

Artificial Intelligence Technologies and Audit Quality: The Moderating Role of Predictive Analytics

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Submitted: Jun 23, 2026

Accepted: Jun 29, 2026

Published: Oct 1, 2026

ABSTRACT

This study examines the effects of artificial intelligence (AI) technologies on audit quality and investigates whether predictive analytics strengthens these relationships. The study focuses on auditors working in Public Accounting Firms (KAP) in DKI Jakarta. Using purposive sampling, 481 auditors participated in the survey. A quantitative approach was employed, with primary data collected through questionnaires and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4. The results show that machine learning, deep learning, natural language processing (NLP), data mining, and robotic process automation (RPA) have positive and significant effects on audit quality. The structural model explains 61.0% of the variance in audit quality ($R^2 = 0.610$), indicating moderate explanatory power. Among the AI technologies, NLP has the strongest effect on audit quality ($\beta = 0.277$, $p < 0.001$). Predictive analytics significantly strengthens the effects of machine learning, deep learning, NLP, and data mining, but its moderating effect on the relationship between RPA and audit quality is not significant. The novelty of this study lies in examining multiple AI technologies, with predictive analytics as a moderating variable, within a single framework. The findings extend Agency Theory and the Technology Acceptance Model (TAM) by demonstrating how predictive analytics enhances the effectiveness of AI technologies in improving audit quality. This study contributes to the AI auditing literature by providing empirical evidence of the complementary role of predictive analytics in strengthening AI's impact on audit quality. The findings are limited to auditors in DKI Jakarta, which may restrict their generalizability.

Keywords: *Audit Quality, Data Mining, Deep Learning, Machine Learning, Natural Language Processing, Robotic Process Automation, Predictive Analytics*

INTRODUCTION

Audit quality is crucial in the auditing profession because it affects how effectively auditors can identify and report material misstatements in financial statements. High-quality audits boost the credibility of financial reports, increase stakeholder trust, and promote strong corporate governance. In an increasingly complex business environment characterized by digital transactions, real-time reporting systems, and large volumes of financial data, maintaining audit quality has become more challenging for auditors. The growing complexity of business operations requires auditors handling large volumes of information accurately and efficiently while complying with professional standards and regulatory requirements. Consequently, improving audit quality has become a strategic priority for both audit firms and regulators seeking to ensure the reliability of financial information (Albahrn et al., 2025; Harjanto, Wardhani, et al., 2024).

The significance of audit quality can be illustrated using Agency Theory. This theory suggests that when ownership is separated from management, information asymmetry occurs because

managers have more detailed knowledge about organizational activities than shareholders and other stakeholders. This imbalance can lead to opportunistic actions and raise the likelihood of biased or misleading financial reports. External audits act as a monitoring tool to mitigate agency conflicts by offering independent verification of the accuracy of financial statements. Hence, audit quality is essential in decreasing information asymmetry, lowering agency costs, and improving the dependability of financial data for stakeholders' decisions.

Rapid advances in digital technology have transformed accounting and auditing practices (Abdullah & Almaqtari, 2024). Organizations increasingly rely on digital systems to handle substantial amounts of both structured and unstructured data, prompting audit firms to adopt advanced technologies to enhance audit effectiveness and efficiency. Artificial intelligence (AI) has become one of the most important innovations in auditing because it enables auditors to automate routine procedures, identify unusual patterns, analyze complex information, and improve risk assessment processes (Wang et al., 2025). The World Economic Forum (2020) emphasizes that adopting AI enhances organizational efficiency and aids strategic decision-making.

The adoption of AI technologies can further be explained through the Technology Acceptance Model (TAM), which states that individuals are more likely to use technologies perceived as useful and capable of improving job performance. In auditing, AI technologies such as machine learning, deep learning, natural language processing, data mining, and robotic process automation provide auditors with enhanced analytical capabilities, improved accuracy, and greater efficiency. Previous studies have shown that AI contributes to audit quality by supporting fraud detection, risk assessment, and audit decision-making (Fedyk et al., 2022; Noordin et al., 2022).

Despite the growing implementation of advanced technologies in auditing practices, several research gaps remain. First, previous studies frequently examine technology-based audit innovations as a broad concept, resulting in a limited understanding of how each technological capability contributes to audit quality. Since different technologies serve different purposes, examining machine learning, deep learning, natural language processing, data mining, and robotic process automation individually provides a more comprehensive explanation of their respective roles in improving audit practices. Therefore, this study addresses the conceptual gap by adopting a multidimensional technology perspective rather than analyzing these technologies as a single integrated construct.

