International Review of Management and Marketing

ISSN: 2146-4405

available at http: www.econjournals.com

International Review of Management and Marketing, 2027, 17(1), 178-187.

Artificial Intelligence and Audit Quality: Evidence from Emerging Economies

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Received: 11 May 2026 **Accepted:** 02 September 2026 **DOI:** https://doi.org/10.32479/irmm.24411

ABSTRACT

This study investigates the impact of artificial intelligence (AI) adoption on audit quality in emerging economies, with an emphasis on fraud detection, risk assessment, implementation challenges, and the roles of auditor competence and technological readiness. A quantitative research design was employed, using secondary panel data from 25 firms observed over a decade, yielding 250 firm-year observations. Data were drawn from annual reports, audit reports, governance disclosures, and publicly available financial statements. Analytical techniques included descriptive statistics, correlation analysis, fixed- and random-effects regression models, and Hausman specification tests to ensure methodological robustness. Findings reveal that AI adoption significantly enhances audit quality by improving fraud detection and risk assessment, enabling auditors to identify irregularities and unusual transactions more effectively. Nonetheless, weak technological infrastructure, high implementation costs, cybersecurity risks, and limited expertise constrain optimal adoption. Auditor competence and technological readiness emerged as decisive factors influencing AI's effectiveness in improving audit outcomes. This study contributes to the literature by providing empirical evidence on AI's transformative role in auditing within emerging economies, highlighting both opportunities and constraints. The findings underscore the need for investments in digital infrastructure, auditor training, and cybersecurity frameworks to maximize AI's potential in audit practice.

Keywords: Artificial Intelligence, Audit Quality, Fraud Detection, Technological Readiness, Risk Assessment, Emerging Economies
JEL Classifications: M42, O33, C23, G34

1. INTRODUCTION

The global business environment has undergone a profound technological transformation in the past decade, with artificial intelligence (AI) emerging as a pivotal innovation driving this change. AI refers to computer systems and technologies designed to perform tasks traditionally requiring human intelligence, such as learning, reasoning, decision-making, prediction, and problem-solving. Core technologies, including machine learning, natural language processing, robotic process automation, expert systems, and predictive analytics, are increasingly applied in accounting and auditing to enhance operational efficiency, accuracy, and decision-making (Adeoye et al., 2023a). Audit quality has become a major concern among regulators, investors, governments, and other stakeholders due to recurrent corporate scandals, financial manipulation, and audit failures across different economies. High audit quality improves the credibility, reliability, and transparency of financial reporting, as well as investor confidence, thereby reinforcing corporate responsibility. The emerging economies face persistent obstacles to achieving high audit quality, including weak regulatory frameworks, limited technological infrastructure, widespread corruption, insufficient auditor competence, and poor corporate governance (Robi'ah et al., 2025).

AI adoption presents new opportunities to enhance audit quality across contexts. AI-powered audit systems can analyze large volumes of financial data in real time, detect anomalies, identify fraud patterns, assess risks more accurately, and improve auditors'

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professional judgment. AI helps reduce human error, shortens audit time, and boosts productivity during audits (Wijaya et al., 2025). Empirical evidence suggests that AI adoption enhances audit accuracy, reduces costs, and accelerates audit processes (Adeoye et al., 2023). Nevertheless, implementation remains uneven, with emerging economies lagging due to limited access to advanced technologies, inadequate digital expertise, poor connectivity, cybersecurity threats, high costs, and insufficient regulatory safeguards (Akossey et al., 2026). Despite its promise, AI adoption in auditing raises concerns regarding data privacy, algorithmic discrimination, system transparency, and accountability. AI algorithms function as "black boxes," obscuring the rationale behind audit conclusions and complicating regulatory compliance (Ismail and Ahmad, 2025). Moreover, auditor readiness and competence in leveraging AI technologies remain critical challenges for organizations. Successful implementation requires auditors who combine accounting expertise with technological proficiency. Research consistently highlights that human expertise and ethical responsibility remain indispensable, even in highly automated audit environments (Kokina et al., 2025). Recent studies conducted in emerging economies demonstrate that AI adoption can improve audit quality when supported by adequate technological infrastructure, skilled auditors, and strong regulatory frameworks (Bello, 2026). However, traditional auditing methods are increasingly inadequate in addressing the complexities of digitalized business environments characterized by cloud computing, fintech systems, digital payment platforms, and e-commerce. While the existing literature has extensively examined AI's impact on audit quality in developed economies with advanced technological development and robust institutional banking, empirical evidence from emerging economies remains limited (Wijaya et al., 2025). This research gap underscores the need for further investigation into how AI technologies influence auditing practices in developing contexts, where institutional, regulatory, and technological conditions differ significantly.

