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Smart Audit: The Role of AI, Risk Management, and Governance in Enhancing Audit Quality

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Abstract. *The development of Artificial Intelligence (AI) has brought significant changes to auditing practices, particularly in improving audit quality. This study aims to examine the effect of AI implementation, risk management, and governance on audit quality. A quantitative approach was employed using a survey method involving 100 auditors in East Java who have implemented AI-based auditing systems. The data were collected through purposive sampling and analyzed using multiple linear regression. The results indicate that AI implementation, risk management, and governance have a positive and significant effect on audit quality. These findings suggest that AI enhances efficiency, accuracy, and auditors' analytical capabilities in identifying risks. However, its effectiveness depends on organizational readiness, data quality, and auditor competence. Therefore, the implementation of AI in auditing should be supported by strengthened risk management, governance, and the development of auditors' professional capabilities.*

Abstrak. Perkembangan Artificial Intelligence (AI) telah membawa perubahan signifikan dalam praktik audit, khususnya dalam meningkatkan kualitas audit. Penelitian ini bertujuan untuk menganalisis pengaruh implementasi AI, manajemen risiko, dan tata kelola terhadap kualitas audit. Penelitian menggunakan pendekatan kuantitatif dengan metode survei terhadap 100 auditor di Jawa Timur yang telah menerapkan sistem audit berbasis AI, dengan teknik purposive sampling dan analisis regresi linear berganda. Hasil penelitian menunjukkan bahwa implementasi AI, manajemen risiko, dan tata kelola berpengaruh positif dan signifikan terhadap kualitas audit. Temuan ini mengindikasikan bahwa AI mampu meningkatkan efisiensi, akurasi, dan kemampuan analitis auditor dalam mengidentifikasi risiko. Namun, efektivitasnya bergantung pada kesiapan organisasi, kualitas data, dan kompetensi auditor, sehingga diperlukan penguatan manajemen risiko, tata kelola, serta kapabilitas profesional auditor.

Keywords:
Artificial Intelligence; Audit Quality; Risk Management

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Introduction

The fourth industrial revolution has brought fundamental changes across many aspects of life, including the auditing field. The rapid development of Artificial Intelligence (AI) has created both significant opportunities and new challenges in financial auditing. It enables the automation of data collection, processing, and analysis, which have traditionally been labor intensive tasks, thereby improving efficiency and accuracy (Huda & DP, 2025; Kau & Fitriana, 2025; Tampubol & Dewayanto, 2025). These advances require auditors to strengthen their digital capabilities to fully leverage this technology. However, its implementation still faces several challenges, including limited technical skills, ethical concerns, and data security issues that demand serious attention (Renta et al., 2025). In Indonesia, the adoption of this technology in auditing remains relatively limited, making it an important area for further investigation.

The urgency of research on Artificial Intelligence in auditing lies in the need to understand how this technology can enhance regulatory compliance and risk management effectiveness in real time across industries. Strategic sectors such as oil and gas and financial technology highlight a growing demand for more responsive and accurate audit systems (Handayani et al., 2025; Munawarah, 2024; Pratama et al., 2023; Suriadi & Muliyono, 2024). It enables continuous monitoring and proactive risk management, thereby reducing non-compliance risks and potential sanctions (Del Caprio, 2025; Semenova et al., 2023). This transformation reflects a shift from periodic auditing toward continuous auditing. However, it also introduces challenges related to data quality, algorithmic bias, privacy, and the need for robust governance frameworks and adaptive regulations (Fatria et al., 2024; Nasir et al., 2026). Therefore, a comprehensive understanding of its benefits, risks, and management practices is essential to ensure responsible and effective implementation.

Survey data indicate that the adoption of Artificial Intelligence in auditing still reflects a gap between expectations and actual practice. While large audit firms have invested substantial resources in developing these capabilities, adoption among practitioners and small to medium firms remains limited. Although auditors recognize its potential to enhance anomaly detection and audit efficiency, resistance and competency gaps continue to hinder full implementation (Nasir et al., 2026; Rawashdeh et al., 2023). Furthermore, it enables auditors to shift their focus from routine tasks to more complex risk analysis; however, its effectiveness depends on organizational readiness and clear ethical frameworks (Hu et al., 2021). This contrast highlights the need for further examination of the factors influencing adoption.