Second, existing studies mainly focus on the direct relationship between technology adoption and audit outcomes, while paying limited attention to factors that may strengthen this relationship. Predictive analytics provides additional capability by using historical and current data to identify potential risks and support proactive decision-making. However, its role in strengthening the relationship between specific audit technologies and audit quality remains limited. Therefore, this study addresses a methodological gap by examining predictive analytics as a moderating variable.

Third, most empirical evidence regarding technology-based auditing has been carried out in developed countries, while evidence from developing countries remains limited, particularly in Indonesia, where digital transformation in auditing is still evolving. This geographical gap highlights the need for further evidence from emerging audit environments. Furthermore, a practical gap exists because Public Accounting Firms continue to invest in digital audit technologies without sufficient evidence on which technological capabilities contribute most to audit quality.

Based on these gaps, this study examines the effects of machine learning, deep learning, natural language processing, data mining, and robotic process automation on audit quality and investigates the moderating role of predictive analytics. This study contributes by developing a multidimensional technology-based audit quality model and providing empirical evidence from Public Accounting Firms in Indonesia. The findings are expected to provide theoretical insights

and practical guidance regarding the effective implementation of digital technologies in contemporary auditing practices.

LITERATURE REVIEW

This research draws on Agency Theory and the Technology Acceptance Model (TAM) to explore how artificial intelligence technologies and predictive analytics relate to audit quality. Agency Theory was introduced by Jensen & Meckling (1976) describes how ownership and management are distinguished, emphasizing information asymmetry and possible conflicts of interest between principals and agents. External auditing serves as a monitoring mechanism to reduce these conflicts by providing reliable assurance over financial reporting. In the context of digital auditing, artificial intelligence technologies strengthen this monitoring role by enabling auditors to analyze large volumes of data, identify anomalies, detect potential fraud, and obtain more reliable audit evidence. Consequently, the use of artificial intelligence is expected to reduce information asymmetry and improve audit quality.

This study also adopts the Technology Acceptance Model (TAM) by Davis (1989) as a complementary theoretical perspective. TAM suggests that individuals are more likely to adopt a technology when it is perceived as useful and easy to use. Although this study does not directly measure the core TAM constructs, the model provides a conceptual explanation for the growing adoption of artificial intelligence technologies in auditing. Technologies that improve audit efficiency, analytical capability, and decision quality are more likely to be accepted and integrated into audit practice.

Predictive analytics complements artificial intelligence by transforming historical and real-time data into insights that support risk assessment and audit planning. From the perspective of Agency Theory, predictive analytics strengthens the auditor's monitoring function by improving risk identification and reducing information asymmetry. From a TAM perspective, predictive analytics enhances the practical value of artificial intelligence technologies, thereby encouraging their use in audit engagements. Therefore, the integration of artificial intelligence technologies and predictive analytics is expected to improve audit quality.

Audit quality is influenced by various factors, including auditor characteristics, professional ethics, regulatory conditions, and the adoption of technology. Previous studies have shown that professional ethics contribute to improving audit quality by strengthening auditors' professional judgment and compliance with auditing standards (Harjanto et al., 2023). Furthermore, audit quality is affected by audit process factors such as audit report lag, audit fee stickiness, and regulatory requirements, which shape the effectiveness of audit engagements (Harjanto, Murianingsih, et al., 2024). In the context of digital transformation, the intention to adopt advanced technologies, including big data analytics, has been found to enhance auditors' efficiency and decision-making capabilities (Auliya & Harjanto, 2026). These findings suggest that technological innovation can play an important role in improving audit quality, thereby providing a foundation for examining the effects of artificial intelligence technologies on audit quality.

Artificial intelligence technologies have become important tools in auditing by improving auditors' ability to analyze information, identify risks, and perform audit procedures more effectively. These technologies support auditors in processing large volumes of data, detecting unusual patterns, and improving the reliability of audit evidence. Through these capabilities, artificial intelligence strengthens audit procedures and contributes to higher audit quality.

Machine learning enables auditors to identify patterns, detect anomalies, and evaluate potential risks based on available data. In audit practice, machine learning enables more efficient analysis of financial information and helps auditors identify transactions that require further examination. Previous studies indicate that machine learning improves audit efficiency, fraud detection, and the quality of audit decision-making (Almaqtari et al., 2024; Fedyk et al., 2022; Kokina et al., 2025). Based on these findings, machine learning is expected to enhance auditors' ability to obtain reliable evidence and improve the quality of audit outcomes.

H1: Machine learning has a positive and significant effect on audit quality.

