Adv. Mgmt. Tech. Volume 7(2)56-73
https://doi.org/10.46977/amt.2026.v07i02.004

Advancement in Management and Technology (AMT)
Online ISSN: 2982-0944
Journal Homepage: www.ajmt.org



Original Article

Risk Management practices as a Mediator in the Correlation between AI Adoption and Audit Quality of Audit Firms in Ghana

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Abstract

Introduction: Digital technology is revolutionizing the accounting sector, and enterprises are starting to recognize its impact. Audit structure, automation of essential tasks, and auditor credentials. This study examines the mediating effect of risk management practices in the relationship between Artificial Intelligence (AI) adoption and audit quality in Ghanaian auditing firms. **Method:** Using a judgemental sampling technique, this study collected data from 342 audit firm managers in Ghana. The collected data were analyzed using partial least squares structural equation modeling (PLS-SEM) in SmartPLS, providing empirical insight into the findings. **Results:** The study revealed that AI adoption had a significant positive effect on audit quality. The study also found that risk management practices positively and significantly affect audit quality. It was also discovered that AI adoption had a significant positive effect on risk management practices and partially and significantly mediated the relationship between AI adoption and audit quality. **Conclusion:** The research enhances the academic literature and auditing methodologies by providing valuable perspectives for audit firms, legislators, regulators, and professionals on integrating AI technology into appropriate risk management structures.

Keywords: ***Artificial Intelligence; Audit Firm; Audit Quality; Ghana; Risk Management Practices***

Introduction

The auditing procedure is analyzed, documented, and executed with the aid of Artificial Intelligence (AI). The growing use of AI has shown its ability to analyze extensive, complex databases; identify anomalous transactions and patterns; and improve risk assessment (Ganapathy, 2023). Growing demand for quality and transparency in auditing has compelled organizations to adopt AI technologies to improve efficiency, consistency, and expert judgment (Al-Omush *et al.*, 2025). These tools are transforming the audit process and risk management. An audit of a corporation goes beyond mere compliance. The audit process enhances the integrity of capital markets and financial reporting (Surya, 2021). The organizational environment is increasingly complex, data is expanding significantly, and information technology is advancing rapidly. Conventional auditing methods may face challenges. Auditors have used technology and AI for ongoing auditing, comprehensive analysis, and improved risk assessment (Dako *et al.*, 2020). These capabilities have strengthened audit firms' ability to address emerging challenges more agilely and with greater expertise. Concerns about the extended use of AI are significant. Further research is needed to assess how AI operational effectiveness affects audit quality. The challenges are professional experience, auditor independence, accountability, and the degree of trust in AI-generated outputs within the auditing process (Munoko *et al.*, 2020). AI can assist in evaluation and selection. The auditor retains final authority. Auditors must exercise prudence and

Received: 1 June 2026; Received in revised form: 13 October 2026; Accepted: 29 October 2026

professional skepticism and adhere to legal obligations under auditing standards. Inadequately designed and executed AI systems can undermine the transparency, consistency, and quality of audit results. Currently, the corporate audit sector is at the forefront of AI research concerning its deployment and regulation. This has reshaped the profession. Researchers have also examined AI's overall impact on audit quality (Fidyah *et al.*, 2024). The obstacles AI poses in auditing extend beyond technological concerns, including maintaining fundamental professional standards such as ethical discernment, professional skepticism, and autonomy. Nonetheless, no genuine study has been conducted. Empirical research remains scarce, and regulators, standard setters, and practitioners lack the resources to develop strategies to enhance audit quality and implement AI technology (Babalola *et al.*, 2022). Existing empirical studies on AI adoption in auditing generally focus on developed economies and primarily on automation, fraud detection, and cost efficiency (Anomah *et al.*, 2024; Alhazmi *et al.*, 2025). Emerging economies, which differ considerably in their institutional frameworks, regulatory environments, technological infrastructures, and professional standards, receive little coverage of such efforts. This limited focus restricts knowledge of the impact of AI on audit quality across contexts. Further, previous studies have largely neglected the internal organizational processes through which AI impacts audit results. Internal risk management, which refers to a firm's capability to identify, assess, and mitigate risks, has a dominant role in determining the extent to which AI will affect audit quality (Teoh *et al.*, 2017). Although AI can enhance risk identification, monitoring, and control processes, evidence on the mediating role of risk management practices in the association between AI adoption and audit quality is limited. The study explores how AI adoption affects audit quality in an emerging economy and the mediating role of risk management practices. This study presents a comprehensive examination of the contemporary application of AI in auditing. It addresses the scientific, psychological, and organizational impediments to AI adoption. The study addresses three fundamental scientific questions:

1. How does AI enhance audit quality and risk management practices?
2. What is the correlation between audit quality and risk management practices?
3. How do risk management practices mediate the relationship between AI and audit quality?

This study enhances the current corpus of knowledge in three significant ways. It advances empirical research on the correlation between AI adoption, audit quality, and risk management practices. Nonetheless, research on AI in auditing remains limited, with few studies comprehensively examining these challenges. This study advances the audit technology literature by examining the organizational factors through which AI influences audit results. It assesses risk mitigation practices that improve understanding of risk management procedures and enhance the efficiency and effectiveness of audit operations. The objective is to better understand how technology investments affect audit results, particularly within a risk-based strategy embedded in the organization's structure.

Audit firms face increasing pressure to strengthen internal controls, mitigate escalating risks, and improve audit quality amid a changing regulatory and operational landscape. A growing need for AI and risk management solutions parallels advances in AI technology. It emphasizes the importance of risk management strategies to help regulators, auditors, and organizational leaders make informed decisions about using and regulating AI technologies. The results are crucial for improving audit quality and reinforcing the integrity of the internal control system in a dynamic, technology-driven audit environment. Ultimately, these efforts are vital to boosting stakeholder confidence and strengthening organizational resilience.