This situation raises a fundamental question in evaluating digital transformation in auditing. Is the adoption of Artificial Intelligence merely about improving technical efficiency, or should it also consider auditor readiness, ethical frameworks, and governance structures? This perspective suggests that its integration cannot be viewed as purely technological. Rather, it represents a socio technical transformation involving changes in auditor roles, professional standards, and stakeholder relationships. Therefore, evaluation frameworks should extend beyond efficiency to include ethics, governance, and the sustainability of audit practices (Onyenahazi, 2025; Senturk, 2025).

This study highlights the importance of a comprehensive examination of Artificial Intelligence implementation in auditing. It focuses on three key aspects: its role in enhancing audit quality and effectiveness, implementation challenges including data quality and algorithmic bias, and governance frameworks to ensure responsible use. Key indicators include task automation, anomaly and fraud detection, real-time compliance monitoring, as well as transparency and accountability in decision making.

Despite growing academic and professional attention, empirical research in this area remains limited. Most studies on digital transformation in auditing focus primarily on technical aspects and operational efficiency (Ghafar et al., 2024; Oyetunji et al., 2024; Raza et al., 2025). Research examining the interaction between Artificial Intelligence usage, auditor readiness, and governance in relation to audit quality remains scarce, particularly in developing countries such as Indonesia.

Previous studies have explored various aspects of implementation. Artificial Intelligence improves audit efficiency and accuracy through the automation of routine tasks, as well as enhanced analytical capabilities and anomaly detection (Ganapathy, 2024). It also enables auditors to focus on more complex risk analysis by reducing routine workloads (Karagül & Selİmoğlu, 2025; Khan et al., 2021; Yang, 2025).

On the other hand, studies on the challenges of Artificial Intelligence implementation in auditing reveal several barriers. Limited technical skills, ethical concerns, and data security represent the main obstacles (Natasya et al., 2025). Algorithmic bias poses a serious threat to audit objectivity (Bouchetara et al., 2024). Furthermore, governance frameworks and standards such as ISO 42001 are essential to ensure responsible use (Khan et al., 2021).

Research on auditor readiness in the Artificial Intelligence era presents mixed findings. Although its importance is recognized, significant competency gaps remain (Bouchetara et al., 2024). Successful implementation depends largely on data quality and organizational capability in managing digital transformation (Naseer & Ahmed, 2025). Furthermore, a holistic approach that integrates technology, people, and processes is essential for its adoption in auditing (Ogunmokun et al., 2021).

Despite numerous studies on Artificial Intelligence in auditing, research remains limited in simultaneously examining the three key dimensions of technology, human resources, and governance within a coherent analytical framework, particularly in developing countries such as Indonesia. Most existing literature addresses these aspects separately or focuses on a single dimension. This study argues that the combined influence of these dimensions reflects organizational readiness to adopt Artificial Intelligence responsibly and effectively. Such readiness may explain variations in implementation outcomes across organizations and sectors that remain underexplored in prior research.

Studies that simultaneously examine technology, human resources, and governance in Artificial Intelligence implementation for auditing remain limited, creating a critical knowledge gap. It remains unclear whether investment in Artificial Intelligence leads to significant improvements in audit quality or instead introduces new risks, such as algorithm bias and overreliance on automated systems. This study aims to address this fundamental gap.

To address this gap, this study makes several substantive contributions. Conceptually, it integrates the three key dimensions of Artificial Intelligence implementation in auditing, namely technology, human resources, and governance, into a coherent analytical framework. This approach provides a more comprehensive basis for assessing organizational readiness and effectiveness compared to partial approaches that focus solely on technology. Empirically, the study uses data from multiple industry sectors in Indonesia, enabling cross sector analysis across different risk and regulatory environments. By focusing on Indonesia as a developing country with unique market and regulatory dynamics, this study offers novel insights into the relationship between Artificial Intelligence adoption and audit quality.

This study provides multidimensional contributions. Theoretically, the findings enrich the application of Socio Technical Systems Theory and Stakeholder Theory in the context of digital transformation in auditing. It examines whether the integration of technology, human resources, and governance leads to sustainable improvements in audit quality. Practically, the results offer insights for accounting firms in designing balanced Artificial Intelligence adoption strategies, for regulators in developing standards and guidelines for its use in auditing, and for professional associations in creating relevant training and certification programs.

