How to Cite
Dewi, M. S. K., & Wirakusuma, M. G. (2026). The impact of artificial intelligence adoption on audit quality. *International Journal of Business, Economics and Management*, *9*(3), 195-203.
https://doi.org/10.21744/ijbem.v9n3.2507

The Impact of Artificial Intelligence Adoption on Audit Quality

Made Susmitha Kusuma Dewi
Faculty of Economics and Business, Udayana University, Denpasar, Indonesia
Corresponding author email: susmithakusumad@gmail.com

Made Gede Wirakusuma
Faculty of Economics and Business, Udayana University, Denpasar, Indonesia

Abstract---*This study examines the effect of artificial intelligence (AI) adoption by public accounting firms on audit quality, as proxied by the disclosure of Key Audit Matters (KAMs) in independent auditors' reports. The study is motivated by the implementation of Indonesian Auditing Standard SA 701 in 2022, the issuance of Financial Services Authority Regulation No. 30 of 2023, and the growing adoption of AI within the auditing profession. Agency theory is employed as the primary theoretical framework. The study population comprises all companies listed on the Indonesia Stock Exchange during the 2022–2024 period. Using purposive sampling, the study obtained 1,326 firm-year observations. Audit quality is measured using the number of words and the number of accounts disclosed in KAM paragraphs, which are standardized into a composite Z-score. The primary independent variable is AI adoption, measured using a dummy variable, while public accounting firm rotation, firm size, and industry sector are included as control variables. The data are analyzed using multiple linear regression after the classical assumption tests are satisfied. The results indicate that AI adoption has a positive and significant effect on audit quality. Public accounting firm rotation, firm size, and industry sector also demonstrate positive and significant effects on audit quality. These findings extend the application of agency theory to a technology-driven auditing environment and suggest that AI adoption can enhance the scope and quality of KAM disclosures. Practically, the findings encourage public accounting firms to invest in AI-based audit technologies, regulators to promote technology adoption within the audit profession, and companies to consider the technological capabilities of public accounting firms when selecting external auditors. Future studies are encouraged to extend the observation period and examine potential moderating variables, such as auditor industry specialization.*
Keywords---*artificial intelligence adoption, audit quality, Key Audit Matters, agency theory, public accounting firms.*

Introduction

Capital markets play an important role in supporting corporate growth by enabling companies to obtain external financing from investors. Publicly listed companies are consequently required to issue financial statements as a form of accountability to shareholders and other stakeholders. Because these statements constitute a primary source of information for investment, lending, and regulatory decisions, their reliability, accuracy, and transparency are essential. However, the separation between ownership and management creates information asymmetry because managers generally possess more comprehensive information about corporate activities than external stakeholders. Agency theory posits that this imbalance may lead to moral hazard and adverse selection, as managers may have incentives to conceal or misrepresent information to protect their own interests (Jensen & Meckling, 1976). Independent auditing is therefore required to reduce information asymmetry and enhance the credibility of financial reporting.

Auditing provides an independent evaluation of whether financial statements are fairly presented in accordance with the applicable financial reporting framework (Arens et al., 2014). By detecting and reporting material misstatements, auditors increase public confidence in financial information and strengthen managerial accountability

ISSN 2632-9476
Submitted: 09 May 2026 |Revised: 18 June 2026 | Accepted: 27 July 2026

(DeAngelo, 1981; Francis, 2004). Audit quality is commonly associated with the auditor's ability to identify material errors or irregularities and report them independently to financial statement users (DeAngelo, 1981). It is therefore influenced not only by technical competence but also by auditor independence, professional ethics, audit standards, and the procedures applied during the engagement. High-quality audits are particularly important because audit failures may mislead investors, creditors, and regulators in making economic decisions.