Deep learning provides more advanced analytical capabilities by identifying complex and nonlinear relationships within large datasets. In auditing, deep learning supports the detection of hidden patterns, potential irregularities, and financial risks that may not be readily identified by traditional audit procedures. Previous research shows that deep learning improves analytical accuracy and supports more effective audit judgments (Choi et al., 2022; Estep et al., 2024; Eulerich, 2023). These capabilities indicate that deep learning can strengthen audit processes and improve audit quality.

H2: Deep learning has a positive and significant effect on audit quality.

Natural language processing enables auditors to examine and interpret unstructured information contained in financial reports, contracts, disclosures, and other audit documents. This capability allows auditors to identify relevant information, inconsistencies, and potential risk indicators more efficiently. Prior studies demonstrate that natural language processing improves audit analysis, supports risk identification, and enhances audit decision-making (Abdullah & Almaqtari, 2024; Küster, 2024; Qatawneh, 2025). Accordingly, the ability of natural language processing to enhance information analysis is expected to improve audit quality.

H3: Natural language processing has a positive and significant effect on audit quality.

Data mining supports audit activities by identifying patterns, relationships, and anomalies within large datasets. Compared with traditional sampling approaches, data mining enables auditors to examine broader audit evidence and improve the detection of unusual transactions or potential misstatements. Previous studies show that data mining techniques enhance fraud detection, audit effectiveness, and the quality of audit evidence (Bakumenko & Elragal, 2022; Ditkaew & Suttipun, 2023; Papík & Papíková, 2022). These findings suggest that data mining provides valuable analytical support that improves audit quality.

H4: Data mining has a positive and significant effect on audit quality.

Robotic process automation improves audit efficiency by automating repetitive, rule-based tasks, including data processing, reconciliation, and documentation. The automation of routine tasks reduces manual errors and enables auditors to focus on activities requiring professional judgment and analytical skills. Previous studies report that robotic process automation improves audit consistency, operational efficiency, and audit service quality (Eulerich, 2023; Perdana et al., 2023; Tiron-Tudor et al., 2024). The ability of robotic process automation to enhance audit processes provides a basis for expecting a positive relationship with audit quality.

H5: Robotic process automation has a positive and significant effect on audit quality.

Predictive analytics enhances audit procedures by using historical and real-time data to predict risks, identify anomalies, and support audit planning. In Agency Theory, predictive analytics strengthens the auditor's monitoring role by reducing information asymmetry. From the TAM perspective, predictive analytics increases the usefulness of technology by supporting more effective audit decisions. Previous studies indicate that advanced analytics improves fraud detection, risk assessment, and audit effectiveness (Broby, 2022; Eulerich et al., 2022; Fedyk et al., 2022). Therefore, predictive analytics is expected to strengthen the effectiveness of artificial intelligence technologies in improving audit quality.

Machine learning improves auditors' ability to identify patterns and detect anomalies from large datasets. Predictive analytics strengthens this capability by providing risk predictions that support audit planning and professional judgment. Previous studies show that machine learning and predictive analytics improve audit analysis and risk assessment (Bakumenko & Elragal, 2022; Fedyk et al., 2022). Therefore, predictive analytics is expected to strengthen the relationship between machine learning and audit quality.

H6: Predictive analytics moderates the relationship between machine learning and audit quality.

Deep learning enables auditors to analyze complex data patterns and identify potential irregularities. Predictive analytics enhances this capability by converting analytical results into forward-looking risk information. Previous studies show that deep learning and predictive analytics improve audit decision-making and analytical effectiveness (Choi et al., 2022; Estep et al., 2024). Hence, predictive analytics is expected to strengthen the relationship between deep learning and audit quality.

H7: Predictive analytics moderates the relationship between deep learning and audit quality.

Natural language processing supports the analysis of unstructured audit information, while predictive analytics improves the identification of future risks from data patterns. Previous research confirms that these technologies enhance audit analysis and risk identification (Küster, 2024; Qatawneh, 2025). Therefore, predictive analytics is expected to strengthen the influence of natural language processing on audit quality.

H8: Predictive analytics moderates the relationship between natural language processing and audit quality.

Data mining helps auditors identify patterns and anomalies in large datasets. Predictive analytics extends this capability by providing predictions of potential risks and material misstatements. Previous studies show that data mining and predictive analytics improve audit effectiveness (Bakumenko & Elragal, 2022; Papík & Papíková, 2022). Hence, predictive analytics is expected to strengthen the relationship between data mining and audit quality.

H9: Predictive analytics moderates the relationship between data mining and audit quality.

