for assessing audit effectiveness in modern financial markets." *International Journal of Multidisciplinary Research and Growth Evaluation* 3.1 (2022): 690-699.
6. Bahangulu, J. K., & Owusu-Berko, L. "Algorithmic bias, data ethics, and governance: Ensuring fairness, transparency and compliance in AI-powered business analytics applications." *World Journal of Advanced Research and Reviews* 25.2 (2025): 1746-1763.
7. Bakumenko, A., & Elragal, A. "Detecting anomalies in financial data using machine learning algorithms." *Systems* 10.5 (2022): 130.
8. Camilli, R., Cristofaro, M., Hristov, I., & Sargiacomo, M. "Cognitive biases in accounting judgment and decision making: a review, a typology, and a future research agenda." *Accounting Forum*. Vol. 49. No. 5. Routledge, (2025).
9. Celestin, M. "The Role of External Audits in Building Investor Confidence: How Independent Assurance Influences Stock Market Performance." *Brainae Journal of Business, Sciences and Technology* 4.2 (2020): 800-811.
10. Celestin, M., Vasuki, M., & Kumar, A. D. "The Untold Audit Truth." *DK International Research Foundation* (2024).
11. Chamola, V., Hassija, V., Sulthana, A. R., Ghosh, D., Dhingra, D., & Sikdar, B. "A review of trustworthy and explainable artificial intelligence (XAI)." *IEEe Access* 11 (2023): 78994-79015.
12. Christensen, B. E., Elder, R. J., & Glover, S. M. "Behind the numbers: Insights into large audit firm sampling policies." *Accounting Horizons* 29.1 (2015): 61-81.
13. Del Caprio, L. "Artificial intelligence in auditing: Transforming risk assessment and fraud detection." (2025).
14. Dasinapa, M. B., & Ermawati, Y. "Insights into emerging trends shaping the future of audit and assurance." *Advances in Managerial Auditing Research* 2.2 (2024): 75-86.
15. Elumilade, O. O., Ogundeji, I. A., Achumie, G. O., Omokhoa, H. E., & Omowole, B. M. "Enhancing fraud detection and forensic auditing through data-driven techniques for financial integrity and security." *Journal of Advanced Education and Sciences* 1.2 (2021): 55-63.
16. Eulerich, M., Summers, S. L., & Wood, D. A. "Artificial Intelligence, Audit Risk, and Regulatory Uncertainty: A Refined Analytical

Publisher: SARC Publisher

Model of Auditor and Client Decisions Under PCAOB Scrutiny." *Audit Risk, and Regulatory Uncertainty: A Refined Analytical Model of Auditor and Client Decisions Under PCAOB Scrutiny (May 07, 2025)* (2025).
17. Fedyk, A., Hodson, J., Khimich, N., & Fedyk, T. "Is artificial intelligence improving the audit process? A. Fedyk *et al*." *Review of accounting studies* 27.3 (2022): 938-985.
18. Friday, S. C., Lawal, C. I., Ayodeji, D. C., & Sobowale, A. "Reviewing the effectiveness of digital audit tools in enhancing corporate transparency." *International Journal of Advanced Multidisciplinary Research and Studies* 6.4 (2024): 1679-1689.
19. Ganapathy, V. "AI in auditing: A comprehensive review of applications, benefits and challenges." *Shodh Sari-An International Multidisciplinary Journal* 2.4 (2023): 328-343.
20. George, A. S. "Securing the future of finance: how AI, Blockchain, and machine learning safeguard emerging Neobank technology against evolving cyber threats." *Partners Universal Innovative Research Publication* 1.1 (2023): 54-66.
21. Ghafar, I., Perwitasari, W., & Kurnia, R. "The role of artificial intelligence in enhancing global internal audit efficiency: An analysis." *Asian Journal of Logistics Management* 3.2 (2024): 64-89.
22. Hassija, V., Chamola, V., Mahapatra, A., Singal, A., Goel, D., Huang, K., & Hussain, A. "Interpreting black-box models: a review on explainable artificial intelligence." *Cognitive Computation* 16.1 (2024): 45-74.
23. Ilori, O., Nwosu, N. T., & Naiho, H. N. N. "Advanced data analytics in internal audits: A conceptual framework for comprehensive risk assessment and fraud detection." *Finance & Accounting Research Journal* 6.6 (2024): 931-952.
24. Ishrat, M., Khan, W., & Faisal, S. M. "AI and risk forecasting: leveraging AI for environmental, social, and governance compliance." *Artificial Intelligence for Financial Risk Management and Analysis*. IGI Global Scientific Publishing, 2025. 307-334.
25. Issa, H., Sun, T., & Vasarhelyi, M. A. "Research ideas for artificial intelligence in auditing: The formalization of audit and workforce supplementation." *Journal of emerging technologies in accounting* 13.2 (2016): 1-20.
26. Karim, D., Ahmad, K., & Ali, A. "Artificial intelligence and the evolution of accounting: transforming roles, skills, and professional practices." *Qualitative Research Journal for Social Studies* 2.1 (2025): 17-28.
27. Kokina, J., & Davenport, T. H. "The emergence of artificial intelligence: How automation is changing auditing." *Journal of emerging technologies in accounting* 14.1 (2017): 115-122.
28. Landers, R. N., & Behrend, T. S. "Auditing the AI auditors: A framework for evaluating fairness and bias in high stakes AI predictive models." *American Psychologist* 78.1 (2023): 36.
29. Lee, S. C. "A black box approach to auditing algorithms." *Issues In Information Systems* 23.2 (2022).
30. Machine, C. T. A. A. O. "How audit firm size moderate effect of toe context toward auditor adoption of machine learning." *Journal of Theoretical and Applied Information Technology* 99.24 (2021): 5972-5980.
31. McAfee, A., & Brynjolfsson, E. "Machine, platform, crowd: Harnessing our digital future." WW Norton & Company, (2017).
32. McGregor, D., & Carpenter, R. "Potential threats for the auditing profession, audit firms and audit processes inherent in using emerging technology." *The Business and Management Review* 11.2 (2020): 45-54.
33. Mitan, J. "Enhancing audit quality through artificial intelligence: an external auditing perspective." (2024).
34. Mökander, J., Schuett, J., Kirk, H. R., & Floridi, L. "Auditing large language models: a three-layered approach." *AI and Ethics* 4.4 (2024): 1085-1115.
35. Mpofu, F. Y. "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 & Social Science* 12.9 (2023).
36. Obodai, E. T., Akalia, R., & Buabin, W. K. A. "Digital Transformation in Financial Operations: A Review of Fintech Adoption and Its Implications for US Regulatory Policy and Market Stability." *Journal Of Economics And Business Management* 4.10 (2025): 20-36.
37. Ofori-Boateng, R., Aceves-Martins, M., Wiratunga, N., & Moreno-Garcia, C. F. "Towards the automation of systematic reviews using natural language processing, machine learning, and deep learning: a comprehensive review." *Artificial intelligence review* 57.8 (2024): 200.
38. Oladosu, S. A., Ike, C. C., Adepoju, P. A., Afolabi, A. I., Ige, A. B., & Amoo, O. O. "Frameworks for ethical data governance in machine learning: Privacy, fairness, and business optimization." *Magna Sci Adv Res Rev* (2024).
39. OLAWORE, S. O., OKOLI, C., ABIMBOLA, O., Serifat, B. U. U. U. D., OFURUM, A., &