Review of Literature

Theoretical Background of the Study

This study draws on agency theory, contingency theory, and information processing theory. Agency theory posits that by concentrating on the relationship between principals (shareholders) and agents (managers and auditors), it advocates for the reduction of information asymmetry and the restriction of unethical or self-interested conduct (Mensah *et al.*, 2024). Risk management practices support this

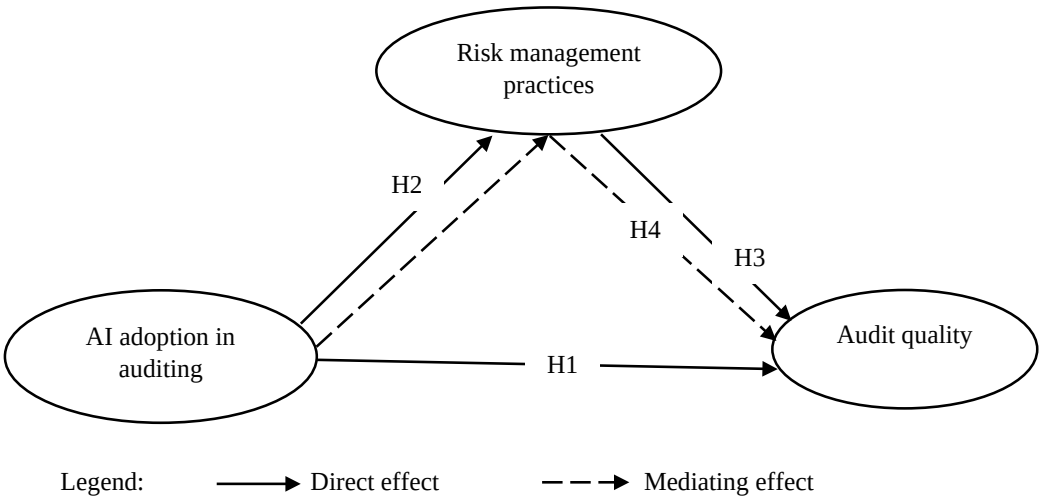
vision by linking managers' behavior to organizational goals through appropriate controls and monitoring, thereby improving the quality of audits. Together, these viewpoints highlight the importance of maintaining audit reliability (and organizational commitment) through ethical considerations.

Contingency theory builds on this idea, arguing that an organization achieves effectiveness in its systems based on how well internal systems are coupled with contextual and environmental conditions (Tosi Jr & Slocum Jr., 1984). In this construct, a firm's internal systems and ethical climate determine the effectiveness of risk management practices by shaping how the organization interprets and applies its policies. Standardized risk management practices alone, therefore, do not automatically translate into improved audit quality; their effectiveness depends on how much they affect corporate culture, ethical attitudes, and audit behavior (Praise & Rapina, 2022).

According to information processing theory, managers and auditors collect, process, and use information in decision-making environments (Brown-Liburd *et al.*, 2015). AI integrated into the system poses a new challenge, vastly expanding the volume of audit-related data and increasing complexity. Auditors' ability to process and interpret this information can also improve audit quality. This information-processing hypothesis helps reduce error rates, improve the accuracy of risk identification, enhance decision-making quality, and support comprehensive analysis (Hamdam *et al.*, 2022). They emphasize the necessity of risk management strategies and artificial intelligence to enhance audit quality and control systems.

Hypothesis Development

Figure 1 presents this study's conceptual framework. It illustrates the relationship between variables and the hypothesis number assigned to each relationship. The legend explains whether each relationship is direct or indirect.



Source: Author's own work

Figure 1: Conceptual Framework

The Relationship Between AI Adoption and Audit Quality

AI is enhancing the efficiency, speed, and accuracy of audits. Auditors can identify trends and irregularities in large datasets that standard sampling methods cannot detect (Venkata, 2025). Applying AI in auditing improves precision in error detection and the reliability of audit outcomes (Celestin, 2020). Information processing evaluates analytical advantages, notably reduced information incongruence, enhanced audit judgments, and improved audit quality. AI methodologies enhance ongoing monitoring and risk assessment, thereby improving audit reliability and reducing financial misstatements (Dako *et al.*, 2020). AI-driven audits reveal more discrepancies and fewer errors (Singh *et al.*, 2025). Agency theory views AI as a tool to monitor auditors' conduct and align it with shareholders' best interests. Such a system could reduce moral hazard and opportunistic behavior. It enables the auditor to automate

repetitive tasks and focus on areas that require expert judgment and meticulous examination. This has led to higher-quality and more diverse audit reports (Groenewald & Kilag, 2024).

AI enhances audit quality by refining audit processes and enabling continuous auditing (Ganapathy, 2023). This results in a more efficient, cost-effective audit process. This suggests that auditors can examine every transaction rather than only a selection (Fedyk *et al.*, 2022; Al-Omush *et al.*, 2025). AI's influence on audit quality depends on the auditor's expertise, organizational context, and existing ethical norms. Evaluation methods mostly rely on specialists' judgements (Nuritdinov *et al.*, 2025). AI enhances these processes, making them more thorough and efficient, thereby increasing reliability and transparency in financial reporting. Based on this, the study proposes the following:

H1: AI adoption significantly and positively influences audit quality.