Robotic process automation improves audit efficiency through task automation but has limitations in complex risk evaluation. Predictive analytics complements automation by providing risk-based insights for audit procedures. Previous studies report that automation and predictive analytics improve audit efficiency and decision quality (Eulerich, 2023; Perdana et al., 2023; Tiron-Tudor et al., 2024). Therefore, predictive analytics is expected to strengthen the relationship between robotic process automation and audit quality.

H10: Predictive analytics moderates the relationship between robotic process automation and audit quality.

METHOD

This research utilizes SmartPLS 4 to perform Partial Least Squares Structural Equation Modeling (PLS-SEM), testing the proposed hypotheses and exploring the moderating role of predictive analytics. PLS-SEM was selected because this study focuses on predicting and explaining relationships among multiple latent constructs, including moderation analysis. Compared with CB-SEM, PLS-SEM is better suited for research focused on prediction, handling complex models, and analyzing questionnaire data without the need for strict multivariate normality assumptions (Hair et al., 2022).

Since the data were obtained from a single-source questionnaire survey, common method bias (CMB) was evaluated using Harman's single-factor test. All measurement items were subjected to exploratory factor analysis, and the first unrotated factor accounted for less than the majority of the total variance. This result indicates that common method bias is unlikely to have substantially affected the findings of this study (Podsakoff et al., 2023).

The variables were measured using indicators adapted from previous studies. Machine learning was measured using system integration, accuracy, fraud-detection capability, and actual system use, adapted from Al-Sayyed et al. (2021), Appelbaum et al. (2017), Issa et al. (2016), and Venkatesh et al. (2003). Deep learning was assessed using perceived ease of use and perceived usefulness, following Oyewole & Akindele (2025) and Putra et al. (2023). Natural language processing was measured based on its application in audit and fraud detection, following Qatawneh (2025). Data mining was measured through job fit and actual system use, adapted from Oyewole & Akindele (2025), Putra et al. (2023), and Venkatesh et al. (2003). Robotic process automation was measured using information quality, system quality, system benefits, user attitude, system satisfaction, and willingness to use the system, adapted from Hsiung & Wang (2022).

Audit quality was operationalized as the auditor's ability to perform effective audit procedures and produce reliable audit results. Although some indicators reflect auditor capabilities, such as knowledge and experience, these dimensions support audit quality by influencing professional judgment, audit effectiveness, and the evaluation of evidence. Therefore, audit quality was measured through knowledge and experience, professional skepticism, understanding of audit systems, audit process and quality control, and evidence evaluation, adapted from Al-Ateeq et al. (2022) and Putra et al. (2023).

RESULT

This study used primary data collected via questionnaires distributed via Google Forms to auditors at Public Accounting Firms in DKI Jakarta. The use of online questionnaires enabled the researcher to efficiently reach respondents from various firms and positions within the auditing profession. A total of 481 responses were obtained, and all respondents fulfilled the established criteria, allowing all data to be included in the hypothesis testing process. This indicates that the collected data were considered valid and relevant to the study's objectives.

Furthermore, the respondents were auditors with diverse levels of experience and professional roles, providing broader insights into the research variables examined. The collected data were then processed and analyzed using SmartPLS software to evaluate the relationships between variables and test the proposed hypotheses. The analysis involved testing both the measurement and structural models to verify the research instrument's validity and reliability, as well as the significance of the proposed relationships.

Table 1. Characteristics Responden

Characteristic	Information	Sum
Gender	Man	174
	Women	307
	Sum	481
Age	<25 Years	392
	26-30 Years	75
	31-40 Years	14
	Sum	481
	D3/D4	1
Education Level	S1	478
	S2	2
	Sum	481
Work Position	Junior Auditor	451
	Senior Auditor	27
	Manager	2
	Partner	1
	Sum	481
Work Experience	<1 Years	26
	1-3 Years	437
	4-5 Years	7
	>5 Years	11
	Sum	481

Source: data processed, 2026

Table 2. Result of Convergent Validity Test

Variable	Indicator	Outer Loading	Status
AQ (Y)	AQ1-AQ6	0.724 – 0.811	Valid

ML (X1)	ML1–ML5	0.863 – 0.882	Valid
DL (X2)	DL1–DL13	0.778 – 0.829	Valid
NLP (X3)	NLP1–NLP8	0.800 – 0.846	Valid
DM (X4)	DM1–DM6	0.830 – 0.868	Valid
RPA (X5)	RPA1–RPA26	0.744 – 0.810	Valid
PA (M)	PA1–PA6	0.815 – 0.843	Valid