This study is important due to its strategic role in addressing challenges faced by the auditing profession in the digital era. Auditors face increasing pressure to improve efficiency and quality amid growing data volumes and more complex business transactions, while also being expected by the public and regulators to maintain professional skepticism, independence, and integrity despite the expanding use of technology. This study addresses a key question: whether the adoption of Artificial Intelligence in auditing represents a sound approach to enhancing quality and professional relevance. The answer to this question will shape the future direction of the auditing profession in an increasingly digital business environment.

Theoretical Foundation of Artificial Intelligence Implementation in Auditing

This study is based on the integration of Socio Technical Systems Theory, Agency Theory, and Stakeholder Theory. Artificial Intelligence in auditing is not solely a technological issue but involves complex interactions between technical components such as hardware, software, and algorithms, and social components including auditors, management, regulators, and other stakeholders. Socio Technical Systems Theory, developed by Trist (1981) and further expanded by Appelbaum (1997), states that system optimization can only be achieved when technical and social aspects are designed together and support each other. In the context of Artificial Intelligence in auditing, this perspective highlights the importance of balancing advanced Artificial Intelligence capabilities with auditor readiness in its application.

Agency Theory, as proposed by Jensen & Meckling (1976), explains conflicts that arise from information asymmetry between management as the agent and owners as the principal. In the context of auditing, auditors act as a mechanism to reduce this asymmetry by providing an independent opinion on the fairness of financial statements. The use of Artificial Intelligence in auditing introduces new dynamics into this relationship. On one hand, it has the potential to improve the ability to detect errors and fraud, thereby strengthening the monitoring role of auditors. On the other hand, it creates new challenges related to transparency and accountability of algorithm based decisions, which may complicate responsibility within the agency relationship.

Stakeholder Theory, developed by Freeman (2010), states that organizations must balance the interests of all parties affected by their operations. In the context of auditing, this includes not only shareholders and management, but also investors, creditors, regulators, employees, and the wider public. The implementation of Artificial Intelligence in auditing has implications for all these stakeholders. For regulators, it creates challenges in developing appropriate standards. For investors, it offers the potential to improve audit quality while also raising concerns about possible algorithm bias. For the public, its use in auditing has implications for transparency and accountability in the public sector. Therefore, these three theories together provide a strong foundation for a comprehensive analysis of Artificial

Intelligence implementation in auditing.

The Role and Potential of Artificial Intelligence in Auditing

Artificial Intelligence in auditing refers to the use of computer systems capable of performing tasks that typically require human intelligence, such as pattern recognition, learning from data, decision making, and natural language processing (Del Caprio, 2025). In particular, machine learning and natural language processing enable the automation of repetitive audit tasks, allowing auditors to focus on higher value activities such as risk assessment and more complex financial analysis.

The implementation of Artificial Intelligence in auditing can improve efficiency and reliability through real time big data analysis that enables faster and more accurate detection of anomalies and potential fraud (Semenova et al., 2023). Its ability to process large volumes of data at high speed supports a shift from traditional sampling methods to full transaction analysis, thereby reducing the risk of material misstatement and improving the accuracy of financial reporting (Fatria et al., 2024). This also enhances fraud detection and allows more responsive adjustments to internal controls in line with changing risk conditions.

However, the success of Artificial Intelligence implementation depends on data quality and auditor competence in using this technology, including understanding ethical considerations and the risks of algorithm bias (Nasir et al., 2026; Rawashdeh et al., 2023). Auditors continue to play a crucial role in maintaining professional integrity, particularly in judgment and decision making that cannot be fully automated. Artificial Intelligence functions as a decision support tool rather than a substitute for professional judgment and auditor skepticism.

Governance, Compliance, and Risk Management in Artificial Intelligence Based Auditing

Compliance and governance are critical dimensions in the implementation of Artificial Intelligence in auditing. This technology plays an important role in supporting regulatory compliance by enabling real time monitoring and transparent reporting, as observed in industries such as oil and gas and financial technology (Hu et al., 2021; Nasir et al., 2026). Its ability to continuously monitor transactions and business activities allows early detection of potential violations, enabling management to take corrective action before issues escalate.