The Relationship Between AI Adoption and Risk Management Practices

AI can support hazard identification, assessment, and mitigation, thereby enhancing risk management strategies (Adekunle *et al.*, 2023). AI systems analyze large datasets (financial, operational, etc.) to identify issues and alert users to potential concerns before they escalate into significant problems. AI identifies operational and financial deficiencies in corporate risk management and formulates suitable mitigation measures (Omopariola & Aboaba, 2021). From an information-processing perspective, data gathering and analysis reduce information gaps, enabling managers to make decisions more efficiently and quickly. It also strengthens risk management systems and internal control frameworks.

AI enhances the precision and resilience of risk management systems (Diameh *et al.*, 2025). Organizations are integrating AI more widely to improve risk assessment accuracy and mitigate disruptions from unforeseen operational crises (Li *et al.*, 2024; Kalogiannidis *et al.*, 2024). It provides a foundation for supervision. AI systems mitigate moral hazard and align management objectives with the organizations. Agency theory may also help explain this connection.

AI improves risk evaluation, allowing risk managers to spend more time on strategic analysis, scenario development, and risk reduction (Yazdi *et al.*, 2024). It also strengthens resilient risk management structures. Real-time surveillance and AI-facilitated coordination and response (Adekunle *et al.*, 2023) empower businesses to implement AI-driven risk solutions to detect threats across sectors and categories. Enhanced risk mitigation. Improved governance. Contingency theory posits that AI's efficacy in risk management depends on personal competencies, moral implications, and system design. Strong leadership skills and solid ethical foundations support resilient, flexible risk management frameworks that perform in complex, evolving environments (Zeriouh and Amara, 2025). Based on this foundation, the study proposes the following:

H2: AI adoption significantly and positively influences risk management practices.

The Relationship Between Risk Management Practices and Audit Quality

High-quality risk management practices improve audits by enabling organizations to identify, assess, and mitigate risks before audits begin (Weekes-Marshall, 2020). Empirical studies indicate that organizations with mature risk management practices experience fewer errors, misstatements, and control deficiencies, allowing auditors to rely more on internal controls and achieve better audit results (Schmidt, 2020). Agency theory clarifies this relationship: effective risk management practices minimize information asymmetry and reduce moral hazard between management and auditors.

Risk management practices provide auditors with relevant internal information and control systems, thereby enabling them to be more confident and accurate in their analysis and audit of financial accounts (Ilori *et al.*, 2024). Risk management practices enhance audits by enabling auditors to make better decisions and conduct more effective risk assessments. The literature shows that organizations with well-designed risk management models help auditors identify errors and exceptions by enabling them to focus on high-risk areas (Nwachukwu *et al.*, 2024). According to the information processing hypothesis, effective internal controls can improve information flow, reduce ambiguity, and allow

auditors to analyze complex financial and operating information. Including structured risk information in the audit makes it more rigorous, accurate, and reliable (Sewpersadh, 2025).

Well-practiced risk mitigation leads to well-designed, proactive audit techniques (Almgrashi & Mujalli, 2024). The literature shows that firms with stronger risk management systems exhibit better planning, clearer scope definition, and continuous audit monitoring, leading to higher-quality audit output (Noch, 2024). Contingency theory supports this relationship, arguing that audit quality depends on factors such as organizational structure, auditor quality, auditor abilities, and the ethical environment. When such organizations have sound risk management practices, auditors may deliver more dependable (clear and timely) audit results (Sonjaya, 2024). This will also increase stakeholder confidence and governance performance. Based on these reviews, this study hypothesized that:

H3: Risk management practices positively and significantly influence audit quality.

The Mediating Effect of Risk Management Practices in the Relationship Between AI Adoption and Audit Quality

AI in auditing facilitates better risk management practices and improves audit quality. AI enables real-time monitoring, anomaly detection, and data processing, improving internal controls, risk identification, and quality assurance (Mirishli *et al.*, 2025). AI-driven audits have also improved internal risk detection, mitigation strategies, and audit consistency (Ghafar *et al.*, 2024). Artificial intelligence can further help auditors make more precise, rational assessments by reducing information asymmetry and delivering timely, high-quality risk data (Kzykeyeva, 2022, Information Processing Theory).

The efficacy of the risk management framework for businesses is closely linked to AI's influence on the auditing process. Risk management practices constitute a prudent examination of potential threats. This framework includes mechanisms to evaluate and mitigate risk. This approach has enabled auditors to focus on high-risk areas and reduce the likelihood of errors (Coetzee & Lubbe, 2014). As agency theory explains, the relationship is complex. Effective risk management can mitigate moral hazard, encourage the adoption of AI technologies, and align managers' and auditors' interests. Incorporating artificial intelligence into risk management frameworks improves audit quality and data analysis (Singh *et al.*, 2025).

Implementing AI in predictive and continuous auditing requires robust risk management strategies to shift the auditor's role from reactive to proactive (Ampofo *et al.*, 2024). Auditors will assess the AI's results, identify errors, and suggest modifications. The relationship is mostly examined through the lens of contingency theory. The study examines internal governance systems, leadership endorsement, and organizational preparedness. Artificial intelligence possesses its essence. However, for certain individuals, it presents a challenge. However, it is not flattering. This outcome aligns with the variation in audit quality across organizations (Nguyen *et al.*, 2025).

Based on this discussion, the study hypothesized that:

H4: Risk management practices partially and significantly mediate the relationship between AI adoption and audit quality.

Methodology

Research Design

The study used an analytical design to evaluate the interconnected relationship among variables (Park, 2007). The methodology suits the research because it allows a comprehensive examination of direct and indirect effects. This method examines how practices for managing business risk affect audit quality.