Source: Output SmartPLS 4

Table 2 presents the outer loading values for all indicators used in this study. The results show that the outer loading values range from 0.724 to 0.882, exceeding the recommended threshold of 0.70. Specifically, the outer loadings range from 0.724–0.811 for Audit Quality (AQ), 0.863–0.882 for Machine Learning (ML), 0.778–0.829 for Deep Learning (DL), 0.800–0.846 for Natural Language Processing (NLP), 0.830–0.868 for Data Mining (DM), 0.744–0.810 for Robotic Process Automation (RPA), and 0.815–0.843 for Predictive Analytics (PA). These findings indicate that all indicators exhibit satisfactory convergent validity and are therefore retained for further analysis.

Table 3. Reability Test and AVE Score

Variable	Cronbach's Alpha	Composite reliability rho_a	Composite Reliability rho_c	AVE
AQ (Y)	0.854	0.856	0.892	0.579
ML (X1)	0.923	0.924	0.942	0.763
DL (X2)	0.952	0.953	0.957	0.633
NLP (X3)	0.932	0.934	0.944	0.677
DM (X4)	0.921	0.922	0.938	0.717
RPA (X5)	0.974	0.974	0.975	0.603
PA (M)	0.907	0.907	0.928	0.682

Source: Output SmartPLS 4

Table 3 presents the results of the reliability and validity assessment of the measurement model, including Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE). Overall, all constructs show satisfactory internal consistency, as indicated by Cronbach's Alpha values ranging from 0.854 to 0.974, which exceed the minimum threshold of 0.70. Similarly, the Composite Reliability values are above 0.70, indicating that all indicators consistently measure their respective constructs.

In terms of convergent validity, the AVE values for all variables range from 0.579 to 0.763, which are above the recommended threshold of 0.50. This confirms that each construct is able to explain more than half of the variance of its indicators. Among all variables, Machine Learning (ML) shows the highest AVE value (0.763), indicating strong convergent validity, while Audit Quality (AQ) records the lowest AVE value (0.579), yet it still meets the acceptable criterion. Overall, the results confirm that all measurement constructs in this study are reliable and valid for further structural model analysis.

Table 4. Heterotrait-Monotrait Ratio (HTMT)

	AQ(Y)	ML(X1)	DL(X2)	NLP(X3)	DM(X4)	RPA(X5)	PA(M)
AQ(Y)	-						
ML(X1)	0.448	-					

DL(X2)	0.420	0.138	-			
NLP(X3)	0.497	0.123	0.159	-		
DM(X4)	0.454	0.199	0.112	0.136	-	
RPA(X5)	0.453	0.128	0.182	0.182	0.167	-
PA(M)	0.648	0.342	0.373	0.391	0.329	0.361

Source: Output SmartPLS 4

Table 4 indicates that all HTMT values are below the recommended threshold of 0.90. The maximum HTMT value is 0.648, observed between Predictive Analytics (PA) and Audit Quality (AQ), and it still stays within the acceptable range. Other values range between 0.112 and 0.497, confirming adequate discriminant validity across all constructs.

These results confirm that Audit Quality (AQ), Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), Data Mining (DM), Robotic Process Automation (RPA), and Predictive Analytics (PA) represent distinct constructs and do not exhibit problematic measurement overlap. Thus, discriminant validity is confirmed for the measurement model, and all constructs are appropriate for further evaluation of the structural model.

R² indicates the explanatory power of the structural model by representing the proportion of variance in the endogenous construct accounted for by the independent variables. According to Hair et al. (2022), R² values of 0.25, 0.50, and 0.75 can be interpreted as weak, moderate, and substantial, respectively.

Table 5. R-Square Test Result

Variable	R ²	R ² Adjusted
Audit Quality (AQ)	0.610	0.601

Source: Output SmartPLS 4

Table 5 shows that Audit Quality (AQ) records an R² of 0.610 and an adjusted R² of 0.601, indicating that 61.0% of the variance in audit quality is determined by machine learning, deep learning, natural language processing, data mining, robotic process automation, predictive analytics, and their interaction effects. The R² value falls between the moderate and substantial ranges, indicating a strong level of explanatory power. Moreover, the adjusted R² value of 0.601 confirm the model remains robust after controlling for the number of independent variables. These findings indicate that AI technologies, together with predictive analytics, offer strong explanatory capability in determining audit quality.