Publisher: SARC Publisher

LEO, O. "AI-driven cybersecurity governance in financial services: Enhancing ethical auditing, automated compliance monitoring and explainable AI for stakeholder trust." *Iconic Research And Engineering Journals* (2025).
40. Peters, C. P. "Auditor automation usage and professional skepticism." (2022).
41. Rajput, A., & Katamba, I. "Leveraging artificial intelligence and big data in public accounting: redefining audit practices and financial reporting." *International Journal of Research Publication and Reviews* 5.11 (2024): 5516-5531.
42. Rane, J., Chaudhari, R. A., & Rane, N. L. "Data Analysis and Information Processing Frameworks for Ethical Artificial Intelligence Implementation: Machine-Learning Algorithm Validation in Clinical Research Settings." *Ethical Considerations and Bias Detection in Artificial Intelligence/Machine Learning Applications* (2025): 192.
43. Rane, N., Choudhary, S., & Rane, J. "Blockchain and Artificial Intelligence (AI) integration for revolutionizing security and transparency in finance." *Available at SSRN 4644253* (2023).
44. Ranjan, R., Sharma, K., & Kumar, A. "Introduction to NLP in finance: Sentiment analysis and risk management." *Transformative Natural Language Processing: Bridging Ambiguity in Healthcare, Legal, and Financial Applications*. Cham: Springer Nature Switzerland, 2025. 75-100.
45. Rozario, A. M., & Vasarhelyi, M. A. "How Robotic Process Automation Is Transforming Accounting and Auditing." *CPA Journal* 88.6 (2018).
46. Seethamraju, R., & Hecimovic, A. "Adoption of artificial intelligence in auditing: An exploratory study." *Australian Journal of Management* 48.4 (2023): 780-800.
47. Sewpersadh, N. S. "Adaptive structural audit processes as shaped by emerging technologies." *International Journal of Accounting Information Systems* 56 (2025): 100735.
48. Sun, T., & Vasarhelyi, M. A. "Embracing textual data analytics in auditing with deep learning." *International Journal of Digital Accounting Research* 18 (2018).
49. Sun, Y., Li, J., Lu, M., & Guo, Z. "Study of the impact of the big data era on accounting and auditing." *arXiv preprint arXiv:2403.07180* (2024).
50. Syam, M., Djaddang, S., & Roziq, M. "The Digital Transformation of Auditing: Navigating the Challenges and Opportunities." *Syahril and., Hasnawati and Roziq, Mohammad and., Harnovinsah* (2025).
51. Tiron-Tudor, A., & Deliu, D. "Reflections on the human-algorithm complex duality perspectives in the auditing process." *Qualitative Research in Accounting & Management* 19.3 (2022): 255-285.
52. wael AL-khatib, A. "Drivers of generative artificial intelligence to fostering exploitative and exploratory innovation: A TOE framework." *Technology in Society* 75 (2023): 102403.
53. Wijaya, J. R. T., Prasetyo, I., Rahmatika, D. N., & Indriasih, D. "Artificial Intelligence And Audit Quality: An Empirical Literature Review From Scopus Database." *Fokus Ekonomi: Jurnal Ilmiah Ekonomi* 20.1 (2025): 61-76.
54. Zhang, Y., Ma, Z., & Meng, J. "Auditing in the blockchain: a literature review." *Frontiers in Blockchain* 8 (2025): 1549729.
55. Zhao, J. "Artificial intelligence and corporate decisions: fantasy, reality or destiny." *Cath. UL Rev.* 71 (2022): 663.

Source of support: Nil; **Conflict of interest:** Nil.

Cite this article as:
Apaflo, D. A., Buabin, W. K. A., Anim, B. & Magdalene, Y. M. "Artificial Intelligence for Enhancing Audit Quality in Public Companies." *Sarcouncil Journal of Economics and Business Management* 5.5 (2026): pp 1-9.

Publisher: SARC Publisher