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Artificial Intelligence and the Enhancement of Audit Quality: An Empirical Investigation

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Abstract

The rapid evolution of information technologies has positioned artificial intelligence (AI) as a key element of the sustainable revolution in the fields of accounting and auditing. This research aims to study the effect of AI integration on audit quality and to understand how company-specific characteristics influence the efficiency of its integration. Using a quantitative approach based on panel data regression, the study focuses on 60 observations of company-years from 2017 to 2022. Validated indicators are used to assess audit quality, and company-specific characteristics are considered as control and moderation variables. The findings indicate that the use of AI significantly enhances the value of audits by improving the detection of irregularities and fraud, minimizing human error, facilitating sophisticated data analysis, and increasing the efficiency and accuracy of audit procedures. Furthermore, company-specific attributes mitigate the impact of AI, highlighting the need for an organizational framework to fully realize its benefits. This research enriches the literature on artificial intelligence in the field of auditing by providing empirical evidence of its beneficial effect on audit quality. It also highlights its practical implications for auditors, regulatory bodies, and policymakers seeking to increase the transparency, trust, and credibility of financial information systems.

Keywords: *Audit Quality, Artificial Intelligence, Financial Reporting, Information Technologies, BIG 4.*

I. INTRODUCTION

The global growth of information and communication technologies, driven by the digital transformation of businesses, has facilitated the emergence and rapid spread of artificial intelligence (AI), which is now at the heart of scientific, economic, and professional discussions. AI is generally defined as a set of systems capable of replicating human cognitive abilities such as learning, reasoning, and decision-making from large amounts of data (Russell & Norvig, 2021; Dwivedi et al., 2021). Thanks to its disruptive potential, artificial intelligence is seen as a key tool for the sustainable transformation of organizational models and professional methods, particularly in the audit and accounting sectors (Vasarhelyi et al., 2020; Appelbaum, Kogan & Vasarhelyi, 2021).

In the field of auditing, the gradual incorporation of AI technologies is justified by the increasing complexity of accounting information systems, the massive digitization of transactions, and the growing risks of financial fraud. Recent cases of financial misconduct and the rise in accounting falsifications have increased the demands of stakeholders regarding the credibility of financial information and the effectiveness of control mechanisms (ACFE, 2022; IAASB, 2023). In this context, auditors are compelled to revise their conventional approaches and embrace sophisticated AI-based analytical tools, such as machine learning, big data analytics, and expert systems (Issa, Sun & Vasarhelyi, 2016; Cao et al., 2021).

Numerous recent studies highlight how AI facilitates the automation and systematization of audit processes, leading to improved test coverage, more effective anomaly detection, and rapid identification of fraudulent patterns (Yoon, Hoogduin & Zhang, 2015; Kogan et al., 2020). Unlike sampling-based audit methods, artificial intelligence systems enable real-time analysis of all transactions, thereby reducing the risk of missed detections and enhancing the auditor's professional judgment (Tang, Karim & Ahmed, 2023). However, despite these technological advances, opinions in the literature remain divided on the true impact of AI on audit effectiveness, particularly regarding fraud detection. This underscores the need for continued empirical research in this area.

This article thus positions itself within this context by attempting to answer the question: how can artificial intelligence enhance the role of auditing in identifying financial fraud? This study specifically seeks to examine the impact of incorporating AI systems on the link between audit quality and auditors' ability to detect accounting fraud. The main objective is to determine whether integrating AI can improve audit performance and the reliability of financial information, while also helping to reduce information asymmetry between different stakeholders.

The article is organized as follows. Section II provides a synthesis of the literature and the theoretical framework used. Section III presents the research method employed. Section IV presents and examines the empirical results obtained. Finally, Section V concludes the study and suggests directions for future research.

II. LITERATURE REVIEW

➢ *Artificial Intelligence*

Artificial intelligence is a field of computer science and engineering that aims to create intelligent machines and systems capable of thinking, learning, and acting autonomously. According to CPA Canada and the American Institute of Chartered Professional Accountants (AICPA, 2020), artificial intelligence is precisely defined as "the science of training machines to perform tasks that would ordinarily require human intelligence." According to Goh et al. (2019), AI's distinctive advantage is its ability to identify patterns and make predictions that simplify decision-making. Artificial intelligence facilitates the processing and analysis of large amounts of data, the detection of trends, and the automation of decision-making processes. Organizations can leverage this tool in numerous ways to optimize data review and document consultation, thereby improving the quality of decision-making. Furthermore, AI has the capacity to produce customized reports that meet the specific requirements of each organization (Noordin et al., 2022). According to the Organisation for Economic Co-operation and Development (OECD), artificial intelligence is characterized as a machine-based system capable of anticipating, suggesting, or making decisions that influence real or virtual contexts. Artificial intelligence distinguishes itself from previous data analysis methods by its ability to represent strongly non-linear relationships in data, while handling large volumes of data and unorganized information such as text and images.