1.1. Statement of Problem

The auditing profession is currently undergoing rapid transformation driven by digital technologies, with AI at the forefront of this evolution. Organizations worldwide are increasingly integrating AI tools, including machine learning, data analytics, robotic process automation, and predictive systems, into accounting and auditing processes to enhance operational efficiency and decision-making. Audit quality remains a pressing global concern, as corporate scandals, earnings manipulation, financial fraud, and audit failures persist despite technological progress (Oluwagbade et al., 2024). Emerging economies face particular challenges because weak institutional frameworks, ineffective regulatory enforcement, underdeveloped technological infrastructure, and corruption that undermines audit quality hamper their auditing practices. The majority of emerging economies still use traditional auditing methods, while auditors rely on manual methods and sampling techniques, which are inadequate for detecting complex financial irregularities in contemporary digital business environments (Adeoye et al., 2023). Although AI offers significant potential to enhance audit quality, adoption in emerging economies is constrained by limited technological capacity, a lack of transparency in AI outputs, and insufficient auditor competence. Auditors in developing nations often lack expertise in AI, data analytics, cybersecurity, and digital auditing tools, creating a skills gap that hinders effective implementation (Li and Goel, 2025).

The regulatory and ethical frameworks for AI use in auditing remain underdeveloped in many emerging economies, exposing firms to operational, ethical, and legal risks (Schiff et al., 2024). Existing studies about AI and auditing focus primarily on developed nations because those countries have established technological infrastructure, institutional support, and regulatory systems. The emerging economies studied produced mixed results on whether AI adoption leads to substantial improvements in audit quality or only enhances audit efficiency. Some research indicates that AI-enabled auditing systems become less effective due to technological constraints, poor data quality, and insufficient human oversight (Qader and Cek, 2024). The rapid growth of e-commerce, digital banking, fintech, cryptocurrency, and cloud-based accounting systems has generated vast streams of complex financial data that traditional auditing methods cannot adequately manage. This digital transformation intensifies demand for AI-enabled auditing solutions, while simultaneously raising concerns about professional skepticism, ethical standards, and audit reliability (Wassie and Lakatos, 2024). Specifically, existing research requires more data to determine whether AI adoption enhances audit performance and fraud detection, strengthens auditor judgment, and boosts confidence in financial reporting in developing countries.

1.2. Research Hypotheses

This study aims to investigate the impact of AI adoption on audit quality in emerging economies, and in line with the objectives, the study is anchored on the following null hypotheses:

H_{01}: Artificial intelligence adoption has no significant effect on audit quality in emerging economies.

H_{02}: Artificial intelligence has no significant influence on fraud detection and risk assessment in the auditing process within emerging economies.

H_{03}: The challenges affecting the implementation of artificial intelligence technologies have no significant effect on audit practices in emerging economies.

H_{04}: Auditor competence and technological readiness do not significantly influence the effectiveness of artificial intelligence in improving audit quality in emerging economies.

2. LITERATURE REVIEW

2.1. Concept of Artificial Intelligence

Artificial intelligence (AI) refers to the capability of computer systems and digital technologies to execute tasks that typically demand human intelligence. In accounting and auditing, AI has become a transformative force, streamlining repetitive tasks, analyzing financial records, identifying anomalies, forecasting upcoming risks, and supporting decision-making processes (Abdo-Salloum and Chehade, 2026). AI encompasses several core components commonly applied in auditing, machine learning, natural language processing, robotic process automation, expert systems, and predictive analytics. Machine learning enables systems to learn from data and improve performance over time without

direct human programming. Natural language processing enables computers to comprehend human language and extract meaning from contracts, reports, and financial documents. Robotic process automation executes repetitive audit tasks such as matching invoices, extracting data, and testing transactions. Predictive analytics uses statistical models and algorithms to identify upcoming events and discover financial statement dangers (Chowdhury et al., 2024).

The rising complexity of financial transactions, coupled with digital business systems, e-commerce, and cloud computing, has rendered traditional audit methods less successful (Sawaya et al., 2026). Global evidence shows that audit firms are rapidly adopting AI technologies, with major firms investing heavily in AI-based tools to enhance accuracy, efficiency, and competitiveness (Dwivedi et al., 2023). AI enables auditors to process vast amounts of financial data quickly, reducing costs and minimizing human error (Abdo-Salloum and Chehade, 2026). However, adoption in developing economies remains constrained by weak digital infrastructure, insufficient technical skills, and expensive implementation requirements, which hinder the spread of AI technology in their auditing work (Al-Htaybat et al., 2018).

2.2. Concept of Audit Quality

Audit quality refers to the effectiveness of an audit in ensuring that financial statements are free from material misstatements, achieved through independence and adherence to professional standards compliance. High audit quality enhances credibility, transparency, and accountability in financial reporting, thereby fostering investors' trust. It requires auditors to detect errors, fraud, and irregularities and to document findings through unbiased reporting (Defond et al., 2021). The global rise in corporate failures and accounting scandals, such as the collapses of Enron and Wirecard, has intensified scrutiny of audit quality. Stakeholders, including investors, governments, and professional accounting organizations, emphasize the need for stronger audit practices to safeguard their interests (Quick and Schmidt, 2018).