The Study Location and Targeted Population

Ghana is an emerging economy with a maturing AI ecosystem, diverse audit firms and modern risk management practices. Given recent significant legislative reform and several initiatives to strengthen

governance, internal audit systems, and risk management practices, this study focuses on Ghana (Tetteh *et al.*, 2021). Ghana has begun operationalizing the Global Internal Audit Standards to strengthen audits and risk management and improve internal controls (Ataribanam, 2024). These reforms are an important part of Ghana's broader goal of improving governance efficiency and professionalizing auditing, making it a viable emerging market for this study.

Audit firms provide an ideal context for this study in Ghana, as they lead investment in and the application of AI technologies (KPMG, 2018; Dickey *et al.*, 2019). These firms utilize modern risk management practices to provide strategic audit and advisory services to clients across all industries. Therefore, studying their approaches, principles, and practices can help explain how risk management practices mediate the relationship between AI and audit quality.

This study surveyed top management at Ghanaian audit firms responsible for adopting and overseeing AI in the audit process. Senior leaders develop strategies, apply AI solutions, and ensure their effective use in risk management practices and audit activities. Their views add vital perspectives on how AI is transforming audit firms and auditing procedures. Focusing on top managers enables this study to elicit informed responses to decision-making. It allows the most experienced respondents to provide empirical evidence on how these technological changes affect audit firms' internal processes and the effectiveness of audits in Ghana.

Sample Size and Selection Criteria

The proposed methodology demonstrated that a sample of 155 senior managers is adequate to achieve 80% power, a minimum path coefficient of 0.2, and a P-value of 0.05 (Kock & Hadaya, 2018).

The research is framed from the perspective of senior audit managers who supervise and implement AI in audit and risk management practices. Their research significantly advances technology, risk management practices, and audit quality. Entities that failed to implement strategic decisions, use AI, or conduct audits were deemed insignificant or superficial. This methodology ensured the data gathered directly addressed the investigation's objectives and research questions.

Sampling Technique and Procedures for Data Collection

This study used judgmental sampling of top managers in 43 audit firms in Ghana, selecting those who directly oversee and implement AI in auditing and risk management practices to provide informed responses. After removing invalid, incomplete, or unexamined responses from the 539 questionnaires sent, the study obtained 342 valid responses, exceeding the 155 indicated by the inverse-square-root method. This was based on collecting responses from top managers across different parts of Ghana, with consistent follow-ups, cooperation with organizations and their representatives, and clear instructions and reminders to maximize participation. The larger sample size improved the reliability and robustness of the study’s results. Although judgmental sampling can introduce selection bias, this risk was minimized by recruiting senior managers from a range of audit firms across all study regions, improving the sample's representativeness.

Data were collected via Computer-Assisted Web Interviewing (CAWI), in which participants completed standardized online questionnaires. CAWI was also ideal, given the dispersed distribution of top managers, as it enabled rapid, accurate data collection with minimal logistical barriers. Data collection spanned six months from July to December 2025, allowing for follow-up, reminders, and engagement with respondents throughout Ghana.

Sources of Instrument Adaptation

This study's measurement criteria were derived from existing measures and adapted to align with the context and requirements of audit firms in Ghana. Ananda *et al.* (2024) developed six questions on AI use in auditing, focusing on key factors affecting the acceptance and implementation of AI in Ghana's auditing sector. Hady and Mudhaffar (2025) developed nine questions to evaluate audit quality, focusing on audit results in terms of precision, dependability, and comprehensiveness. Weeks-Marshall (2020)

evaluated risk management practices using a two-dimensional framework for hazard identification and management, which applied to the Ghanaian audit firm context.

All items were evaluated using a five-point Likert scale, with 1 representing "strongly disagree" and 5 representing "strongly agree." The scale allowed respondents to express their views on the application of AI, risk management practices, and auditing practices within audit firms in Ghana. The responses were all typical and apathetic.

Ethical Considerations

Informed consent was obtained from participants before data collection. Participation was voluntary, and confidentiality and anonymity were maintained throughout the study. Data were used solely for academic purposes. Ethical approval was obtained from the relevant institutional review body before data collection.

Statistical Tool for Data Analysis

The data were analyzed utilizing Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS. PLS-SEM is particularly appropriate for complex mediation models, small sample sizes, and data that violate normality assumptions (Nitzl, 2016). Compared with covariance-based SEM, it offers greater flexibility for predictive modelling, exploratory research, and theory development (Russo & Stol, 2021). Latent variable scores and interrelations within the model are computed via path weighting, centroid, and factor-score methodologies.

This study utilized bootstrapping to examine both direct and indirect impacts. It does this by averaging multiple resamples to improve the precision of estimates. Outer loadings were calculated utilizing a bootstrap sample of 5000 with a 95% confidence interval. The study used the average variance extracted (AVE) and outer loadings to assess convergent validity. This study used bootstrapping to evaluate the asserted correlations and both direct and indirect effects. This study assessed discriminant validity using HTMT ratios and evaluated internal consistency reliability with Cronbach's alpha (Hair & Alamer, 2022). To reduce sampling uncertainty, the study used bootstrapping to improve precision and account for mediating effects.

Results

Common Method Bias (CMB) Assessment

Because participant data are self-reported, the study examined prevalent technique bias using Harman's single-factor test. The first component accounted for 16.246% of the total variance (Appendix 1). This falls below the 50% bias detection threshold (Edonomokumor, 2025; Obeng *et al.*, 2026). The absence of a single factor explaining most of the variance indicates a low likelihood of common method bias and supports the reliability and validity of the collected data. These results strengthen confidence in the study's analyses, suggesting that the relationships observed reflect effects rather than methodological artifacts.