A strong governance framework and certification standards such as ISO 42001 are required to ensure that Artificial Intelligence in auditing is implemented responsibly and in line with regulations (Khan et al., 2021). This framework includes principles of algorithm transparency, risk oversight, and technical auditability as the foundation for managing Artificial Intelligence related risks. Algorithm transparency refers to the need to understand how systems generate specific decisions or recommendations so that outcomes can be explained and justified. Risk oversight involves identifying, assessing, and mitigating potential risks arising from its use, including bias, errors, or misuse. Technical auditability refers to the ability to independently examine and verify system performance.

From a risk management perspective, Artificial Intelligence enables continuous auditing that proactively identifies issues and potential fraud, while improving transparency and communication with stakeholders (Karagül & Selİmoğlu, 2025; Yang, 2025). Continuous auditing represents a shift from periodic approaches toward ongoing monitoring of business processes and controls. With this capability, auditors can monitor transactions in real time, detect anomalies as they occur, and provide early warnings to management.

However, significant challenges remain, particularly in managing large scale data accurately and securely, as well as ensuring ethical use of algorithms to avoid harmful bias (Natasya et al., 2025). Data quality forms the foundation of reliability in

Artificial Intelligence based auditing. Inaccurate, incomplete, or biased data can lead to misleading analysis, regardless of the sophistication of the algorithms used. Similarly, bias in algorithms, whether intentional or unintentional, may result in unfair or discriminatory audit conclusions. Therefore, developing auditor competence through training and education in Artificial Intelligence is essential to maximize its benefits while mitigating associated risks.

Research Method

This study uses a quantitative approach with a quasi-experimental design to analyze the effect of Artificial Intelligence (AI) implementation on audit quality, fraud detection effectiveness, and regulatory compliance. The quantitative approach is used because it allows objective and measurable analysis of relationships between variables, where AI implementation is the independent variable and audit quality is the dependent variable (Sugiyono, 2022). Risk management and governance are also included as supporting variables. The quasi-experimental design is applied because the researcher cannot fully control the conditions, since AI has already been implemented naturally in organizations (Ghozali, 2021), but it still provides a strong basis for quantitative analysis (Ghozali, 2018).

The respondents in this study are auditors from public accounting firms and internal audit units in East Java that have used AI-based audit systems. The sample is selected using purposive sampling with criteria of auditors who have at least one year of experience using AI and work in organizations that have implemented AI for at least two years (Raza et al., 2025). A total of 100 respondents are used, which is considered adequate for multiple regression analysis (Chiu et al., 2019).

Primary data are collected using a structured questionnaire with a five-point Likert scale, covering AI implementation, risk management, governance, and audit quality variables. The instrument is tested through a pilot study with 10 respondents to ensure validity and reliability using Pearson correlation and Cronbach's Alpha (Natasya et al., 2025; Bouchetara et al., 2024; Bommali et al., 2025).

Data are analyzed using descriptive and inferential statistics with SPSS (Sugiyono, 2022). Before regression analysis, classical assumption tests are conducted, including normality, multicollinearity, heteroscedasticity, and linearity, to ensure the model meets BLUE assumptions (Ishtiaq, 2019; Creswell & Miller, 2000). Hypothesis testing uses multiple linear regression to examine the partial and simultaneous effects of AI implementation, risk management, and governance on audit quality, using the following model:

$$Y=\alpha+\beta 1X1+\beta 2X2+\beta 3X3+\varepsilon$$

Notes:
Y: Audit Quality
X1: Artificial Intelligence implementation
X2: Risk Management
X3: Governance
α: Constant
β_1, β_2, β_3: Partial regression coefficients
ε: Error term

Hypothesis testing is conducted by looking at regression coefficients, t-values, and significance values. A hypothesis is accepted if the significance value is below 0.05. The F-test is used to test the simultaneous effect of all variables, while the coefficient of determination (R^2) shows how much variation in audit quality is explained by the independent variables. The results are interpreted carefully because AI in auditing may involve complexity, including algorithmic bias and ethical issues (Kau & Fitriana, 2025).

Result and Discussion

Normality Test (Kolmogorov-Smirnov)

A normality test was conducted to examine whether the residual data followed a normal distribution. The test results are presented in Table 1.

Table 1. Normality Test Results of Residuals

Variabel	Kolmogorov-Smirnov Statistic	Asymp. Sig. (2-tailed)
Residual	0,082	0,200*

Source: Processed primary data, 2025
**Note: p > 0.05 indicates that the data are normally distributed*

Based on Table 1, the significance value from the Kolmogorov-Smirnov test is 0.200 (> 0.05), indicating that the residual data are normally distributed and that the regression model satisfies the normality assumption.