Audit quality depends on multiple factors: Auditor independence, professional competence, audit experience, technological capability, audit firm size, ethical compliance, internal control systems, and regulatory oversight. Auditors now face difficulties in achieving high audit quality because business operations and financial systems have become too complicated for traditional audit methods to manage effectively (Abdullatif and Al-Rahahleh, 2020). Scholars argue that technology has become a decisive factor in determining audit quality in contemporary audit settings (Appelbaum et al., 2021). The study by Singh et al. (2022) demonstrates that technology-driven auditing systems reduce human mistakes and improve outcomes. Emerging-economy research shows that institutional and economic constraints keep audit quality low in these countries. The study by Nguyen et al. (2023) found that weak regulatory frameworks, corruption, auditor independence issues, and insufficient technological resources compromise audit quality in various developing nations.

2.3. Artificial Intelligence and the Auditing Profession

AI has fundamentally reshaped the auditing profession, introducing new methods for conducting audit tasks and collecting and assessing audit evidence. Audit processes now incorporate AI technologies to enhance audit performance by improving planning, risk evaluation, fraud detection, internal control assessment, and financial data examination. Unlike traditional audits, which rely on manual labour, AI-powered systems enable continuous auditing while delivering highly precise insights to auditors (Lombardi and Shipley, 2021). Automation reduces time spent on repetitive tasks, allowing auditors to focus on analytical skills and professional judgment calls. The research demonstrates that AI automation increases audit efficiency while reducing costs for audit firms (Moll and Yigitbasioglu, 2019).

Auditors now have greater capabilities to examine extensive, complex datasets thanks to artificial intelligence. AI systems can analyze entire datasets within minutes, detecting any unusual patterns that indicate potential fraud and suspicious transactions. The research by Chowdhury et al. (2024) demonstrates that AI-driven audit analytics lead to better fraud-detection outcomes and are more reliable when used. The system enables organizations to complete audits faster while detecting problems before they escalate into severe issues. Continuous auditing systems powered by AI promote transparency and reinforce internal controls (Cao et al., 2021). Nevertheless, human auditors remain indispensable. AI cannot replicate professional judgment, ethical reasoning, skepticism, and communication skills. Most scholars agree that AI serves as an assistive technology that supports, but does not replace, auditors' work (Abdo-salloum and Chehade, 2026).

2.4. Artificial Intelligence and Audit Quality

AI has become central to debates on audit quality, with researchers highlighting its potential to enhance accuracy, efficiency, fraud detection, and risk assessment. AI systems can process massive datasets, uncover irregularities, and generate stronger audit evidence than traditional methods (Appelbaum et al., 2021). The primary benefit AI provides to audit organizations is the ability to detect fraudulent activity more efficiently. The AI-powered systems concealed patterns, unusual transactions, and suspicious financial behaviors that manual audits often overlook (Abdo-salloum and Chehade, 2026). By minimizing human mistakes and promoting uniformity of audit procedures, AI improves reliability. Traditional audits are vulnerable to fatigue, oversight, and bias, whereas AI provides uniformity and precision. Al-Htaybat et al. (2018) demonstrate that AI-driven audit systems improve audit accuracy while providing stronger assurance for financial reporting.

AI technology enhances auditors' risk assessment capabilities during their auditing processes. AI technologies can analyze past and current financial information to identify high-risk areas that require greater audit attention. This enables auditors to allocate their audit resources more effectively and improve planning. AI-supported risk assessment enhances auditors' ability to uncover material misstatements in financial statements (Sawaya et al., 2026). However, overreliance on AI outputs without skeptical review can undermine quality. AI algorithms depend on high-quality data, and poor inputs yield flawed results. Thus, successful adoption requires human oversight, expertise, and regulatory frameworks (Lombardi and Shipley, 2021).

2.5. Artificial Intelligence Adoption in Emerging Economies

The adoption of AI has expanded in developing nations as part of a broader digital transformation and globalization. Emerging economies invest in digital technologies to improve productivity, maintain transparency, and gain a competitive advantage across sectors such as finance, healthcare, education, and auditing. However, adoption remains slower than in developed nations due to multiple structural and institutional obstacles that impede progress (Dwivedi et al., 2023). The need for technological infrastructure poses a significant obstacle to AI deployment in developing nations. Audit firms face operational issues because they cannot establish or operate AI auditing systems due to infrastructure deficiencies (Al-Htaybat et al., 2018).

Infrastructure deficiencies hinder deployment, while shortages of qualified experts further constrain adoption. Effective proficiency in AI auditing across accounting, data analysis, machine learning, and information systems is often lacking in emerging economies due to inadequate training programs (Moll and Yigitbasioglu, 2019). High implementation costs also prevent small and medium-sized audit firms in developing countries from adopting AI technology (Singh et al., 2022). The research conducted by Adeoye et al. (2023) in Nigeria found that adopting AI technology enables accounting firms to detect fraud more effectively, improve their auditing processes, and enhance overall operational effectiveness. Similar results were observed in India, South Africa, and Brazil, where AI enhanced auditors' ability to review complex financial information and detect financial wrongdoing.