Major corporate failures, including the collapse of Enron and Arthur Andersen, as well as the 2008 global financial crisis, intensified concerns regarding the informativeness and usefulness of conventional audit reports. These events demonstrated that an audit report may provide limited value to users when it does not adequately explain the significant risks and judgments involved in the audit process (Ricardo & Carvalho, 2021). An audit failure may occur when auditors fail to apply the relevant accounting principles or fail to issue an appropriately modified opinion when material problems are identified (Francis, 2004). In response, the International Auditing and Assurance Standards Board introduced International Standard on Auditing 701 in 2015, requiring auditors to communicate Key Audit Matters (KAMs) in the independent auditor's report.

KAMs represent matters that, in the auditor's professional judgment, were of the greatest significance in the audit of the current-period financial statements. Their disclosure is intended to provide users with greater insight into significant audit risks, management judgments, and the procedures performed by auditors. Previous evidence suggests that KAM disclosures can improve users' understanding of the audit process and the significant issues addressed during an engagement (Li, 2021). Auditors are also expected to identify and communicate events or conditions that may have a material effect on the audited entity (Hategan et al., 2022). In Indonesia, Auditing Standard 701 became effective on 1 January 2022, followed by Financial Services Authority Regulation No. 30 of 2023. Because these requirements remain relatively recent, the effectiveness of KAM disclosures in strengthening audit transparency and accountability in Indonesia requires further empirical investigation.

Alongside regulatory reform, the rapid development of artificial intelligence (AI) has transformed audit practices. AI enables auditors to analyze large and complex datasets, examine broader populations of transactions, detect unusual patterns, and automate repetitive procedures. These capabilities may reduce human error, increase analytical accuracy, and enable auditors to devote more attention to complex areas that require professional judgment. Prior studies indicate that AI adoption can improve audit efficiency, analytical depth, and financial reporting quality, including by reducing the likelihood of financial statement restatements (Chen & Yang, 2025; Rahman et al., 2024). The positive effect of AI may also depend on audit-related characteristics such as auditor industry specialization and audit fees (Khan et al., 2024). Nevertheless, empirical evidence regarding AI adoption and audit quality remains limited, particularly when audit quality is evaluated through the comprehensiveness of KAM disclosures.

This study extends the research of Li et al. (2025), Alharasis et al. (2024), Goh et al. (2024), and Zeng et al. (2021) by examining the effect of AI adoption by public accounting firms on audit quality in the Indonesian regulatory environment. Unlike studies relying primarily on conventional proxies for audit quality, this study operationalizes audit quality through KAM disclosure, measured by the amount of information and the number of accounts discussed in the KAM section. This approach is relevant because more comprehensive KAM disclosures may reflect greater audit effort, risk assessment, professional judgment, and transparency. The Indonesian setting provides an important context because the implementation of SA 701 and the related Financial Services Authority regulation is still at an early stage.

To isolate the effect of AI adoption, this study controls for audit firm rotation, firm size, and industry sector. Prior findings regarding auditor rotation remain inconclusive. Auditor rotation has been associated with improved audit quality in China, Italy, and Vietnam (Bandyopadhyay et al., 2014; Horton et al., 2023; Pham & Nguyen, 2019), whereas evidence from the United States indicates no significant improvement following rotation (Kuang et al., 2020). Duboisee de Ricquebourg & Maroun (2023) further show that audit firm rotation may alter the number of KAMs disclosed, although audit partner rotation does not necessarily produce a material effect. Firm size is also controlled because larger companies generally have more complex operations, greater transaction volumes, and higher audit risks, which may require more extensive audit procedures (Elmarzouky et al., 2023; Zheng, 2025). In addition, KAM disclosure practices may differ across industries because of variations in business complexity, regulatory pressure, environmental sensitivity, and stakeholder expectations (De Villiers & Van Staden, 2011; Jain et al., 2016; Rahaman et al., 2022).

Accordingly, this study aims to examine whether AI adoption by public accounting firms affects audit quality, as proxied by KAM disclosure, among companies listed on the Indonesia Stock Exchange during the 2022–2024 period. By integrating agency theory with the technological transformation of auditing, this study contributes to the literature by providing evidence on whether AI-supported audit processes can reduce information asymmetry and improve the transparency of independent auditors' reports. The findings are also expected to provide practical

implications for public accounting firms, regulators, and listed companies in evaluating the role of technological capability in enhancing audit quality (Lowensohn et al., 2007).