Table 6. Hypothesis Test Result

Hypothesis	Path	β (O)	Mean (M)	STDEV	T-Stat	p-value	Decision
H1	ML (X1) → AQ (Y)	0.231	0.232	0.034	6.808	0.000	Supported
H2	DL (X2) → AQ (Y)	0.215	0.216	0.035	6.111	0.000	Supported
H3	NLP (X3) → AQ (Y)	0.277	0.278	0.033	8.376	0.000	Supported
H4	DM (X4) → AQ (Y)	0.222	0.224	0.030	7.316	0.000	Supported
H5	RPA (X5) → AQ (Y)	0.236	0.236	0.033	7.240	0.000	Supported
H6	ML×PA → AQ	0.074	0.075	0.032	2.324	0.010	Supported
H7	DL×PA → AQ	0.072	0.072	0.034	2.103	0.018	Supported
H8	NLP×PA → AQ	0.097	0.097	0.033	2.927	0.002	Supported

H9	DM×PA → AQ	0.123	0.120	0.029	4.257	0.000	Supported
H10	RPA×PA→ AQ	0.041	0.041	0.031	1.311	0.095	Rejected

Source: Output SmartPLS 4

Table 7. Effect Size Result (f^2)

	AQ
AQ	
DL	0.098
DM	0.112
ML	0.120
NLP	0.163
PA	0.050
RPA	0.120
PA x DL	0.011
PA x NLP	0.020
PA x ML	0.012
PA x RPA	0.004
PA x DM	0.034

Source: Output SmartPLS 4

The effect size (f^2) analysis was conducted to assess the contribution of each exogenous construct to audit quality. The results show that natural language processing (NLP) has the strongest effect on audit quality ($f^2 = 0.163$), followed by machine learning (ML) and robotic process automation (RPA) ($f^2 = 0.120$), data mining (DM) ($f^2 = 0.112$), and deep learning (DL) ($f^2 = 0.098$). These findings indicate that AI technologies contribute to improving audit quality to varying degrees, with NLP having the greatest explanatory impact. Predictive analytics (PA) shows a small direct effect ($f^2 = 0.050$), while its moderating effects on machine learning ($f^2 = 0.012$), deep learning ($f^2 = 0.011$), natural language processing ($f^2 = 0.020$), data mining ($f^2 = 0.034$), and robotic process automation ($f^2 = 0.004$) indicate relatively small contributions. Overall, the results suggest that the direct application of AI technologies contributes more substantially to audit quality than the additional moderating role of predictive analytics.

Table 8. Predictive Relevance Assessment

	Q ² predict	RMSE	MAE
AQ	0.570	0.658	0.531

Source: Output SmartPLS 4

The model's predictive relevance was assessed using Q²predict, RMSE, and MAE. The results show that audit quality (AQ) has a Q²predict value of 0.570, indicating that the model has good predictive relevance. The RMSE of 0.658 and MAE of 0.531 indicate acceptable prediction accuracy, suggesting that the proposed model has sufficient capability to predict audit quality.

Table 9. Model Fit Assesment

	Saturated model	Estimated model
SRMR	0.034	0.034
d_ULS	2.868	2.870
d_G	1.138	1.138
Chi-square	2911.281	2912.670
NFI	0.887	0.887

Source: Output SmartPLS 4

The model fit was evaluated using SRMR, d_ULS, d_G, Chi-square, and NFI metrics. An SRMR of 0.034 for both the saturated and estimated models suggests a good fit, since it is below the recommended threshold. The NFI of 0.887 further supports an acceptable model fit, validating that the proposed model is suitable for hypothesis testing.

DISCUSSION

Machine Learning and Audit Quality

The findings reveal that machine learning has a positive and significant effect on audit quality. Therefore, H1 is accepted. This finding indicates that machine learning enhances auditors' ability to process large volumes of data, identify anomalies, and improve the accuracy of risk assessments. This finding is in line with research by Fedyk et al. (2022), who found that investments in advanced analytical technologies are associated with lower audit restatement risk and improved audit efficiency. Similarly, Kokina et al. (2025) reported that machine learning improves real-time audit analysis and supports higher-quality audit decisions. Almaqtari et al. (2024) also found that analytical technologies contribute positively to audit reliability and information quality. From the perspective of Agency Theory, enhanced anomaly detection reduces information asymmetry between management and stakeholders. In addition, the finding supports the Technology Acceptance Model (TAM), which suggests that technologies perceived as useful are more likely to be adopted and utilized effectively by auditors.