Multicollinearity Test (VIF)

A multicollinearity test was conducted to identify potential correlations among the independent variables. The results are presented in Table 2.

Table 2. Multicollinearity Test Results

Independent Variable	Tolerance	VIF
AI Implementation (X_1)	0,724	1,381
Risk Management (X_2)	0,698	1,433
Governance (X_3)	0,711	1,406

Source: Processed primary data, 2025

Based on Table 2, all independent variables have VIF values below 10 and tolerance values above 0.10. Therefore, it can be concluded that no multicollinearity issues exist among the independent variables in the regression model.

Heteroskedasticity Test (Glejser)

A heteroskedasticity test was conducted to examine whether there is inequality in the residual variances. The results are presented in Table 3.

Table 3. Heteroskedasticity Test Results (Glejser)

Independent Variable	Coefficient	t-value	Sig.
AI Implementation (X_1)	0,042	0,847	0,399
Risk Management (X_2)	0,038	0,765	0,446
Governance (X_3)	0,051	1,024	0,308

Source: Processed primary data, 2025

Based on Table 3, all independent variables have significance values greater than 0.05. Therefore, it can be concluded that no heteroskedasticity problem exists in the regression model.

Model Feasibility Test (F-Test)

The F-test was conducted to examine whether all independent variables simultaneously affect the dependent variable (audit quality). The results are presented in Table 4.

Table 4. F-Test Results (Simultaneous)

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Square (MS)	F-value	Sig.
Regression	28,416	3	9,472	28,45	0,000*
Residual	31,984	96	0,333		
Total	60,400	99			

Source: Processed primary data, 2025
**Note: p < 0.05 indicates a significant effect*

Based on Table 4, the calculated F-value is 28.45 with a significance of 0.000 (< 0.05). These results indicate that collectively the independent variables (AI implementation, risk management, and governance) have a significant effect on the dependent variable, namely audit quality.

Hypothesis Test Results (T-Test)

The t-test was conducted to examine the partial effect of each independent variable on the dependent variable. The results are presented in Table 5.

Table 5. T-Test Results (Partial)

Variable	Beta Coefficient (B)	Std. Error	t-value	Sig.
Constant	1,245	0,342	3,641	0,000
AI Implementation (X_1)	0,620	0,091	6,813	0,000*
Risk Management (X_2)	0,430	0,102	4,216	0,000*
Governance (X_3)	0,290	0,105	2,762	0,007*

Source: Processed primary data, 2025
**Note: p < 0.05 indicates a significant effect*

The partial t-test results indicate that all independent variables in this study have a positive and significant effect on audit quality at the 0.05 significance level. The AI implementation variable has a beta coefficient of 0.620 with a significance of 0.000, which is below 0.05. This indicates that AI implementation has a positive and significant impact on audit quality. In other words, the more optimally AI technology is applied in the audit process, the higher the resulting audit quality. This finding aligns with previous studies stating that AI can enhance audit efficiency and accuracy through automation of routine tasks and improved analytical capabilities in detecting risks and anomalies. The risk management variable has a beta coefficient of 0.430 with a significance of 0.000, which is below 0.05. This indicates that risk management positively and significantly affects audit quality. It implies that effective application of risk management frameworks in AI-based audits contributes to higher audit quality. Structured risk management enables organizations to identify, assess, and mitigate risks arising from AI technology in a more systematic manner. The governance variable has a beta coefficient of 0.290 with a significance of 0.007, below 0.05. This suggests that governance has a positive and significant effect on audit quality. The results indicate that a strong governance framework, including clear AI usage policies, algorithmic transparency, and adequate accountability mechanisms, contributes to improved audit quality. Auditors operating in environments with robust AI governance report higher confidence in technology-assisted audit outcomes.

Coefficient of Determination (R^2)

The coefficient of determination is used to measure the proportion of variance in the dependent variable that can be explained by the independent variables. The results are presented in Table 6.

Table 6. Coefficient of Determination (R^2) Results

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0,686	0,471	0,454	0,577

Source: Processed primary data, 2025

Based on Table 6, the Adjusted R Square value is 0.454. This indicates that 45.4% of the variation in the dependent variable (audit quality) can be explained by the independent variables (AI implementation, risk management, and governance). The remaining 54.6% is influenced by other factors outside the research model.