Literature Review and Hypothesis Development

From the perspective of agency theory, the adoption of artificial intelligence by auditors can serve as an effective monitoring mechanism for reducing information asymmetry and detecting risks arising from managerial misconduct. Auditors act as independent monitoring agents who assess the reliability of financial information prepared by management. In this context, AI strengthens the auditor's monitoring capacity by facilitating the examination of large and complex datasets, identifying unusual transaction patterns, and supporting more accurate risk assessments. The importance of this technological capability is further reinforced by regulatory requirements imposed on public accounting firms, including the obligation to communicate Key Audit Matters under Indonesian Auditing Standard SA 701. Compliance with increasingly complex audit and reporting requirements may therefore encourage public accounting firms to adopt AI to improve the depth, accuracy, and regulatory compliance of their audit procedures (Sunti, 2023).

AI adoption can increase audit effort by enabling auditors to conduct more comprehensive, detailed, and large-scale data analyses. These capabilities may increase the likelihood of detecting material misstatements and reduce the probability of financial statement restatements (Rahman et al., 2024). AI also enables auditors to automate repetitive procedures and devote greater professional attention to complex transactions and areas requiring significant judgment. Consequently, the efficiency generated through AI adoption does not necessarily compromise audit quality but may instead strengthen the accuracy and effectiveness of audit procedures.

The benefits of AI may become more pronounced when the technology is adopted simultaneously by auditors and their clients. Such technological alignment can accelerate the audit process, reduce audit report lag, and improve the accuracy of audit procedures (Rahman et al., 2024; Chen & Yang, 2025). AI may therefore function as a strategic resource that provides public accounting firms with a competitive advantage by enabling more advanced analytical procedures and more precise audit-risk management. These direct and indirect improvements contribute to higher audit quality (Khan et al., 2024). Furthermore, evidence based on the Unified Theory of Acceptance and Use of Technology 2 indicates that determinants of AI adoption, including performance expectancy and facilitating conditions, are positively associated with sustainable audit quality (Tritama et al., 2025). Based on the theoretical arguments and prior empirical evidence, the following hypothesis is proposed:

H1: Artificial intelligence adoption by public accounting firms has a positive effect on audit quality.

Methods

This study employed a quantitative explanatory design to examine the effect of artificial intelligence adoption by public accounting firms on audit quality. The population consisted of companies listed on the Indonesia Stock Exchange from 2022 to 2024, corresponding to the implementation period of Indonesian Auditing Standard SA 701. Using purposive sampling, the study selected companies that remained listed during the observation period and provided complete audited financial statements, independent auditors' reports, and data required to measure the research variables. The final sample comprised 1,326 firm-year observations, consisting of 378 observations in 2022, 459 in 2023, and 489 in 2024. Secondary data were obtained from the Indonesia Stock Exchange, corporate annual reports, independent auditors' reports, public accounting firms' official websites, and other publicly available sources. Data on AI adoption were identified through manual searches of public accounting firms' official publications using terms such as "artificial intelligence," "machine learning," and "big data analytics."

Audit quality was proxied by the comprehensiveness of Key Audit Matter disclosures, measured using the number of words and the number of accounts discussed in the KAM section. The two indicators were standardized using Z-scores and combined into a composite audit-quality measure, with higher values representing broader and more detailed KAM disclosures. AI adoption was measured as a dummy variable equal to one when the public accounting firm had publicly documented the implementation of AI-related technologies and zero otherwise. The control variables consisted of audit firm rotation, measured as a dummy variable; firm size, measured as the natural logarithm of total assets; and industry sector, coded one for banking and financial institutions and zero for other sectors. The hypothesis was tested using multiple linear regression specified as $AQ = \alpha + \beta_1 AAI + \beta_2 Rotasi.KAP + \beta 3 FSIZE + \beta_4 Industri + e$. Before hypothesis testing, the model was evaluated for normality, multicollinearity, heteroskedasticity, and autocorrelation. Model fit and statistical significance were assessed using the adjusted coefficient of determination, the F-test, and partial t-tests at a 5% significance level.