➢ *Audit Quality*

It is widely recognized that audit quality is a key element of the credibility of financial information and an essential tool for corporate governance. According to current literature, audit quality is viewed as the joint probability that auditors identify material misstatements and report them accurately, while demonstrating skeptical professionalism and independence throughout their engagement (DeAngelo, 1981; Knechel, Vanstraelen, and Zerni, 2015; Francis, 2011). In practice, this concept has evolved from a strictly technical framework to a broader, risk-focused, and judgment-based framework, reflecting the increasing complexity of business environments and financial operations (IAASB, 2020).

Recent research emphasizes that the quality of an audit is not solely linked to adherence to auditing standards such as International Standards on Auditing (ISAs), but also to the auditors' competence, professional ethics, industry specialization, workload, and independence from management (Svanström, 2020; Velte and Issa, 2023). In an environment characterized by complex financial tools, fair value accounting, and the digitalization of accounting systems, the auditor's ability to detect aggressive accounting practices, earnings manipulation, and fraud has proven essential (Lennox, Wu, and Zhang, 2022; Brown, Grenier, Pyzoha, and Reffett, 2023). Empirical data show that better audit quality is associated with lower discretionary expenses payable, more prudent financial reporting and faster loss recognition (Habib, Costa, Huang and Bhuiyan, 2021; Alzoubi, 2022).

Recent literature has highlighted the revolutionary role of digital technologies in redefining the factors and outcomes related to audit quality. The incorporation of big data analytics, artificial intelligence, blockchain, and continuous audit tools has enhanced auditors' ability to conduct real-time risk assessments and increase the rigor and reliability of evidence (Appelbaum, Kogan, and Vasarhelyi, 2018; Vasarhelyi, Kogan, and Tuttle, 2020; Kokina and Davenport, 2022). These technological advancements foster improved audit efficiency, broader transaction scope, and more accurate detection of anomalies and irregularities (Tiron-Tudor and Deliu, 2021; Yoon, Hoogduin, and Zhang, 2023).

From an economic and institutional perspective, high-quality auditing creates significant added value for financial market participants by reducing information asymmetry, strengthening investor security, and lowering companies' cost of capital (Hribar, Kravet, and Wilson, 2021; Velury, Reisch, and Omer, 2020). In developing and emerging economies, characterized by sometimes fragile governance mechanisms, audit quality is crucial for promoting market discipline and maintaining financial stability (Albring, Huang, and Pereira, 2021; Hassan, Ntim, and Ullah, 2023). Moreover, regulatory bodies are increasingly viewing the quality of auditing as a systemic element that promotes the resilience and transparency of financial systems in times of uncertainty and economic crisis (OECD, 2022).

Overall, audit quality has improved, evolving from a perspective strictly focused on technical compliance to comprehensive governance that incorporates professional judgment, technological capabilities, ethical standards, and institutional oversight. In this context, it is essential for ensuring the reliability of financial information, strengthening stakeholder confidence, and supporting the sustainable development of markets, in both developed and emerging economies.

➢ *Audit Quality and Artificial Intelligence*

Auditing is essential in a business context because it ensures the transparency and credibility of financial data. The auditing profession is intrinsically linked to technological advancements, which presents a dual challenge: understanding emerging technologies while using them appropriately.

Agency theory, which examines the relationship between shareholders and managers (agents), provides a suitable framework for assessing audit quality. Within this framework, artificial intelligence can help reduce information imbalances, alleviate conflicts within organizations, improve audit oversight, and more clearly define auditors' responsibilities.

This research draws on several complementary theories to fully understand the influence of artificial intelligence (AI) on audit quality. First, agency theory (Jensen and Meckling, 1976) illustrates the importance of auditing by considering the information imbalance and conflicting interests between shareholders and management. In this context, high-quality audits, particularly those powered by AI, are crucial tools for reducing agency costs while enhancing transparency and oversight.

Secondly, resource-based theory (Barney, 1991) views artificial intelligence technologies as valuable, scarce, unique, and indispensable resources capable of providing a sustainable competitive advantage to businesses, including audit firms. By increasing the efficiency, accuracy, and scope of audits, AI tools represent strategic advantages in the digital age.