Table 1: Common Method Bias (CMB)

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	16.585	61.426	61.426	16.246	60.169	60.169
2	4.994	18.498	79.924			
3	1.284	4.756	84.680			
4	0.774	2.868	87.548			
5	0.468	1.733	89.281			
6	0.431	1.597	90.878			
7	0.385	1.427	92.305			
8	0.305	1.131	93.436			
9	0.260	0.965	94.400			
10	0.224	0.830	95.230			
11	0.193	0.715	95.945			
12	0.183	0.677	96.622			

13	0.149	0.552	97.175			
14	0.137	0.506	97.681			
15	0.108	0.399	98.080			
16	0.102	0.377	98.457			
17	0.085	0.314	98.771			
18	0.062	0.230	99.001			
19	0.058	0.214	99.215			
20	0.052	0.192	99.407			
21	0.040	0.148	99.555			
22	0.034	0.125	99.680			
23	0.032	0.119	99.799			
24	0.021	0.079	99.879			
25	0.015	0.055	99.934			
26	0.011	0.041	99.975			
27	0.007	0.025	100.000			
Extraction Method: Principal Axis Factoring.						

Socio-demographic Analysis of Top Managers (Auditors) in the Audit Firms of Ghana

Table 2 presents the demographic and socio-demographic features of the targeted top managers (auditors) in Ghanaian audit firms. Of these, 79.82% were male, and 20.18% were female, highlighting women's underrepresentation in senior audit roles. This may indicate that men are more influential in decisions about AI adoption and risk management practices.

Firm size analysis revealed that 42% of audit firms were small, 37% medium-sized, and 19% large, based on the European Union employee classification: fewer than 50 employees for small firms, 50–249 for medium-sized firms, and 250 or more for large firms. The organizations in the sample have the following age distribution: 38.89% are 4-6 years old, 26.90% are 7-10 years old, and 31.87% are over 10 years old.

The sample consists of 42.40% senior managers and 31.87% senior managers with 4-6 years and 7-10 years of experience in the auditing industry, respectively. Consequently, participants recognize auditing procedures that enhance the dependability of their evaluations. Participants' educational qualifications included a master's degree (46.20%), professional certification (32.46%), a bachelor's degree (12.28%), and a doctoral degree (5.56%). It reflects the perspectives of a substantial group of experienced and accomplished executives whose encounters with AI, risk management protocols, and audit integrity within their organizations are highly relevant.

Table 2: Socio-demographic Analysis (top managers)

		N	Marginal Percentage
Gender	Males	273	79.82
	Female	69	20.18
Audit firm size	Small	145	42.40
	Medium	129	37.72
	Large	68	19.88
Age of the audit firm	1-3 years	12	3.51
	4-6 years	133	38.89
	7-10 years	92	26.90
	More than 10 years	105	30.70
Tenure of the managers	1-3 years	34	9.94
	4-6 years	145	42.40
	7-10 years	109	31.87
	More than 10 years	54	15.79
Education level of the managers	Bachelor degree	42	12.28
	Master’s degree	158	46.20
	PhD	19	5.56
	Professional qualification	111	32.46
	Other	12	3.51
Total		342	100

Descriptive Statistical Analysis

Table 3 presents the descriptive analysis of respondents' scores across the study variables. The findings indicate that AI adoption is widely embedded within audit firms, as reflected in the mean score. This suggests that audit firm managers may use AI to support decision-making and improve operational efficiency. The mean score for audit quality further indicates that firms perceive audits as highly accurate and reliable, with strong processes for evaluating financial information. Similarly, the results on risk management practices suggest that firms have relatively strong control mechanisms in place. However, risk identification and management practices still have room for improvement.

Table 3: Descriptive Analysis

Variables	N	Min	Maxi	Mean	Std. Deviation
AI adoption	342	1	5	4.434	0.966
Audit quality	342	1	5	4.484	1.022
Risk management practices	342	1	5	4.082	0.901

Measurement Evaluation

Table 4 presents the PLS-SEM results relating to model fit, convergent validity, and reliability. This study assessed model fit using the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI). The SRMR value of 0.031 is below the recommended threshold of 0.08, and the NFI value of 0.922 exceeds the benchmark of 0.90 (Sureshchandar, 2023; Arhinful *et al.*, 2026a), indicating good fit with minimal residual error. Overall, these results suggest that the model is robust and provides a sound basis for examining both direct and indirect (mediating) relationships among the key determinants of audit quality.

Convergent validity is a component of construct validity and is significant. It indicates the extent to which a data collection can be regarded as a latent construct (Cheah *et al.*, 2018; Obeng *et al.*, 2026). This was assessed using average variance extracted (AVE) and standardized loadings. The established criteria AVE > 0.50 and standardized loadings > 0.70 are recommended (Haji-Othman & Yusuff, 2022). Figure 2 illustrates the proposed model (Evaluation of Measurement Model).

Reliability was assessed to determine how well the indicators reflected the specified measurement construct. Composite reliability and Cronbach's alpha were used to assess the internal consistency and reliability of the items. Scores above 70% indicate high measurement precision and reliability (Arhinful *et al.*, 2026b). The results meet or exceed the minimum acceptable thresholds for the construct. This suggests that the measurement instrument is reliable and suitable for further analysis.