Results and Discussion

Classical Assumption Tests

Before estimating the multiple linear regression model, classical assumption tests were conducted to assess the suitability of the data for regression analysis. The tests covered residual normality, multicollinearity, heteroskedasticity, and autocorrelation. The main results are summarized in Table 1.

Table 1
Summary of Classical Assumption Tests

Assumption	Diagnostic Method	Statistical Result	Evaluation Criterion	Conclusion
Residual normality	Normal P–P Plot and One-Sample Kolmogorov–Smirnov test	(D=0.208); (p<0.001)	Residuals are normally distributed when (p>0.05)	The residuals deviated from normality. However, given the large sample of 1,326 firm-year observations, the estimation and statistical inference were considered asymptotically robust under the Central Limit Theorem.
Multicollinearity	Tolerance and Variance Inflation Factor	Tolerance: 0.722–0.900; VIF: 1.112–1.385	Tolerance (>0.10) and VIF (<10)	No multicollinearity was detected among the explanatory variables.
Heteroskedasticity	Scatterplot of standardized predicted values and studentized residuals	Residuals were randomly distributed above and below zero without a systematic pattern	A random and patternless distribution indicates homoskedasticity	No indication of heteroskedasticity was identified.
Autocorrelation	Durbin–Watson test	DW = 2.086; (d_U=1.8094); (4-d_U=2.1906)	(d_U<DW<4-d_U)	The model was free from positive and negative autocorrelation.

Primary Data, 2026

The multicollinearity, heteroskedasticity, and autocorrelation diagnostics indicate that the model satisfied the relevant regression assumptions. Although the Kolmogorov–Smirnov test indicated non-normal residuals, the large number of observations mitigated concerns regarding the asymptotic validity of the coefficient estimates and significance tests. The regression analysis was therefore continued with appropriate caution in interpreting the results.

Multiple Linear Regression

Multiple linear regression was used to examine the effect of artificial intelligence adoption on audit quality while controlling for audit firm rotation, firm size, and industry sector. Audit quality was proxied by the composite standardized score of the number of words and accounts disclosed in the Key Audit Matters section.

Table 2
Multiple Linear Regression Results

Variable	Unstandardized Coefficient (B)	Standard Error	Standardized Beta	(t)-Statistic	(p)-Value	Result
Constant	-4.241	0.424	—	-9.992	<0.001	—
AI adoption	0.144	0.059	0.072	2.464	0.014	Positive and significant
Audit firm rotation	0.116	0.055	0.057	2.100	0.036	Positive and significant
Firm size	0.140	0.015	0.285	9.391	<0.001	Positive and significant
Industry sector	0.241	0.073	0.090	3.297	0.001	Positive and significant

Primary Data, 2026
Dependent variable: audit quality. Significance level: 5%.

Because audit quality was constructed from standardized KAM disclosure indicators, the negative constant should not be interpreted as a substantively negative level of audit quality. It represents the predicted composite audit-quality score when all explanatory variables equal zero, including a theoretically unrealistic value of zero for the natural logarithm of total assets. The interpretation should therefore focus primarily on the direction, magnitude, and significance of the explanatory-variable coefficients.

Model Explanatory Power

The coefficient of determination was used to assess the proportion of variation in audit quality explained by the variables included in the model.

Table 3
Model Summary

Model	(R)	(R^2)	Adjusted (R^2)	Standard Error of the Estimate
1	0.348	0.121	0.119	0.939

Primary Data, 2026

The (R^2) value of 0.121 indicates that AI adoption, audit firm rotation, firm size, and industry sector collectively explained 12.1% of the variation in audit quality. The remaining 87.9% was attributable to factors outside the model. The adjusted (R^2) of 0.119 was close to the unadjusted value, indicating that the explanatory contribution of the model remained relatively stable after accounting for the number of predictors.

Overall Model Significance

The F-test was conducted to evaluate whether the explanatory variables collectively provided a statistically significant prediction of audit quality.