Regression Analysis Results

Multiple linear regression analysis was conducted to examine the effect of AI implementation on audit quality, fraud detection effectiveness, and the roles of risk management and governance. The results are presented in Table 7.

Table 7. Regression Analysis Results: Effect of AI on Audit Quality

Variable	Coefficient (β)	Significance (p)
AI Implementation	0,620	< 0,01
Risk Management	0,430	< 0,01
Governance	0,290	< 0,05

Source: Processed primary data, 2025

The regression results indicate that AI implementation has a positive and significant effect on audit quality, with a beta coefficient of 0.620 and a significance level below 0.01. This finding suggests that the more effectively AI is applied in audit processes, the higher the resulting audit quality. AI enables auditors to process large volumes of data with greater speed and accuracy, while identifying anomalies and patterns that may be overlooked by human auditors. This aligns with previous studies by K. Tushar (2024), Naseer & Ahmed (2025), also Adelakun et al. (2024), which highlight that AI enhances audit efficiency and accuracy through automation of routine tasks and improved analytical Furthermore, risk management shows a positive and significant influence on audit quality, with a beta coefficient of 0.430

and a significance level below 0.01. This indicates that the more effectively risk management frameworks are implemented in audit processes, the higher the quality of audit outcomes. Effective risk management enables organizations to identify, assess, and mitigate potential risks arising during audit activities, including those associated with AI usage. This finding is consistent with Bouchetara et al. (2024) and Natasya et al. (2025), who emphasize that structured risk management allows organizations to detect issues early and respond with timely corrective actions.

Governance also demonstrates a positive and significant impact on audit quality, with a beta coefficient of 0.290 and a significance level below 0.05. This result indicates that a robust governance framework, including clear technology use policies, process transparency, and adequate accountability mechanisms, contributes to improved audit quality. SGS (Société Générale de Surveillance (2025) highlights that technology adoption in auditing requires solid governance and standards such as ISO/IEC 42001 to ensure transparent, accountable, and compliant audits. Similarly, Mökander (2023) notes that strong governance facilitates regulatory compliance through real-time audit monitoring, supporting transparent and auditable reporting.

Discussion

The Effect of AI Implementation on Audit Quality

The analysis results indicate that the use of Artificial Intelligence in the audit process has a positive and significant impact on audit quality, with a beta coefficient of 0.620 and a significance level below 0.01. This finding highlights the fundamental role of AI technology in transforming traditional audit practices into processes that are more efficient, accurate, and responsive to risk dynamics. Auditors who integrate AI into their work report notable improvements in their ability to detect anomalies and potential fraud that were previously difficult to identify using manual methods.

From a theoretical perspective, this finding is consistent with Resource Based View Theory, which states that technological capability, including Artificial Intelligence, represents a strategic resource that provides competitive advantage in performing monitoring and compliance functions. Barney (1991) emphasizes that valuable, rare, difficult to imitate, and non substitutable resources can become a source of sustained competitive advantage. The ability of AI to process large volumes of data in real time and perform predictive analysis enables organizations to develop early detection systems for compliance risks and potential fraud. These capabilities represent strategic resources that are not easily replicated by competitors.

The positive relationship between AI implementation and audit quality also supports the proposition of Agency Theory, where the use of advanced technology serves as a tool for auditors to meet stakeholder expectations for transparency, accountability, and accuracy in financial reporting. Jensen & Meckling (1976) explain that agency conflict arises from information asymmetry between management as the agent and owners as the principal. Auditors act as a mechanism to reduce this asymmetry. With the support of Artificial Intelligence, auditors have enhanced capability to detect errors and fraud, thereby strengthening their role as an effective monitoring mechanism. This, in turn, helps reduce agency costs and improve firm value.

Existing literature consistently supports this relationship, with various studies showing that AI based automation can reduce the limitations of traditional auditing, which relies on sampling methods and subjective auditor judgment. Nasir et al., (2026) and Rawashdeh et al., (2023) find that AI improves audit efficiency and accuracy through automation of routine tasks as well as enhanced analytical capability and anomaly detection. Hu et al., (2021) and Onyenahazi, (2025) also highlight the potential of AI to enable auditors to focus on more complex risk analysis.