Table 4: PLS-SEM (Model Fitness, Convergent Validity and Reliability)

Construct (dimension)	**Item**	**Standardized loadings**	**Average variance Extracted (AVE)**	**Composite Reliability (CR)**	**Cronbach alpha (CA)**
AI adoption in Auditing	AIIA1	0.938	0.694	0.938	0.850
	AIIA2	0.973			
	AIIA3	0.921			
	AIIA4	0.953			
	AIIA5	0.965			
	AIIA6	0.864			
Audit quality	ADQT1	0.824	0.646	0.933	0.946
	ADQT2	0.755			
	ADQT3	0.747			
	ADQT4	0.747			
	ADQT5	0.754			
	ADQT6	0.836			
	ADQT7	0.851			
	ADQT8	0.846			
	ADQT9	0.864			
	CORO1	0.939	0.586	0.940	0.956

Risk management practices	CORO2	0.942			
	CORO3	0.931			
	CORO4	0.924			
	CORO5	0.961			
	LERO1	0.936			
	LERO2	0.899			
	LERO4	0.933			
	LERO5	0.888			
	LERO6	0.912			
	LERO7	0.810			
Normed Fit Index (NFI) (0.922), Standardized Root Mean Square Residual (SRMR) (0.031)					

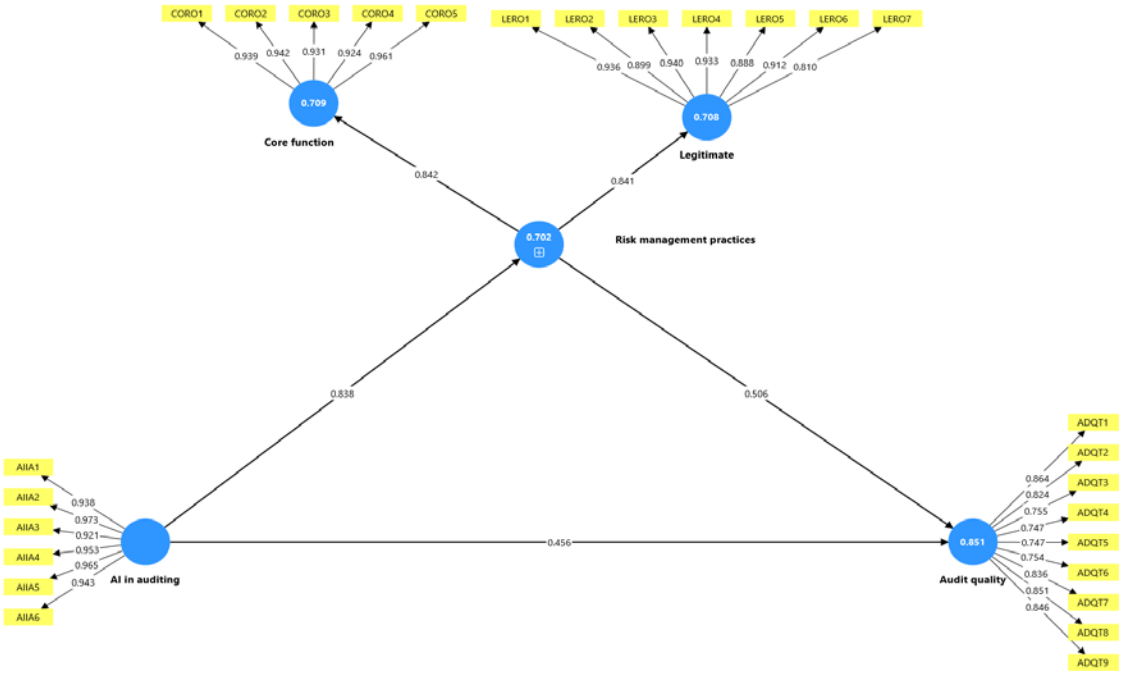


Figure 2: Measurement Model (standardized loadings)

Discriminant Validity

This study assessed discriminant validity to ensure the model's constructs represent distinct theoretical concepts. Table 5 presents the Heterotrait-Monotrait (HTMT) ratio findings used for evaluation. All HTMT values fell below the 0.85 threshold (Feng *et al.*, 2017; Arhinful *et al.*, 2026c), indicating that the constructs showed both conceptual and practical diversity. The findings confirmed the discriminant validity and improved the dependability of the research outcomes.

Table 5: Discriminant Validity (Heterotrait-Monotrait) Ratio

Constructs	**1**	**2**	**3**
(1) AI adoption	-	-	
(2) Audit quality	0.430		
(3) Risk management practices	0.334	0.510	

Structural Model Evaluation

Table 6 illustrates the structural model's forecasting and explanatory capabilities. It encompasses R^2, Q^2 forecasts, f^2, and the Variance Inflation Factor (VIF). The R^2 statistic quantifies the fraction of variance in the dependent variable explained by the independent variables. A score of 0.25 indicates moderate explanatory power. A score of 0.50 indicates robust explanatory capability. An explanatory efficacy of 0.75 indicates an exceptionally high degree of explanatory strength. The R^2 coefficient for

audit quality is 0.848. The AI and risk management practices explain 84.8% of the variance in audit quality. All constructs exceeded the threshold, indicating they explained a large portion of the variance.

Q^2 predict assesses the model's predictive relevance; values greater than 0 indicate the model's ability to predict observed outcomes. All the Q^2 predict values were greater than 0. For example, a Q^2 predict of 0.774 for audit quality implies that risk management practices and AI adoption are predicted to account for 77.4% of the variance in audit quality, indicating a strong predictive role.

Effect size (f^2) reflects how much each predictor influences the endogenous constructs; small, medium, and large effects are defined by minimum values of 0.02, 0.15, and 0.35, respectively. All f^2 values in the present analysis exceeded the minimum threshold because the predictors had small to large effects.

The study evaluated multicollinearity among predictor variables using the variance inflation factor (VIF). Values < 5 suggest that there is no association problem across constructs.This threshold was met for all VIF values in the present study, confirming the absence of multicollinearity (Mensah *et al.*, 2024; Mensah *et al.*, 2026).

Meeting these assessment criteria confirms the structural model's reliability, robustness, and effectiveness. This finding supports its potential to examine the direct, mediating, and moderating associations proposed in this study and provides strong empirical support for managerial policy and theory development.