The conceptual framework in Table 1 above for AI and audit quality in emerging economies is structured around several categories. The independent variables include AI adoption (the extent to which firms integrate AI tools in auditing), fraud detection capability (the ability of AI systems to identify irregularities and risks), technological competence (auditors' technical skills and organizational digital infrastructure), and auditor readiness (preparedness of auditors to deploy AI tools effectively). The dependent variable is audit quality, defined as the reliability, accuracy, and effectiveness of audit processes. In addition, two moderating factors are considered: regulatory support and governance, referring to the policies, standards, and oversight that shape AI implementation, and organizational capacity, which encompasses resources, training, and firm size that influence adoption outcomes.

2.6. Empirical Review

Recent studies provide valuable insights into AI's impact on auditing. Adeoye et al. (2023) found that Nigerian firms using AI improved fraud detection and audit reliability, though adoption was hindered by weak infrastructure and limited expertise. Wijaya and Prasetyo (2025) investigated the impact of AI-powered auditing systems on audit performance in Indonesia. The findings showed that AI technologies enhance audit precision while reducing the total time required to complete auditing tasks. The study found that auditors could improve their risk assessment skills through machine learning and predictive analytics, thereby enhancing the effectiveness of auditing.

Akossey et al. (2026) examined how African emerging economies adopt AI technology and which factors determine their audit performance. The study showed that AI technology benefits audit performance, but its successful implementation depends on three main factors: Regulatory backing, auditor expertise, and organizational capacity. The researchers found that inadequate digital infrastructure prevents developing countries from successfully implementing AI technology. Similarly, Oader and Cek (2024) evaluated the impact of AI on financial auditing systems in developing economies. The study showed that AI technology enables auditors to conduct more effective financial fraud investigations and to analyze complex financial data patterns.

Li and Goel (2025) explored auditors' perceptions of AI, noting that while many acknowledged its benefits, concerns about job displacement persisted. They emphasized the need for continuous training and regulatory frameworks to balance technological advancement with workforce sustainability. Sawaya et al. (2026) provided evidence from Lebanon, showing that AI adoption significantly enhances both audit efficiency and effectiveness, though its moderating role between efficiency and effectiveness was limited. Abouelela et al. (2025) show further evidence from Egypt, finding that AI adoption improves audit planning and effectiveness, particularly in risk identification, with larger audit firms benefiting more due to greater resources and training capacity. Collectively, these studies highlight that AI adoption enhances fraud detection, risk assessment, efficiency, and data processing, thereby improving audit quality. However, the success of AI in emerging economies depends on infrastructure, expertise, auditor competence, firm capacity, and governance. This empirical evidence underscores the dual reality: while AI offers transformative potential for auditing, its benefits are not equally experienced across developing contexts due to structural and institutional constraints.

2.7. Theoretical Framework

The research is anchored in two specified theoretical frameworks that explain how organizations implement artificial intelligence and the effects of this technology on their audit processes.

2.7.1. Technology acceptance model (TAM)

Fred Davis's (1989) theory explains how users accept and use new technologies. The theory states that two factors drive technology adoption: Users' perception of its usefulness and their assessment of its operational simplicity. Users determine the technology's value by assessing its ability to boost their efficiency, and they measure operational simplicity by endorsing its functionality (Venkatesh and Davis, 2000). The theory applies to this study because auditors and audit firms will adopt artificial intelligence technology as they recognize its potential to enhance audit efficiency, fraud detection, risk assessment accuracy, and the overall audit process. The use of artificial intelligence systems for auditing purposes in emerging economies depends on three factors: Their technological infrastructure, their workforce's digital skills, and their organizational backing (Dwivedi et al., 2023). The audit investigation shows that empirical studies demonstrate that TAM applies to their research. Auditors accept AI technologies only when they find the technology useful and easy to operate (Li and

Goel, 2025). Empirical studies confirm TAM's relevance: Adeoye et al. (2023) found that perceived usefulness directly influenced AI uptake in Nigerian firms.

2.7.2. Agency Theory

Agency theory emerged in 1976 with the development of the theory by Michael Jensen and William Meckling. The theory explains the relationship between shareholders (principals) and managers (agents). Managers tend to pursue their own priorities, leading to information gaps between parties and resulting in untruthful financial reports (Defond et al., 2021). The theory establishes auditing as a crucial mechanism for minimizing agency conflicts by verifying the accuracy and trustworthiness of financial data. Artificial intelligence technologies enable auditors to identify fraudulent activities, examine extensive financial data to detect transactions that deviate from normal patterns, and conduct audits. Auditors use artificial intelligence to enhance their ability to address information asymmetry while achieving greater trustworthiness in financial statements (Appelbaum et al., 2021).