Deep Learning and Audit Quality

The results indicate that deep learning has a positive and significant effect on audit quality, H2 is accepted. This finding suggests that deep learning improves auditors' ability to identify complex, non-linear relationships in financial data, enabling more effective detection of hidden risks and irregularities. The result is consistent with Choi et al. (2022), who found that deep neural network models generate more accurate estimates than conventional statistical approaches in audit-related tasks. Likewise, Eulerich (2023) reported that advanced audit technologies significantly improve audit task outcomes and risk assessment quality. Estep et al. (2024) further demonstrated that advanced technological applications contribute positively to financial reporting and auditing processes. These findings indicate that deep learning provides valuable support for auditor judgment and audit evidence evaluation.

Natural Language Processing and Audit Quality

The findings reveal that natural language processing has a positive and significant effect on audit quality, H3 is accepted. Notably, NLP shows the strongest effect among all independent variables, indicating the importance of textual information analysis in auditing. This result can be explained by the fact that auditors rely not only on numerical data but also on unstructured information, such as reports, contracts, and disclosures. NLP enables auditors to extract relevant information, identify risk signals, and detect inconsistencies in textual data, thereby improving audit judgment and risk assessment. The result suggests that auditors benefit from the ability to analyze annual reports, contracts, disclosures, and management communications more effectively. This finding is consistent with Küster (2024), who demonstrated that linguistic characteristics within key audit matters reflect important auditor judgments and risk assessments. Similarly, Qatawneh (2025) reported that natural language processing improves auditing effectiveness through better identification of risk indicators embedded in textual information. Abdullah & Almaqtari (2024) also found that textual analysis technologies contribute to more effective fraud detection and audit assessments. These findings suggest that the increasing volume of unstructured information has enhanced the relevance of text analytics in modern audit practices.

Data Mining and Audit Quality

The results show that data mining has a positive and significant effect on audit quality, H4 is accepted. This finding indicates that data mining improves auditors' ability to identify hidden

patterns, unusual transactions, and financial irregularities across large datasets. The result is consistent with Papík & Papíková (2022), who found that data mining techniques effectively detect accounting fraud and outperform traditional approaches. Ditkaew & Suttipun (2023) also reported that audit data analytics positively influences audit quality and audit review continuity. Furthermore, Bakumenko & Elragal (2022) demonstrated that advanced analytical techniques applied to financial data can improve anomaly detection and audit effectiveness. These findings reinforce the importance of data-driven auditing approaches in supporting higher audit quality.

Robotic Process Automation and Audit Quality

The results indicate that robotic process automation has a positive and significant effect on audit quality, H5 is accepted. This finding suggests that the automation of repetitive audit procedures enables auditors to allocate more time to professional judgment, risk assessment, and analytical activities. The result is consistent with Eulerich et al. (2022), who found that robotic process automation improves audit effectiveness and efficiency when appropriately implemented. Similarly, Perdana et al. (2023) reported that automation contributes to greater accuracy and consistency in repetitive audit procedures. Tiron-Tudor et al. (2024) further demonstrated that automation technologies are transforming accounting and auditing services by reducing manual workloads and standardizing workflows. These findings indicate that automation not only improves operational efficiency but also enhances the reliability and consistency of audit procedures, ultimately contributing to higher audit quality.

Moderating Effect of Predictive Analytics on the Relationship Between Machine Learning and Audit Quality

The significant moderating effect of predictive analytics on the relationship between machine learning and audit quality supports H6. This finding indicates that predictive analytics enhances machine learning applications' ability to generate forward-looking insights and to identify potential risks. As a result, auditors can obtain more relevant information for risk assessment and audit planning, leading to higher audit quality. This result is consistent with Kokina et al. (2025), who reported that advanced analytical technologies strengthen audit effectiveness when integrated into audit workflows. Similarly, Ditkaew & Suttipun (2023) found that analytical capabilities improve risk identification and audit performance by better leveraging data-driven technologies. Fedyk et al. (2022) also demonstrated that investments in advanced technological tools contribute positively to audit outcomes when combined with sophisticated analytical capabilities. These findings suggest that predictive analytics increases the usefulness of machine learning outputs and supports more effective audit decision-making.

Moderating Effect of Predictive Analytics on the Relationship Between Deep Learning and Audit Quality

The findings indicate that predictive analytics strengthens the relationship between deep learning and audit quality, thereby confirming H7. This result suggests that predictive analytics enhances deep learning applications' ability to identify complex patterns, detect emerging risks, and provide more relevant audit insights. Consequently, auditors can make more informed judgments based on comprehensive analyses of financial information. The finding is consistent with Eulerich (2023), who found that advanced analytical capabilities improve the effectiveness of technology-based audit techniques. Likewise, Choi et al. (2022) reported that deep neural network models generate more accurate audit-related estimates, while Estep et al. (2024) concluded that advanced analytical technologies improve the quality of audit judgments and decision-making processes. The result indicates that predictive analytics enhances the practical benefits derived from deep learning applications in auditing.