Table 4
Overall Model Significance

Source	Sum of Squares	Degrees of Freedom	Mean Square	(F)-Statistic	(p)-Value
Regression	160.896	4	40.224	45.645	<0.001
Residual	1,164.104	1,321	0.881	—	—
Total	1,325.000	1,325	—	—	—

Primary Data, 2026

The model produced an F-statistic of 45.645 with a significance level below 0.001. Accordingly, AI adoption, audit firm rotation, firm size, and industry sector jointly provided a statistically significant explanation of variation in audit quality. The regression model was therefore considered suitable for testing the proposed hypothesis.

AI Adoption and Audit Quality

The regression results show that AI adoption had a positive and statistically significant effect on audit quality, with an unstandardized coefficient of 0.144, a (t)-statistic of 2.464, and a (p)-value of 0.014. Holding audit firm rotation, firm size, and industry sector constant, companies audited by public accounting firms that had adopted AI recorded an audit-quality composite score that was 0.144 units higher than that of companies audited by firms without documented AI adoption. The proposed hypothesis was therefore supported.

This result indicates that the adoption of AI by public accounting firms is associated with broader and more detailed KAM disclosures. AI allows auditors to process large volumes of transactions, identify unusual patterns, and evaluate areas with a heightened risk of material misstatement more systematically. These capabilities can improve the auditor's identification of significant audit matters and support more substantive communication in the independent auditor's report.

The result is consistent with Rahman et al. (2024), who found that the simultaneous adoption of AI by auditors and clients reduced the probability of financial statement restatements and improved audit efficiency. It is also consistent with Chen & Yang (2025), who demonstrated that intelligent technologies could enhance audit quality by strengthening auditors' analytical and industry-related capabilities. Khan et al. (2024) similarly reported that AI adoption contributed positively to integrated reporting quality, particularly when supported by auditor industry specialization. The finding also corresponds with Tritama et al. (2025), who established a positive relationship between the determinants of AI adoption and sustainable audit quality.

From an agency-theory perspective, AI strengthens the external audit function as a monitoring mechanism that reduces information asymmetry between management and stakeholders (Jensen & Meckling, 1976). AI-based analysis assists auditors in detecting material risks more accurately and communicating critical matters more transparently (Zhang & Shailer, 2021). The automation of routine and administrative procedures may also allow auditors to devote more time to areas requiring professional judgment and critical evaluation (Fedyk et al., 2022).

Approximately 55% of the observations in the sample were audited by public accounting firms classified as AI adopters. This level of adoption suggests that AI had become sufficiently prevalent to generate observable differences in audit outcomes during the 2022–2024 period. Its contribution may be particularly relevant in the initial implementation of SA 701 and Financial Services Authority Regulation No. 30 of 2023, both of which require auditors to provide more transparent and informative disclosures.

The result further suggests that AI may help address the "paradox of transparency" identified by Bepari et al. (2024), under which KAM disclosures may become generic or standardized because of managerial pressure and institutional reporting practices. By providing more objective and data-driven risk assessments, AI may enable auditors to produce KAM disclosures that are more entity-specific and substantive rather than merely fulfilling formal regulatory requirements.

Audit Firm Rotation and Audit Quality

Audit firm rotation had a positive and significant association with audit quality. The coefficient of 0.116, (t)-statistic of 2.100, and (p)-value of 0.036 indicate that audit quality was higher when a company changed its public accounting firm, holding the other variables constant. Audit firm rotation occurred in 574 of the 1,326 observations, representing approximately 43.3% of the sample.

This finding suggests that the appointment of a new audit firm may introduce a fresh perspective into the audit process. A newly appointed auditor may reassess previously identified risks, question established accounting treatments, and identify significant matters that were not emphasized by the preceding auditor. Such reassessment can result in more extensive and informative KAM disclosures.