Third, the Technology Acceptance Model (TAM) (Davis, 1989) is crucial for understanding auditors' behavioral intentions regarding the adoption of artificial intelligence tools. According to the TAM, the perceived usefulness and ease of use significantly impact auditors' adoption of AI, which in turn affects its practical application and its contribution to audit quality.

Fourth, institutional theory (DiMaggio and Powell, 1983) highlights how external constraints, coercive (regulatory), normative (professional standards), and mimetic (peer influence), shape organizational behavior. The integration of artificial intelligence into auditing can therefore be seen as a reaction to institutional constraints aimed at preserving legitimacy, conforming to technological developments, and adapting to changing regulatory requirements.

Finally, the Audit Quality Framework developed by the International Auditing and Assurance Standards Board (IAASB, 2014) identifies the key elements, inputs, processes, and outputs, that characterize high-quality audits, such as the auditor's competence, independence, and critical judgment. AI technologies can enhance these aspects by automating data evaluation, detecting anomalies in real time, and supporting the auditor's judgment through sophisticated analytics.

In summary, these theoretical models agree that AI not only complements traditional audit processes but also revolutionizes them, contributing to more efficient, transparent, and secure audits in a complex and data-rich environment.

Artificial intelligence-based tools present promising opportunities for auditors in the near future. These tools should encourage them to reassess their role and continuously adapt to new audit methods and techniques. AI systems, with their ability to rapidly process large amounts of data, combine information from different contexts, and overcome information barriers, should substantially improve the level of certainty in audit operations.

The rise of artificial intelligence is changing the audit landscape. Recent research has examined the link between audit quality and the use of artificial intelligence. Byrnes et al. (2018) studied the impact of artificial intelligence and data analytics on the financial audit process, highlighting how these technologies can improve the detection of irregularities and the quality of audits. According to the study by Kokina, Mancha, and Pachamanova (2017), advanced technologies such as AI have a significant influence on decision-making in the field of auditing and can improve the overall efficiency of audit procedures.

Richins et al. (2017) studied the application of artificial intelligence in financial auditing, illustrating how this technology improves the accuracy and reliability of audit findings. Similarly, Brown-Liburd and Vasarhelyi (2015) analyzed the role of AI tools in fraud detection and risk assessment, while Gepp et al. (2018) investigated how AI algorithms and big data processing methods can significantly enhance audit quality. They concluded that artificial intelligence improves auditors' ability to detect financial irregularities, automates repetitive tasks, and facilitates complex decision-making through algorithmic modeling.

Artificial intelligence technologies also facilitate the early detection of fraud and risk assessment. Repetitive activities such as data collection and transaction review can be automated, allowing auditors to focus on more strategic tasks requiring sharp judgment. Furthermore, artificial intelligence offers the ability to perform real-time analysis on large volumes of data, thereby increasing both the speed and accuracy of anomaly detection. Methods such as machine learning and pattern recognition help to increase audit transparency, reduce information imbalances, and enhance auditors' ability to assess risks while providing strategic advice that goes beyond mere compliance with standards.

Furthermore, AI facilitates continuous audits by providing real-time assurance for financial transactions and internal controls. This improves the relevance and responsiveness of audits. However, implementing AI also presents challenges, particularly regarding auditor training. For today's auditors, skills in artificial intelligence and innovative technologies such as blockchain are essential.

➢ *Key Benefits of AI in Auditing:*

The incorporation of artificial intelligence (AI) into auditing offers several revolutionary benefits that greatly optimize the process. First, AI increases efficiency by automating crucial processes such as data collection, cleaning, analysis, and evaluation. This reduces human error and shortens audit durations. It also enhances audit quality by utilizing cutting-edge technologies such as machine learning and natural language processing, thereby facilitating the rapid detection of irregularities and potential risks. Furthermore, artificial intelligence facilitates broader and more in-depth analyses by handling large and complex volumes of data, giving auditors the ability to conduct more comprehensive and detailed assessments. One of AI's key advantages is its ability to detect anomalies at an early stage, often in real time, enabling swift action and improved regulatory compliance. In addition, AI automates standardized and repetitive tasks, allowing auditors to focus on strategic, high-value activities. This technology also aids in data visualization by producing interactive and intuitive visualizations that facilitate the interpretation and communication of results. In terms of costs, artificial intelligence reduces audit expenses by optimizing resources and automating certain processes. Ultimately, its deployment improves the transparency and integrity of audit reports, thereby strengthening stakeholder confidence. All these benefits highlight the revolutionary potential of AI in the field of auditing, increasing the efficiency, accuracy, and reliability of the process.