Table 6: Structural Model Evaluation

	***R*-square**	***Q*²predict**
Audit quality	0.848	0.774
Risk management practices	0.768	0.763
	***f*-square**	***VIF***
AI adoption -> Audit quality	0.238	1.325
AI adoption -> Risk management practices	0.316	1.338
Risk management practices -> Audit quality	0.468	1.020

Hypothesis Testing

Table 7 reports the analysis results, and Figure 3 illustrates the structural model and the relationships among constructs. Based on these results, the study reviewed the research hypotheses.

The findings show that AI adoption in auditing has a significant positive effect on audit quality ($\beta = 0.395$, $t = 5.322$, $p < 0.01$) and on risk management practices ($\beta = 0.877$, $t = 76.155$, $p < 0.01$). Risk management practices, in turn, strongly and positively influence audit quality ($\beta = 0.555$, $t = 7.616$, $p < 0.01$). These findings support hypotheses H1, H2, and H3.

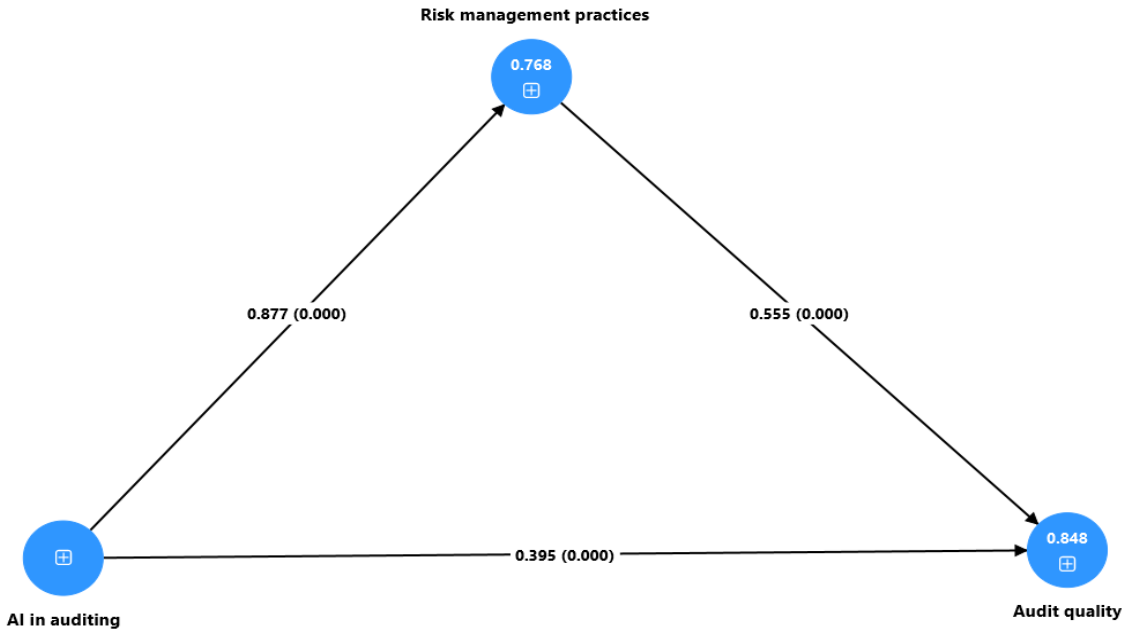
In addition, the study demonstrated that risk management practices partially mediate the relationship between AI adoption and audit quality ($\beta = 0.486$, $t = 7.280$, $p < 0.01$). The mediation is partial because the direct effect of AI adoption on audit quality remains significant, confirming H4.

Table 7: The Relationship Between the Construct (Empirical Findings)

Relationship	**Hypothesis**	***β***	**S. E**	***t*-test**	***p* values**
Direct effect					
AI adoption -> Audit quality	H1	0.395 ***	0.074	5.322	0.000
AI adoption -> risk management practices	H2	0.877 ***	0.012	76.155	0.000
Risk management practices -> Audit quality	H3	0.555 ***	0.073	7.616	0.000
Mediation effect					
AI adoption -> risk management practices -> Audit quality	H4	0.486 ***	0.067	7.280	0.000

**** p<0.01, ** p<0.05, * p<0.10*

Figure 3: Structural Model



Discussion

The study finds that AI adoption significantly and positively enhances audit quality, aligning with the findings of Anomah *et al.* (2024), Alhazmi *et al.* (2025), and Ananda *et al.* (2024). They can identify issues, assess risks, and formulate superior solutions (Ganapathy, 2024). Legislative advancements in Ghana are facilitating the integration of these technologies, driving increased corporate investment in AI, auditor education, and enterprise-wide digital transformation (Anomah, 2025). Systemic audit and internal control methodologies, structured governance structures, capable audit staff, and organization-based processes further reinforced these advantages. As a result, audits are more precise, financial errors are minimized, transparency increases, investor confidence improves, capital allocation improves, and market stability is maintained. These results indicate that integrating technology with professional judgment can enhance efficiency, client confidence, and auditing's competitive advantage (Shemshaki, 2024).

AI adoption also improved risk management by creating systems that align management and auditors' interests and reduce information asymmetry. Well-designed risk management practices increase the reliability of financial reporting, strengthen internal controls and limit managerial opportunism. Regulatory interventions in Ghana also supported these results by promoting strong governance and controls. Effective audit teams, with rigorous staff and standard practices, also maintained control quality, reduced the risk of financial errors, and sustained investor confidence, which, together with a high level of safety, ensured control assurance and strengthened investor trust. These findings highlight the importance of a robust internal control framework for audit effectiveness and optimal audit outcomes, minimizing errors, protecting the firm's reputation, and demonstrating that the firm upholds an internal control system for client interests.