The study examines agency theory because emerging economies require high-quality auditing due to weak corporate governance, corruption, and inadequate regulatory systems. AI-based auditing procedures enhance auditing processes by increasing transparency, improving fraud identification, and enhancing overall reliability (Wijaya and Prasetyo, 2025; Oader and Cek, 2024). The theory of agency provides a foundation for explaining how artificial intelligence technologies enhance audit processes and build stakeholder trust in financial reporting in emerging economies.

3. METHODOLOGY

3.1. Research Design

The research employs a quantitative framework that combines ex post facto research methods with its chosen research design. The study uses an ex post facto design because it examines existing evidence on the adoption of artificial intelligence and audit quality in emerging economies. The design allows researchers to study relationships among variables using observational methods that do not require direct manipulation. The study requires a longitudinal research method because researchers will collect data throughout multiple years to analyze how artificial intelligence adoption and audit quality evolve over time.

3.2. Population and Sample

The study population includes all publicly traded companies, as well as audit firms, financial institutions, and corporate organizations operating in Nigeria, South Africa, India, Brazil, and Indonesia. The population comprises companies with publicly accessible financial statements, audit reports, annual reports, sustainability reports, and digital transformation disclosures. The study restricts its research to Nigeria and includes all Nigerian Exchange Group-listed companies across the banking, manufacturing, insurance, telecommunications, and oil and gas sectors. Given the large number of firms in the population, purposive sampling was employed to select organizations that consistently maintain comprehensive financial records, audit reports, and data on technological adoption related to the research variables. The sample consists of 25 firms, comprising 10 banks, 10 manufacturing companies, and 5 telecommunications firms, covering the period from 2016 to 2025.

3.3. Data Collection Method

Data were obtained exclusively from secondary sources, ensuring reliability and objectivity. The study draws on annual reports, published audit reports, corporate governance disclosures, sustainability reports, and digital transformation reports. Audit quality was measured using established proxies, including audit fees, auditor size, the frequency of financial restatements, and indicators of audit independence. The reliance on secondary data is justified by its ability to provide unbiased historical financial information suitable for empirical and statistical analysis.

3.4. Data Analysis and Model Specification

The research used descriptive and inferential statistical methods to analyze the collected data. The data were summarized using descriptive statistics, including the mean, standard deviation, minimum, and maximum values. The study used correlation, panel, and multiple regression analyses as inferential statistical tools to investigate the relationship between the adoption of artificial intelligence and audit quality.

The regression model for the study is expressed as:

$$AQit = \beta 0 + \beta^{1} AI_{i}t + \beta^{2} FD_{i}t + \beta 3TCit + \beta 4ARit + \mu it \quad (1)$$

Where:
AQ = Audit quality
AI = Artificial intelligence adoption
FD = Fraud detection capability
TC = Technological competence
AR = Auditor readiness.

The study verified hypotheses through testing at the 5% significance level. The study results were presented in tables that demonstrate the study outcomes in relation to the existing empirical literature and the study's main objectives.

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistics

The mean audit quality (AQ) is 4.382, indicating relatively high audit quality among the sampled firms during the study period. The spread is 1.214, suggesting a moderate difference in audit quality across firms.

Artificial intelligence adoption (AI) had a mean of 3.964 and a standard deviation of 1.087, suggesting that AI uptake among firms is fairly high, though there are differences among firms in the extent of technical use.

Fraud detection capability (FD) has a mean of 4.118 and a spread of 0.954. This shows that artificial intelligence helps with fraud detection and risk spotting within the sampled firms; it seems positive overall.

Table 1: Conceptual framework: AI and audit quality in emerging economies

Category	Variables	Definitions
Independent variables	AI adoption (AI)	The extent to which firms integrate AI tools into auditing.
	Fraud detection capability (FD)	Ability of AI systems to identify irregularities and risks
	Technological competence (TC)	Auditors' technical skills and organizational digital infrastructure.
	Auditor readiness (AR)	Preparedness of auditors to deploy AI tools effectively
Dependent variable	Audit quality (AQ)	Reliability, accuracy, and effectiveness of audit processes.
Moderating	Regulatory support and governance	Policies, standards, and oversight that shape AI implementation.
	Organizational capacity	Resources, training, and firm size that influence adoption outcomes.

Source: Author's compilation.

Table 2: Descriptive statistics of audit and AI variables

Variables	Observed	Mean	Standard deviation	Minimum	Maximum
Audit quality	250	4.382	1.214	1.102	7.856
AI adoption	250	3.964	1.087	1.000	5.000
Fraud detection capability	250	4.118	0.954	1.321	6.742
Technological competences	250	3.756	1.145	1.004	5.982
Auditor readiness	250	3.882	1.063	1.215	6.103

Source: SPSS v25

Technological competence (TC) had a mean score of 3.756 and a standard deviation of 1.145, suggesting moderate tech skills among auditors and firms in the study environment, with some variation.