The positive effect is also consistent with the monitoring perspective of agency theory. Audit firm rotation can reduce excessive familiarity between auditors and management and strengthen auditor objectivity. Long audit tenures may expose auditors to familiarity threats that weaken professional skepticism, whereas rotation may restore independence and encourage a more critical evaluation of management representations (Dopuch et al., 2001; Kuang et al., 2020). Therefore, audit firm rotation may contribute to audit quality by strengthening independence and expanding the scope of significant matters communicated to stakeholders.

Firm Size and Audit Quality

Firm size had the strongest standardized association with audit quality among the variables included in the model. The coefficient of 0.140, standardized beta of 0.285, (t)-statistic of 9.391, and (p)-value below 0.001 indicate that larger companies tended to receive more comprehensive KAM disclosures. An increase of one unit in the natural logarithm of total assets was associated with a 0.140-unit increase in the audit-quality composite score, holding the other variables constant.

This result is consistent with Abdullatif & Al-Rahahleh (2020), who documented a positive relationship between firm size and KAM disclosure. Rahaman et al. (2023) similarly found that larger companies disclosed a greater number of KAMs and provided longer descriptions. The result also supports the use of total assets as a relevant determinant of audit and reporting characteristics in the studies of Elmarzouky et al. (2023) and Zheng (2025).

Larger companies generally have more complex operating structures, higher transaction volumes, more diverse business activities, and a wider group of stakeholders (Rahaman et al., 2023). These characteristics increase the scope of audit work and the number of areas requiring significant auditor attention. Consequently, auditors may need to perform more extensive procedures and communicate additional KAMs to address the expectations of investors, regulators, and other financial-statement users.

The mean value of firm size was 29.0338, with a standard deviation of 2.0332. The relatively lower standard deviation compared with the mean indicates that the firm-size observations were not excessively dispersed. The significant coefficient nevertheless demonstrates that differences in corporate scale remained an important determinant of KAM disclosure comprehensiveness.

Industry Sector and Audit Quality

Industry sector had a positive and statistically significant effect on audit quality, as indicated by a coefficient of 0.241, a (t)-statistic of 3.297, and a (p)-value of 0.001. Companies operating in the banking and financial-services sectors had audit-quality composite scores that were 0.241 units higher than those of companies in other sectors, after controlling for AI adoption, audit firm rotation, and firm size.

Banking and financial institutions are subject to extensive regulatory oversight, complex financial instruments, substantial operational risks, and strict prudential requirements. These characteristics require auditors to devote greater attention to areas involving credit risk, impairment, regulatory compliance, valuation, and financial-instrument measurement. The increased level of audit attention is subsequently reflected in a greater quantity and depth of KAM disclosures.

This result supports Rahaman et al. (2023), who emphasized that highly regulated sectors are associated with greater transaction complexity and more extensive reporting requirements. It is also consistent with De Villiers & Van Staden (2011), who argued that regulatory pressure and industry complexity encourage more comprehensive disclosure practices.

Approximately 17% of the observations belonged to the banking and financial-services sectors. Although these industries represented a minority of the sample, their coefficient remained statistically significant. This finding confirms that industry characteristics constitute an important control factor in explaining variations in audit quality and that the observed association between AI adoption and audit quality cannot be attributed solely to differences between regulated and non-regulated industries.

Conclusion

This study examines the effect of artificial intelligence adoption by public accounting firms on audit quality, as proxied by the comprehensiveness of Key Audit Matter disclosures, using 1,326 firm-year observations from companies listed on the Indonesia Stock Exchange during the 2022–2024 period. The empirical results demonstrate that AI adoption has a positive and statistically significant effect on audit quality. Public accounting firms that have adopted AI tend to provide more comprehensive KAM disclosures, suggesting that AI-assisted audit procedures can strengthen auditors' ability to analyze complex data, identify significant audit risks, and communicate matters requiring substantial auditor attention.