Moderating Effect of Predictive Analytics on the Relationship Between Natural Language Processing and Audit Quality

The findings also support H8, indicating that predictive analytics strengthens the effect of natural language processing on audit quality. This result implies that predictive analytics enables

auditors to transform textual information into meaningful indicators of future risk, thereby supporting audit planning, evidence evaluation, and fraud detection. The finding is consistent with Qatawneh (2025), who found that the effectiveness of language-processing technologies in auditing increases when supported by advanced analytical capabilities. Similarly, Küster (2024) reported that textual analysis techniques improve the identification of risk signals embedded in audit disclosures. Abdullah & Almaqtari (2024) further concluded that advanced analytical technologies enhance the value of unstructured information by generating insights that support audit decision-making. Therefore, predictive analytics appears to increase the contribution of textual analysis technologies to audit quality.

Moderating Effect of Predictive Analytics on the Relationship Between Data Mining and Audit Quality

The strongest moderating effect is observed in the relationship between data mining and audit quality, supporting H9. This finding suggests that predictive analytics substantially enhances the value of data mining by converting historical transaction patterns into useful indicators of future risk. As a result, auditors can identify anomalies more accurately and allocate audit resources more effectively. This finding is consistent with Papík & Papíková (2022), who found that data mining techniques significantly improve the detection of financial irregularities. Bakumenko & Elragal (2022) similarly reported that advanced analytical approaches improve risk assessment and anomaly detection capabilities. Furthermore, Almaqtari et al. (2024) concluded that the integration of analytical technologies significantly improves the effectiveness of audit procedures and the detection of financial misstatements. The result highlights the importance of combining historical data analysis with predictive capabilities to enhance audit quality.

Moderating Effect of Predictive Analytics on the Relationship Between Robotic Process Automation and Audit Quality

In contrast, H10 is not supported because predictive analytics does not significantly moderate the relationship between robotic process automation and audit quality. This finding suggests that RPA's contribution is primarily related to operational efficiency, process consistency, and workflow standardization rather than to analytical decision-making. From a technological perspective, RPA operates based on predefined rules and structured processes, making it effective for repetitive audit tasks such as data extraction, reconciliation, and standardized testing. Meanwhile, predictive analytics focuses on identifying future risks and generating insights that may not directly enhance rule-based automation processes. Therefore, the effectiveness of RPA in improving audit quality appears to depend more on automation capability and process reliability than on predictive analytical capabilities (Eulerich, 2023; Perdana et al., 2023; Tiron-Tudor et al., 2024).

CONCLUSION

The findings of this study demonstrate that machine learning, deep learning, natural language processing, data mining, and robotic process automation contribute positively and significantly to audit quality in Public Accounting Firms in Indonesia. The implementation of these technologies enables auditors to process and evaluate large volumes of data more accurately, identify irregularities more effectively, and improve the efficiency of audit procedures. Among the various artificial intelligence technologies examined, natural language processing emerged as the most influential factor, indicating that the ability to analyze unstructured information is increasingly important for supporting audit activities.

The study also reveals that predictive analytics strengthens the influence of machine learning, deep learning, natural language processing, and data mining on audit quality, suggesting that predictive capabilities enhance the value these analytical technologies deliver. In contrast, predictive analytics does not significantly affect the relationship between robotic process automation and audit quality, which may be attributed to the operational nature of robotic process automation that primarily focuses on automating repetitive tasks rather than supporting predictive judgments.

This study contributes to Agency Theory and Technology Acceptance Model (TAM) by showing that AI technologies reduce information asymmetry and support technology adoption in

auditing. In practice, the findings suggest that Public Accounting Firms should adopt AI-based audit tools, supported by adequate infrastructure and auditor training, to enhance audit quality.

This study has a few limitations that need to be recognized. The study was conducted exclusively among auditors employed by Public Accounting Firms, which could restrict how widely the results apply. Furthermore, reliance on questionnaire-based responses creates the possibility of subjective perceptions and response bias. Another limitation is that the analysis concentrates on a limited number of artificial intelligence technologies and predictive analytics without considering other digital innovations that may also influence audit quality.

Future studies are therefore recommended to include a wider range of respondents, examine additional technologies, such as blockchain, cloud computing, and cybersecurity, and employ longitudinal or mixed-methods research designs to better understand the evolving impact of digital transformation within the auditing profession.

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