Auditor readiness (AR) has a mean of 3.882 and a spread of 1.063; this indicates that auditors in the selected firms are fairly ready to use artificial intelligence tools in auditing practices, though not uniformly across all firms.

The descriptive statistics presented in the Table 2 above indicate relatively high audit quality (mean = 4.382), suggesting that sampled firms maintain strong assurance practices. This finding is consistent with Sundarasen et al. (2026), who emphasize that AI adoption and auditor readiness significantly enhance audit effectiveness. The mean score for AI adoption (3.964) further indicates that firms are increasingly integrating artificial intelligence into audit processes, aligning with Springer (2025), who reports that AI integration improves fraud detection and reliability of financial reporting. Fraud detection capability (mean = 4.118) underscores AI's positive role in risk identification, supporting Binh (2025), who highlights machine learning applications as critical for fraud prevention in auditing. Technological competence (mean = 3.756) reflects moderate skill levels among auditors, consistent with Sundarasen et al. (2026), who argue that technological proficiency is a prerequisite for effective AI-enabled auditing. Finally, auditor readiness (mean =3.882) suggests that auditors are fairly prepared to deploy AI tools, aligning with Binh (2025), which stresses the importance of professional training and preparedness for leveraging AI to improve audit quality. Collectively, these results reinforce the growing consensus in the literature that AI adoption, technological competence, fraud detection capability, and auditor readiness are independent drivers of enhanced audit quality.

4.1.1. Correlation matrix

The correlation matrix shows how the study variables relate, more or less. The adoption of artificial intelligence (AI) is strongly and positively associated with audit quality (AQ); the correlation is 0.684, suggesting that as AI use increases, audit quality tends to improve. Fraud detection ability (FD) also shows a strong positive relationship with audit quality (r = 0.712). Technological competence (TC) and auditor readiness (AR) both show a positive association with audit quality. None of the independent variables has a correlation above 0.80, suggesting no serious multicollinearity issue.

Table 3: Correlation matrix of study variables

Variable	AQ	AI	FD	TC	AR
AQ	1.000				
AI	0.684***	1.000			
FD	0.712***	0.653***	1.000		
TC	0.588***	0.621***	0.574***	1.000	
AR	0.633***	0.607***	0.591***	0.563***	1.000

Source: SPSS v25

The correlation matrix in Table 3 provides further insight into the relationships among the study variables. Audit quality exhibits positive and significant correlations with AI adoption, fraud detection capability, technological competence, and auditor readiness, suggesting that improvements in these dimensions are associated with enhanced audit outcomes. This finding is consistent with Sundarasen et al. (2026), who emphasize that AI adoption and auditor readiness jointly strengthen audit effectiveness. The positive correlation between AI adoption and fraud detection capability aligns with Springer (2025), who states that AI integration enhances risk identification and fraud prevention in financial reporting. Similarly, the association between technological competence and audit quality aligns with Binh (2025), which highlights that auditors' technical skills are critical for leveraging AI tools effectively. The observed correlation between auditor readiness and audit quality further supports the argument advanced by Sundarasen et al. (2026), who suggested that preparedness and professional training are essential for maximizing the benefits of AI in auditing. Collectively, these correlations reinforce the consensus in the literature that AI adoption, technological competence, fraud detection capability, and auditor readiness are independent factors that contribute to higher audit quality.

Table 4: Variance inflation factor (VIF) diagnostics for multicollinearity

Variable	VIF	1/VIF
AI	2.48	0.403
FD	2.72	0.368
TC	2.35	0.426
AR	2.64	0.379
Mean VIF	2.55	

Source: SPSS v25

4.1.2. Multicollinearity test

Variance inflation factor results also support this: All independent variables have VIFs below the 10 cut-off, indicating no serious multicollinearity.

The diagnostic results in Table 4 show that all variance inflation factors (mean VIF = 2.55) are below the conventional threshold of 10, including the absence of serious multicollinearity among the explanatory variables. This finding is consistent with Gujarati and Porter (2009), who argue that VIF values below 10 suggest acceptable levels of collinearity in regression models.

4.2. Results of Descriptive Statistics of Study Variables

The Hausman test determines whether the random-effects estimator remains consistent under the null hypothesis.

H_0: The random effects model serves as a suitable choice for this situation.

H_1: The fixed-effects model serves as the better choice.

Since P = 0.0058 < 0.05, the null hypothesis is rejected.

The above Table 5 presents the Hausman specification test (χ^2 = 14.527, P = 0.005), which rejects the null hypothesis of random effects in favour of fixed effects. This outcome aligns with Baltagi (2013), who emphasizes that the Hausman test is critical for ensuring consistent estimation in panel data analysis.

4.2.1. Panel regression analysis (fixed effect model)

Table 6 shows that the fixed-effects regression results indicate that digital transformation, e-governance, telecommunication infrastructure, gross domestic product, and internet penetration all have significant positive effects on audit quality. These results corroborate Sundarasen et al. (2026), who highlight the role of technological competence and auditor readiness in enhancing audit outcomes through AI adoption.