Risk management practices positively influence audit quality. Agency theory supports this relationship, arguing that aligning management and auditors' objectives and reducing information asymmetry facilitate more accurate reporting. Good risk management practices lead to accurate financial reporting, stronger controls, and reduced managerial abuse (Manginte, 2024). Regulatory support in Ghana was in place (the governance regime and compliance with internal control regulations (Afriyie *et al.*, 2019)), including robust audit teams and standardized procedures, which further strengthened these outcomes. Good risk management practices can minimize financial errors, improve focus and clarity, increase

investor confidence, improve capital utilization, and strengthen auditors' efficiency, authenticity, and business confidence (Nwachukwu *et al.*, 2024).

The research revealed that risk management practices partially mediate the relationship between AI adoption and audit quality. AI enables the timely, reliable, and complete collection, analysis, and management of risk data, and strong risk management practices ensure this information is used effectively to improve audit outcomes (Ganapathy, 2023). Adopting risk practices supported by advanced technology corroborates information processing theory, which holds that improved audit reliability makes decision-making easier. Well-qualified audit groups facilitated results based on robust corporate governance, organizational uptake of AI technologies (Hilb, 2020), and compliance with recognized risk management practices in Ghana (Bauer *et al.*, 2019). The mediating effect yields significant economic benefits by reducing errors, clarifying messages, improving business decision-making, and boosting investor confidence. The study found that AI adoption alone is not enough. Firms must complement it with adequate risk management practices to improve audit quality, client trust and efficiency.

Limitations and Future Scope

The research is confined to the particular environment in which it was executed. The study is limited to Ghana, which constrains the external validity of the findings for countries with different legal, technological, and socio-economic contexts. The information can help other African governments and developing economies assess AI utilization, implement safeguards against potential risks, and understand the ethical implications for audit integrity.

The results are significant for audit firms. Insurance firms, international corporations, and financial institutions also warrant further examination. The primary drawback of judgmental sampling is its susceptibility to selection bias. Subsequent research may use random sampling techniques to improve the sample's representativeness and the reliability of the results.

Individuals may provide false information on surveys, which can significantly influence outcomes. Future studies using objective performance metrics, audit trails, or independently verified datasets will deepen explanatory power and strengthen empirical reliability. Future studies should examine how AI integration, along with moderating factors such as the caliber of corporate governance, the effectiveness of audit committees, organizational learning, digital transformation, and technical preparedness, affects audit quality and risk management strategies.

Conclusion

This study examines how AI implementation affects audit quality. It also examines the mediating function of risk management strategies in the relationship. The study collected data from 342 senior audit managers at auditing firms in Ghana using judgment sampling. Data were evaluated with PLS-SEM. The study shows that using AI enhances audit and risk management practices. AI influences the efficacy of audit and risk management practices. The research indicated that technical competencies and robust risk management practices are essential for enhancing audit performance and quality.

Theoretical implications

The results indicate that integrating information processing theory would enhance audit activities. Ghanaian audit institutions can apply this insight by investing in the latest AI technologies and ongoing training to support auditors, including in critically analyzing complex datasets. Technology-driven processes help firms identify additional risks, minimize errors, and improve audit quality, enhancing audit reliability.

The study advances agency theory by emphasizing the importance of risk management practices and alignment between management and auditors. To address knowledge gaps, Ghanaian audit firms must strengthen governance frameworks and formalize risk management practices. By incorporating these into standard operating procedures, firms can monitor internal controls continuously, minimize managerial opportunism, and equip auditors to deliver accurate, reliable appraisals.

Policy implications

This research supports the view that the optimal effectiveness of technology-led auditing practices depends on stronger regulatory frameworks. Ghanaian authorities could strengthen compliance with the Companies Act 2019 and the standards set by the Institute of Chartered Accountants, Ghana (ICAG). Clear, enforceable rules that promote the appropriate use of advanced auditing technologies would encourage audit firms to adopt them and help ensure auditors have the skills to assess complex financial data critically. They boost organizational reliability and minimize the risk of financial errors using automated audits.

This effect demonstrates the efficacy of risk management practices and the importance of policies/standards in promoting compliance with corporate governance, internal controls, and internal supervision in organizations. The Ghana Corporate Governance Code and the Bank of Ghana's Risk Management Guidelines help firms establish strong internal controls and align managers' decisions with the organization's goals. Adherence to such regulations enables honest financial reporting, limits managerial opportunism, and improves auditors' capacity to provide high-quality audits.

Practical implications

The results suggest a critical need to integrate AI into practical auditing. Ghanaian audit firms must adopt sophisticated AI tools and processes to improve data analysis and detect issues promptly. Integrating technology increases audit reliability and reduces errors, allowing auditors to identify potential threats more efficiently and, in turn, improve overall job performance.

The effectiveness of risk management practices depends on strong controls. Companies must conduct rigorous risk analysis, standardize internal audit procedures, and implement processes to identify and assess risks, monitor internal controls, and evaluate effectiveness and performance improvement across the organization. They also ensure continuous supervision, mitigate managerial opportunism, provide independent management control over both external and internal oversight, and enable auditors to produce accurate and reliable financial statements, thereby improving the quality of their reviews.

Credit authorship contribution statement

KTKG: Software, Conceptualization, writing, formal analysis, Methodology, Investigation, Analysis. **SAS:** Conceptualization, writing, reviewing, Methodology, Investigation, Analysis, Supervision

Conflict of Interest

The authors declare that they have no competing interests.

Acknowledgement

Not applicable.

Funding

This study did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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