III. EMPIRICAL ANALYSIS: IMPACT OF ARTIFICIAL INTELLIGENCE ON AUDIT QUALITY

This section presents empirical validation of the link between the use of artificial intelligence (AI) and audit quality (AQ), using regression models based on panel data. The aim is to determine whether incorporating AI tools into audit procedures leads to more effective fraud detection and improves overall audit quality. The study is based on a sample of 60 observations per firm per year, collected from 2017 to 2022. The information is drawn from audited financial reports, company publications, and databases specializing in audit practices and AI implementation within firms. This comprehensive dataset allows for a rigorous examination of the impact of AI on audit results, controlling for firm-specific characteristics such as size, profitability, debt level, and auditor type.

➢ *Model Specification*

We estimate the following panel data regression model:

$$AQ_{it} = \alpha + \beta_1 * AI_{it} + \beta 2 * Size_{it} + \beta_3 * ROA_{it} + \beta_4 * Leverage_{it} + \beta_5 * Big4_{it} + \varepsilon_{it}$$

Where:

- AQ_{it}: Audit quality for firm i at time t
- AI_{it}: Level of AI integration
- $Size_{it}$: Firm size (log of total assets)
- ROA_{it}: Return on assets
- $Leverage_{it}$: Financial leverage (total debt/total assets)
- $Big4_{it}$: Dummy variable for Big 4 audit firm (1 if yes, 0 otherwise)
- ε_{it}: Error term

➢ *Descriptive Statistics*

The descriptive statistics of the variables used in the study are presented in Table 1. These statistics provide an overview of the central tendency and dispersion of each variable, which is essential to understand the dataset's characteristics before proceeding with the regression analysis.

Table 1 Descriptive Statistics for the Main Variables (N = Number of Observations)

Variable	Mean	Std. Dev.	Min	Max
Audit Quality (AQ)	0.745	0.120	0.500	0.980
Artificial Intelligence (AI)	0.430	0.250	0.000	1.000
Size	5.600	1.200	3.200	8.700
Return on Assets (ROA)	0.120	0.090	-0.100	0.350
Leverage	0.450	0.200	0.100	0.900
Big4	0.350	0.480	0.000	1.000

The mean value of Audit Quality (AQ) is 0.745, indicating a relatively high average level of audit quality among the entities sampled. The Artificial Intelligence (AI) variable shows a mean of 0.430, reflecting moderate adoption of AI technologies in the audited firms. Firm size (Size) averages 5.6 on a logarithmic scale, demonstrating variability in company sizes. The average return on assets (ROA) is positive at 12%, suggesting overall profitability. Leverage averages 0.45, indicating that firms on average finance nearly half of their assets through debt. Finally, the Big4 variable, a dummy indicating whether the auditor belongs to the Big Four firms, has a mean of 0.35, meaning 35% of audits were performed by these top firms.

➢ *Correlation Matrix*

Table 2 Correlation Matrix

	AI	Size	ROA	Leverage	Big4	AQ
AI	1.000	0.063	0.092	-0.020	-0.035	0.351
Size	0.063	1.000	0.035	-0.008	0.031	0.653
ROA	0.092	0.035	1.000	0.017	-0.040	0.126
Leverage	-0.020	-0.008	0.017	1.000	-0.020	-0.087
Big4	-0.035	0.031	-0.040	-0.020	1.000	0.358
AQ	0.351	0.653	0.126	-0.087	0.358	1.000

The correlation matrix reveals several noteworthy relationships among the studied variables. There is a moderate positive correlation (0.351) between the use of artificial intelligence (AI) and audit quality (AQ), suggesting that the adoption of AI technologies contributes to improving audit outcomes. Firm size (Size) shows a strong positive correlation with audit quality (0.653), indicating that larger firms tend to receive higher-quality audits, possibly due to better resources or greater regulatory scrutiny. Profitability, measured by return on assets (ROA), has a weak but positive correlation with audit quality (0.126), implying that better financial performance may be slightly associated with higher audit quality. Conversely, leverage shows a slightly negative correlation (-0.087), indicating that higher levels of debt might be linked to lower audit quality, potentially due to increased financial pressure or risk. Finally, the use of a Big Four audit firm demonstrates a moderate positive correlation with audit quality (0.358), supporting the idea that audits conducted by Big Four firms are generally associated with higher professional standards.

➢ *Estimation Method*

We use fixed and random effects models for panel data. The Hausman test is employed to determine the appropriate model specification. Based on the test result ($p < 0.05$), the fixed effects model is preferred.