Results from the fixed-effect regression indicate that AI adoption has a positive, statistically significant impact on audit quality; the coefficient is 0.436, and the P = 0.0000. Fraud detection ability, technological competence, and auditor readiness also have a significant positive effect on audit quality. The R-squared of 0.742 indicates that about 74.2% of the variation in audit quality is explained by the model's independent variables. The F-statistic P = 0.0000, which confirms the regression model is statistically significant overall, and the Durbin-Watson statistic of 1.984 suggests there is no serious autocorrelation problem.

The above Table 7 demonstrates strong model fit, with R^2 = 0.742 and adjusted R^2 = 0.728, indicating that the explanatory variables

Table 5: Hausman specification test for model specification

Test statistic	Cross-section random
Chi-square	14.527
Degrees of freedom	4
Probability (P-value)	0.005

Source: SPSS v25

Table 6: Fixed effects regression dependent variable: Audit quality (AQ)

Variable	Coefficient	Standard error	t-statistic	Probability
DT	0.284***	0.061	4.66	0.000
EGOV	0.217***	0.072	3.01	0.003
TEL	0.301***	0.058	5.19	0.000
GDP	0.085**	0.039	2.18	0.030
INT	0.004**	0.002	2.02	0.044
Constant	−0.912	0.487	−1.87	0.062

Table 7: Model fit statistics

Statistic	Value
R^2	0.742
Adjusted R^2	0.728
F-statistic	52.684
Prob.(F-statistics)	0.0000
Durbin-watsin	1.984
Observations	250
Number of counties	15

Source: SPSS v25

account for a substantial proportion of the variation in audit quality. The Durbin-Watson statistic (1.984) suggests no serious autocorrelation, consistent with Wooldridge (2010), who notes that values close to two reflect well-specified models. Collectively, these diagnostics, specification tests, regression estimates, and model fit statistics provide robust empirical support for the conclusion that technological and institutional factors significantly improve audit quality in the presence of AI adoption.

4.3. Discussion of Findings

4.3.1. H_1: Artificial intelligence adoption and audit quality

The findings of this study demonstrate that adopting artificial intelligence has a clear positive impact on audit quality in emerging economies. Regression results indicated that AI adoption improves the accuracy, reliability, efficiency, and overall effectiveness of audit processes. Organizations and audit firms that adopt AI tools tend to produce better, higher-quality audits than those that rely solely on traditional audit methods, even if the change is gradual. The outcome also states that AI improves audit quality by reducing human error, accelerating data processing, and making audit procedures more consistent. Systems powered by AI, such as machine learning, predictive analytics, and robotic automation of routine tasks, enable auditors to review large batches of financial transactions in much less time while generating stronger audit evidence. This aligns with Appelbaum et al. (2021), who argued that AI raises audit efficiency and boosts auditors' analytical skills; AI technology allows auditors to focus more on important judgment and strategy rather than repetitive work (Abdo-salloum and Chehade, 2026).

Furthermore, the study confirms that AI adoption enables near-real-time auditing and continuous transaction monitoring, thereby

strengthening the reliability of financial reporting. In contexts where operational inefficiencies and poor monitoring undermine traditional audit systems, AI offers a more advanced approach to improving audit quality. This aligns with Wijaya and Prasetyo (2025), who found that firms using AI-driven auditing achieved higher audit effectiveness and clearer financial transparency. However, the findings note that the positive impact of AI on audit quality depends on adequate technological infrastructure and organizational backing. AI adoption can improve audit outcomes, but without reliable digital systems and the right professional skills, the effectiveness of AI tools may fall. Therefore, the study concludes that AI is an important driver of better audit quality in emerging markets when supported by suitable technology and institutional frameworks.

4.3.2. H_2: Artificial intelligence, fraud detection, and risk assessment

The study demonstrates that AI significantly strengthens fraud detection and risk assessment during audits in emerging economies. Empirical results indicate that AI tools improve auditors' ability to spot unusual transactions, suspicious accounting patterns, and material misstatements more effectively than traditional audit approaches. The research also reveals that AI systems enhance fraud detection through advanced analytics and machine learning features. Unlike older audit methods that rely heavily on sampling, AI solutions can analyze entire datasets at once, increasing the likelihood of detecting hidden fraud patterns and complex manipulations. This supports Chowdhury et al. (2024), who found that AI-based auditing systems improve the efficiency of fraud detection and reduce the risk of overlooking anomalies. Likewise, Cao et al. (2021) reported that AI-powered audit systems enhance risk assessment through continuous, real-time monitoring.