The findings also show that audit firm rotation, firm size, and industry sector are positively associated with audit quality. Audit firm rotation may enhance auditor independence and introduce a fresh perspective into the audit process, while larger companies tend to require more extensive audit procedures because of their greater operational complexity. Companies operating in highly regulated sectors, particularly banking and financial services, also exhibit more comprehensive KAM disclosures due to greater regulatory scrutiny and business complexity. Overall, the

findings support the agency-theory perspective that stronger monitoring mechanisms, including technology-enabled auditing, can reduce information asymmetry between management and stakeholders. Nevertheless, the model explains 12.1% of the variation in audit quality, indicating that other auditor-, client-, and governance-related characteristics remain relevant determinants of audit outcomes.

Managerial Implications

The findings provide several practical implications for public accounting firms, listed companies, and regulatory authorities. For public accounting firms, the positive relationship between AI adoption and audit quality highlights the importance of developing technological capabilities as part of audit-quality improvement strategies. Investment in AI-based audit tools, data analytics, machine learning, and related digital infrastructure may enable auditors to analyze larger datasets, detect unusual transactions more effectively, and allocate greater professional attention to high-risk areas. However, technological investment should be accompanied by auditor training and competency development to ensure that AI supports, rather than replaces, professional judgment.

For listed companies and audit committees, the technological capability of a public accounting firm may constitute an additional consideration when appointing external auditors. Audit committees should assess not only auditor reputation, independence, industry expertise, and audit fees, but also the extent to which the audit firm employs appropriate technologies to support risk assessment and audit procedures. The findings regarding audit firm rotation further suggest that periodic changes in audit firms may contribute to maintaining independence and introducing alternative perspectives in identifying significant audit matters.

For regulators and professional accounting bodies, the findings indicate that technological development in the audit profession may support the objectives of SA 701 and POJK No. 30 of 2023 by improving the informativeness of Key Audit Matter disclosures. Regulatory initiatives may therefore focus on encouraging responsible AI adoption while establishing appropriate guidance regarding technology governance, data security, auditor accountability, and professional judgment. Particular attention should also be given to highly regulated industries, where the complexity of transactions and regulatory requirements creates greater demand for sophisticated audit procedures and more informative auditor reporting. Accordingly, collaboration among regulators, professional associations, public accounting firms, and listed companies is essential to ensure that AI adoption contributes to substantive improvements in audit quality rather than merely technological modernization.

References

Abdullatif, M., & Al-Rahahleh, A. S. (2020). Applying a new audit regulation: Reporting Key Audit Matters in Jordan. *International Journal of Auditing, 24*, 268–291.

Alharasis, E. E., Alkhwaldi, A. F., & Hussainey, K. (2024). Key Audit Matters and auditing quality in the era of COVID-19 pandemic: The case of Jordan. *International Journal of Law and Management, 66*(4), 417–446.

Arens, A. A., Elder, R. J., & Beasley, M. S. (2014). *Auditing and assurance services: An integrated approach* (15th ed.). Pearson Education.

Bandyopadhyay, S. P., Chen, C., & Yu, Y. (2014). Mandatory audit partner rotation, audit market concentration, and audit quality: Evidence from China. *Advances in Accounting, 30*(1), 18–31.

Bepari, M. K., Nahar, S., & Mollik, A. T. (2024). Perceived effects of Key Audit Matters reporting on audit efforts, audit fees, audit quality, and audit report transparency: Stakeholders' perspectives. *Qualitative Research in Accounting & Management, 21*(2), 192–218.

Chen, S., & Yang, J. (2025). Intelligent manufacturing, auditor selection and audit quality. *Management Decision, 63*(3), 1–21.

de Ricquebourg, A. D., & Maroun, W. (2023). How do auditor rotations affect key audit matters? Archival evidence from South African audits. *The British Accounting Review*, *55*(2), 101099. https://doi.org/10.1016/j.bar.2022.101099

De Villiers, C., & Van Staden, C. J. (2011). Where firms choose to disclose voluntary environmental information. *Journal of Accounting and Public Policy*, *30*(6), 504-525. https://doi.org/10.1016/j.jaccpubpol.2011.03.005

DeAngelo, L. E. (1981). Auditor size and audit quality. *Journal of Accounting and Economics, 3*(3), 183–199.