IV. REGRESSION RESULTS

The regression results using the fixed effects model are summarized below:

Table 3 Regression Results of the Model

Variable	Coefficient	Std. Error	t-Statistic	Prob
AI	0.153421	0.061782	2.483915	0.0164 **
Size	0.087236	0.046918	1.859201	0.0687 *
ROA	0.210547	0.072394	2.907134	0.0054 ***
Leverage	-0.075182	0.034615	-2.171842	0.0341 **
Big4	0.092418	0.041276	2.239106	0.0292 **
Constant	0.514673	0.198547	2.593821	0.0121 **

**: Significant at 1%, ** Significant at 5%, * Significant at 10%

The data presented in the table above reveals that artificial intelligence has a positive and significant impact on audit quality. Higher profitability and the verifications performed by Big Four firms are also linked to improved audit quality, while a higher debt ratio tends to have a negative effect.

Empirical findings from regression analysis of panel data support the idea that artificial intelligence (AI) significantly enhances audit quality. The AI variable exhibits a statistically significant positive coefficient, indicating that the integration of AI-based technologies is positively correlated with improved audit quality. This conclusion is corroborated by research conducted by Rahman, Zhu, and Yue (2024), which demonstrated that the combined use of artificial intelligence by audit firms and their clients enables faster and more accurate fraud detection.

The variable “Size” has a positive impact, indicating that larger companies are better positioned to adopt AI and possess the resources required to ensure superior audit quality. This finding echoes the results of Khan, Jan, and Zia-ul-haq (2024), who demonstrated that AI adoption leads to a significant improvement in the quality of integrated financial reporting in Gulf Cooperation Council (GCC) markets, particularly for large companies.

Le ROA (Return on Accounts) met en évidence une influence positive importante, signifiant qu'une meilleure performance financière est souvent liée à un audit de meilleure qualité. Cela peut être dû au fait que les sociétés les plus profitables ont la capacité d'investir dans des technologies avancées et de séduire des auditeurs hautement qualifiés.

The "leverage effect" variable shows an inverse correlation with audit quality, indicating that highly indebted companies tend to adopt risky accounting practices, thus making the auditor's task more complex. This observation confirms concerns expressed in the literature regarding the challenges of preserving audit independence in the face of rising financial risk.

Finally, belonging to a Big Four firm shows a positive correlation with audit quality. This finding is consistent with previous studies, including research by Chen and Wang (2022), which revealed that the use of AI tools by Big Four firms significantly reduces the risk of audit errors.

These findings highlight the revolutionary impact of AI on auditing methods, while emphasizing the crucial role of each company's individual financial and structural characteristics in the performance of these technologies. However, as Al-Sulaiti et al. (2023) point out, the effectiveness of AI depends heavily on the technological context, the auditors' expertise, and the ethical considerations associated with the clarity of the algorithms deployed.

V. CONCLUSION

This research primarily aimed to analyze the effect of artificial intelligence (AI) on audit quality, with a particular focus on its contribution to strengthening fraud detection and the credibility of financial data. Based on a regression model using panel data, the empirical analysis demonstrates that integrating AI significantly improves audit quality.

The findings reveal a significant positive association between AI use and audit performance, highlighting the revolutionary ability of advanced technologies to modernize audit methods. Artificial intelligence facilitates the automation of tasks requiring intensive data handling, the rapid detection of irregularities, and allows auditors to focus on higher-value strategic actions. Furthermore, company-specific factors, such as size, profitability, debt level, and affiliation with a Big Four audit firm, also have a significant impact on audit quality.

These findings indicate that adopting technology can serve as a strategic means to strengthen financial governance, increase transparency, and boost stakeholder confidence. Institutions are therefore urged to invest in AI-powered audit tools, while regulators and professional bodies should encourage the establishment of ethical frameworks and standards to oversee this technological transition.

However, this study has several limitations. First, the analysis is subject to geographical and sectoral restrictions that may impact the transferability of the results. Second, the study primarily adopts a quantitative approach and does not consider qualitative aspects such as auditor evaluation, ethical considerations, or resistance to technological innovation. Third, the rapid advancement of artificial intelligence tools means that the technologies examined in this analysis could quickly become outdated and require regular updates and revisions.

Future studies could expand the database to include more nations and sectors, prioritize combined methods to understand the technical and human dimensions of AI implementation, and compare various AI technologies (such as machine learning and expert systems) to gain more detailed insights. Public policy research could also examine how regulation and continuing education can facilitate the ethical and efficient integration of AI into auditing procedures.

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