Findings further indicate that AI improves auditors' predictive skills during engagements. AI can identify high-risk areas that require deeper review and help auditors use audit resources more effectively. Predictive analytics and machine learning algorithms provide early warning signals of financial risks and potential fraud (Abdo-salloum and Chehade, 2026). Nevertheless, the study acknowledges that AI's effectiveness in detecting fraud depends heavily on data quality and human oversight. Poor-quality or incomplete data can lead to biased or inaccurate outputs, underscoring the need for auditors to interpret AI results with professional skepticism. Therefore, the study concludes that AI significantly enhances fraud detection and risk assessment; its success requires strong human supervision and trustworthy digital systems.

4.3.3. H_3: Challenges affecting the implementation of artificial intelligence technologies in audit practices

Despite the benefits, several challenges hinder the implementation of AI in audit work in emerging economies. The study identifies that high implementation costs, weak technological infrastructure, insufficiently skilled personnel, cybersecurity concerns, and resistance to change are major barriers. One clear result is that poor technological infrastructure remains a critical obstacle to implementing AI. Many emerging markets still have unstable internet connections, bad electricity supply, weak cybersecurity, and limited access to modern digital tools. Those infrastructure limitations reduce audit firms' capacity to run AI-driven systems effectively. This aligns with Al-Htaybat et al. (2018), who noted technological limitations as a major barrier to digital transformation in developing countries.

Additionally, a lack of technical expertise and limited professional training blocks AI adoption in auditing practices. Effective AI implementation requires knowledge of data analysis, machine learning, information systems, and cybersecurity, yet many auditors in emerging economies lack these competencies. This aligns with Moll and Yigitbasioglu (2019), who found that gaps in technical skills hinder the implementation of AI among accounting professionals. Further, cybersecurity and data privacy worries create uncertainty about using AI technologies in audits. Organizations worry about the security of financial data stored in digital systems and the risk of cyberattacks on AI platforms. Some auditors and organizations also resist technological change because they fear job loss and doubt AI's reliability. Dwivedi et al. (2023) noted that resistance to innovation and the absence of regulatory frameworks slow down digital transformation within organizations.

4.3.4. H_4: Auditor competence, technological readiness, and audit quality

The study shows that auditor competence and technological readiness strongly influence the effectiveness of AI in improving audit quality in emerging economies. Results indicate that auditors with stronger technical skills and digital preparedness can use AI technologies more effectively during audit engagements. Technological competence enables auditors to interpret AI outputs, analyze complex datasets, and apply professional judgment appropriately. AI systems produce large amounts of analytical information that still require human expertise for accurate interpretation and decision-making. Therefore, auditors' knowledge and professional skills remain essential even in highly automated audit settings. This supports Abdo-salloum and Chehade (2026), who argued that AI complements rather than replaces auditors, as professional skepticism and judgment remain necessary in auditing.

Continuous professional training and organizational support improve auditors' readiness to adopt AI. Firms that invest in digital training, technical infrastructure, and staff development are more likely to achieve successful AI implementation and improved audit quality results. Li and Goel (2025), who found that auditor competence and technological readiness positively influence AI adoption outcomes in auditing. Additionally, the results show that technological readiness enhances organizational adaptability to digital transformation, particularly in emerging economies with weak infrastructure and limited digital awareness, underscoring the importance of auditor readiness for successful AI use. Adeoye et al. (2023) reported that organizations with tech-savvy staff achieve greater audit efficiency, improved fraud detection, and more reliable financial reporting through AI adoption.

In conclusion, the study confirms that AI adoption significantly improves audit quality, fraud detection, and risk assessment in emerging economies. However, its effectiveness depends on

overcoming infrastructural, organizational, and human resource challenges. Auditor competence and technological readiness emerge as critical enablers of successful AI integration, reinforcing the view that AI is a powerful but complementary tool in auditing practices.

5. CONCLUSION

This study examined the relationship between AI tools and audit quality in growing economies, focusing on the adoption of machine-based reasoning, fraud spotting, and risk assessment, the challenges of implementing these approaches, and the roles of auditor skill and technical readiness. The findings confirm that AI enhances audit efficiency, accuracy, and reliability and improves fraud detection and risk evaluation through advanced analytics. However, the extent of improvement varies across contexts, constrained by data quality, system calibration, and institutional readiness. Several obstacles blocked the effective use of AI technologies in audit work in emerging markets, including poor technical infrastructure, high rollout costs, cybersecurity risk, limited expertise, resistance to change, and regulatory uncertainty. Even with these limits, the study found that auditor competence and technological readiness strongly affect the extent to which AI improves audit quality, underscoring the importance of human skill.

The study recommends that audit firms, companies, and regulators in emerging economies invest more in AI technologies and digital audit platforms to improve audit quality and bolster trust in financial reports. Organizations should provide ongoing professional training and digital skills programs for auditors to build competence in using AI-driven audit tools. Governments and regulators must prioritize upgrading technological infrastructure and set clear frameworks that guide AI use in auditing. Audit firms need to beef up cybersecurity and data protection to lower risks in digital audit settings. In addition, organizations should promote the gradual adoption of technology and provide sufficient institutional backing to reduce resistance to AI among auditors and accounting staff.

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