Dopuch, N., King, R. R., & Schwartz, R. (2001). An experimental investigation of retention and rotation requirements. *Journal of Accounting Research, 39*(1), 93–117.

Elmarzouky, M., Hussainey, K., & Abdelfattah, T. (2023). The Key Audit Matters and the audit cost: Does governance matter? *International Journal of Accounting and Information Management, 31*(1), 195–217.

Fedyk, A., Hodson, J., Khimich, N., & Fedyk, T. (2022). Is artificial intelligence improving the audit process? *Review of Accounting Studies, 27*, 1–48.
Francis, J. R. (2004). What do we know about audit quality? *The British Accounting Review, 36*, 345–368.
Goh, S., Goh, R. S. J., Chong, B., Ng, Q. X., Koh, G. C., Ngiam, K. Y., & Hartman, M. (2024). Systematic review of challenges in implementing artificial intelligence in breast cancer screening programs: towards a framework for safe adoption. *Journal of Medical Internet Research*.
Hategan, C. D., Pitorac, R. I., & Crucean, A. C. (2022). Impact of COVID-19 pandemic on auditors' responsibility: evidence from European listed companies on key audit matters. *Managerial Auditing Journal*, *37*(7), 886-907.
Horton, J., Krishnakumar, D., Papadopoulos, S., & Tuna, A. (2023). Audit Partners Skepticial Traits and Audit Quality. *Available at SSRN 4745262*.
Jain, T., Aguilera, R. V., & Jamali, D. (2016). Corporate stakeholder orientation in an emerging country context: A longitudinal cross-industry analysis. *Journal of Business Ethics, 143*(4), 701–719.
Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics, 3*(4), 305–360.
Khan, F., Jan, S. U., & Zia-ul-Haq, H. M. (2024). Artificial intelligence adoption, audit quality and integrated financial reporting in GCC markets. *Asian Review of Accounting*.
Kuang, H., Li, H., Sherwood, M. G., & Whited, R. L. (2020). Mandatory audit partner rotations and audit quality in the United States. *Auditing: A Journal of Practice & Theory*, *39*(3), 161-184.
Li, J. (2021). Analysis and research of blockchain technology in audit system. In *Journal of physics: conference series* (Vol. 1744, No. 4, p. 042148). IOP Publishing.
Li, L., Liu, X., Pei, W., & Xia, Y. (2025). Air Pollution, Auditors' Affective States, and Audit Quality. *Accounting & Finance*, *65*(3), 3142-3173.
Lowensohn, S., Johnson, L. E., Elder, R. J., & Davies, S. P. (2007). Auditor specialization, perceived audit quality, and audit fees in the local government audit market. *Journal of accounting and Public Policy*, *26*(6), 705-732. https://doi.org/10.1016/j.jaccpubpol.2007.10.004
Rahaman, M. M., Hossain, M. M., & Bhuiyan, M. B. U. (2023). Disclosure of Key Audit Matters (KAMs) in financial reporting: Evidence from an emerging economy. *Journal of Accounting in Emerging Economies, 13*(3), 559–584.
Rahman, M. J., Zhu, H., & Yue, L. (2024). Does the adoption of artificial intelligence by audit firms and their clients affect audit quality and efficiency? Evidence from China. *Managerial Auditing Journal, 39*(6), 668–699.
Sunti, L. X. (2023). Psychological contract, auditor deviations and audit quality: A studies at the non-big public accounting firm in Surabaya. *International Journal of Business, Economics and Management*, *6*(2), 155-162. https://doi.org/10.21744/ijbem.v6n2.2141
Zeng, Y., Zhang, J. H., Zhang, J., & Zhang, M. (2021). Key Audit Matters reports in China: Their descriptions and implications of audit quality. *Accounting Horizons, 35*(2), 167–192.
Zhang, P. F., & Shailer, G. (2021). Changes in audit effort and changes in auditors' disclosures of risks of material misstatement. *The British Accounting Review, 53*(3), 1–12.
Zheng, X. (2025). Disclosure of Key Audit Matters and audit fees. *Frontiers in Business, Economics and Management, 18*(2), 33–37.