This finding is also relevant to the concept of continuous auditing, as explained by Oyetunji et al., (2024) and Senturk (2025), where AI enables auditing to be conducted on an ongoing basis to proactively identify issues and potential fraud, while enhancing transparency and communication with stakeholders. The ability of AI to process data in real time supports a shift from a periodic approach toward continuous monitoring of business processes and controls. This allows early detection of potential issues and faster corrective actions, which ultimately improves overall audit quality.

The Effect of Risk Management on Audit Quality

The regression analysis results reveal that risk management has a positive and significant effect on audit quality, with a beta coefficient of 0.430 and a significance level below 0.01. This finding confirms that the success of audit implementation, including AI-based auditing, is not solely determined by technological sophistication but also by the readiness of an adequate risk control infrastructure.

From the perspective of Socio Technical Systems Theory by Trist (1981), system optimization in auditing can only be achieved when technical and social aspects are designed together and complement each other. Risk management represents a critical social component in ensuring that the application of AI does not introduce new and uncontrolled risks. Auditors working within organizations that have strong risk management frameworks report higher levels of confidence in technology based audit results and reduced concern regarding potential system errors.

This finding reinforces the concept of continuous auditing enabled by Artificial Intelligence, where compliance monitoring and anomaly detection can be performed in real time without relying on periodic audit cycles. Ghafar et al., (2024) and Raza et al., (2025) highlight that effective risk management supports a shift from a reactive approach toward a more proactive approach in managing risk. The implementation of structured risk management allows organizations not only to identify issues at an early stage but also to respond with timely and appropriate corrective actions.

Bommali et al., (2025) add that a major challenge in the implementation of Artificial Intelligence lies in managing large volumes of data accurately and securely, as well as ensuring ethical use of algorithms to avoid harmful bias. Therefore, comprehensive risk management becomes a critical foundation to ensure that Artificial Intelligence can deliver optimal benefits in improving audit quality.

The Effect of Governance on Audit Quality

The analysis results indicate that governance has a positive and significant effect on audit quality, with a beta coefficient of 0.290 and a significance value of less than 0.05. This finding suggests that a strong governance framework, including clear policies on the use of Artificial Intelligence, algorithmic transparency, and adequate accountability mechanisms, contributes to the improvement of audit quality.

From the perspective of Stakeholder Theory, Freeman (2010) emphasizes that firms must balance the interests of all parties affected by their operations. In the context of AI implementation in auditing, this spectrum of stakeholders includes not only management and auditors but also regulators, investors, and the broader public. A robust AI governance framework is therefore necessary to ensure that the interests of all stakeholders are properly accommodated.

Ghafar et al. (2024) and Raza et al. (2025) explain that AI governance frameworks encompass principles such as algorithmic transparency, risk oversight, and technical auditability, which serve as the foundation for controlling AI-related risks. Algorithmic transparency refers to the need to understand how AI arrives at specific decisions or recommendations, so that such decisions can be explained and held accountable to stakeholders.

Naseer & Ahmed (2025) find that AI plays a crucial role in facilitating regulatory compliance by enabling real-time compliance monitoring and transparent reporting. However, the effectiveness of this role is highly dependent on the quality of the supporting governance framework. Leocádio et al., (2024) and Ogunmokun et al., (2021) emphasize the need for a strong AI governance framework and certification standards such as ISO/IEC 42001 to ensure that AI-based audits are conducted responsibly and in accordance with regulations.

Karagül & Selİmoğlu (2025) highlight that enhancing the capacity of internal auditors in understanding AI technology remains a major challenge across regions, making continuous training programs an urgent necessity. Good governance encompasses not only policies and procedures but also the continuous development of human resource competencies to ensure that auditors can utilize AI technology optimally and responsibly.

Conclusions and Recommendations

This study demonstrates that the implementation of Artificial Intelligence (AI) in the audit process has a positive and significant effect on improving audit quality. The effectiveness of AI is enhanced when supported by strong risk management and robust governance, enabling audits to become more efficient, accurate, and responsive to dynamic risks. Therefore, AI can be considered a strategic instrument in transforming modern audit practices.

Regulators are encouraged to formulate policies that promote the responsible adoption of AI in auditing practices. Organizations and auditors should enhance human resource competencies, strengthen risk management, and implement transparent and accountable governance to maximize the benefits of AI. Future research is recommended to expand the geographical scope and apply longitudinal approaches as well as mixed methods to gain more comprehensive insights into the implementation of AI in auditing.

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