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Artificial Intelligence and Intelligent Analytical Models in the Evaluation of Audit Report Quality: Evidence from the Tehran Stock Exchange

Elena. Hosseinpour[1*]

1. Department of Accounting, Faculty of Management, Nt.C., Islamic Azad University, Tehran, Iran

*** Corresponding author email address:** elenahosseinpour05@gmail.com

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ABSTRACT

Audit report quality is one of the central mechanisms through which public trust in financial reporting and information transparency in capital markets are strengthened. With the expansion of artificial intelligence and analytical technologies in accounting and auditing, intelligent models provide new opportunities for evaluating audit report quality through data-driven prediction. This study aimed to design and compare intelligent analytical models for evaluating audit report quality among companies listed on the Tehran Stock Exchange. The study used a quantitative empirical design. Audit report quality was operationalized as the issuance of a modified audit opinion. The independent variables included financial leverage, firm size, profitability, auditor tenure, audit fee, operating cash flow ratio. The sample consisted of 150 listed companies over the period 2017–2023. Logistic regression, decision tree, random forest, and gradient boosting models were used to analyze the data. Model performance was evaluated using accuracy, precision, recall, F1-score, and ROC-AUC. The results indicated that financial leverage had a positive and significant association with the probability of receiving a modified audit opinion, whereas firm size, profitability, auditor tenure, and operating cash flow were negatively associated with modified audit opinions. Among the predictive models, random forest achieved the strongest performance (accuracy = 0.83, precision = 0.81, recall = 0.79, and ROC-AUC = 0.88). Variable-importance analysis showed that financial leverage, firm size, auditor tenure, and profitability were the most influential predictors. The findings suggest that intelligent analytical models, particularly random forest, can support audit-risk assessment, regulatory monitoring, and investor decision-making in the Iranian capital market.

Keywords: *audit report quality; artificial intelligence; intelligent analytical models; random forest; modified audit opinion; Tehran Stock Exchange.*

1. Introduction

Audit report quality is a fundamental pillar of financial reporting systems because it strengthens the credibility of financial statements, reduces information asymmetry, and improves investor confidence in capital markets. Audited financial statements can serve as a reliable basis for decisions by investors, creditors, analysts, and other stakeholders only when users are confident in the quality of the audit process and the reliability of the auditor's report. In weak audit-reporting environments, the probability of misleading information increases, investment risk intensifies, and capital-market efficiency may decline. These concerns are consistent with the broader audit-quality literature, which defines audit quality as a multidimensional construct linked to auditor competence, independence, reporting incentives, and the information environment (DeAngelo, 1981; DeFond & Zhang, 2014; Francis, 2004).

Audit quality can be evaluated through several proxies, including the probability of issuing a modified audit opinion, discretionary accruals, litigation risk, auditor size, audit fees, audit tenure, and the auditor's ability to detect and report material misstatements (Dechow et al., 1995; Palmrose, 1988; Simunic, 1980). Prior studies have identified audit firm size, audit fees, auditor tenure, industry specialization, client complexity, ownership structure, leverage, and financial performance as important determinants of audit quality (Francis & Yu, 2009; Geiger & Raghunandan, 2002; Myers et al., 2003). However, many empirical studies rely on traditional statistical models, such as linear or logistic regression, which may not fully capture nonlinear, conditional, or interaction effects in financial and audit data.

Recent digital transformation and the expansion of artificial intelligence have changed accounting and auditing practice. Big data analytics and artificial intelligence can support audit planning, anomaly detection, fraud detection, risk assessment, and professional judgment by identifying patterns in large datasets that may not be visible through traditional procedures (Appelbaum et al., 2017; Brown-Liburd et al., 2015; Kokina & Davenport, 2017; Sutton et al., 2016). Empirical evidence also suggests that investment in artificial intelligence by audit firms may improve audit quality and efficiency (Fedyk et al., 2022). These developments indicate that intelligent analytical models may complement, rather than replace, professional auditing judgment.

Machine-learning models such as decision trees, random forests, and gradient boosting can model complex relationships without some of the restrictive assumptions of traditional regression models. Random forests are particularly useful for classification tasks because they combine multiple decision trees and reduce model instability through ensemble learning (Breiman, 2001). Gradient boosting is also designed to improve predictive accuracy through sequentially constructed weak learners that reduce prior model errors (Francis, 2004; Hastie et al., 2009). In auditing research, machine-learning algorithms have already shown promise in financial statement fraud detection and risk classification (Perols, 2011).

In the Iranian capital market, empirical evidence regarding the systematic application of intelligent analytical models to audit report quality remains limited. Accordingly, this study examines audit report quality among companies listed on the Tehran Stock Exchange by integrating the audit-quality literature with agency theory, signaling theory, and machine-learning-based prediction. Audit quality is commonly defined as the joint probability that an auditor will detect and report a material misstatement, emphasizing both professional competence and independence (DeAngelo, 1981). Agency theory explains the demand for auditing as a monitoring mechanism that reduces conflicts of interest between managers and owners and improves the credibility of reported information (Jensen & Meckling, 1976). Signaling theory further suggests that credible audit reporting and auditor choice may communicate information quality to capital-market participants (Spence, 1973), while reputation theory implies that larger audit firms may have stronger incentives to protect audit quality (DeAngelo, 1981; Francis & Yu, 2009). From this perspective, financial leverage, firm size, profitability, auditor tenure, audit fees, and operating cash flows may influence audit-reporting outcomes through client risk, audit effort, auditor independence, and client-specific knowledge (DeFond & Zhang, 2014; Geiger & Raghunandan, 2002; Myers et al., 2003; Simunic, 1980). Traditional logistic regression remains useful for hypothesis testing and interpretation; however, audit report quality may also depend on nonlinear and interacting relationships among firm-level and audit-related characteristics. Machine-learning models can capture such nonlinearities and interactions without imposing strict functional-form assumptions (Breiman, 2001; Friedman, 2001; Hastie et al., 2009). Therefore, the problem addressed in this study is whether intelligent analytical models can evaluate audit report quality more effectively than traditional logistic regression in the Tehran Stock Exchange context, and which financial and audit-related variables have the strongest role in explaining modified audit opinions. More specifically, the study is guided by the following research questions: Is financial leverage associated with a higher probability of receiving a modified audit opinion? How are firm size, profitability, auditor tenure, audit fees, and operating cash flows associated with audit report quality? Do intelligent analytical models provide higher predictive performance than logistic regression? Which variables emerge as the most important predictors in the random forest model?

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2. Methods and Materials

2.1. Research Design

This study is applied in purpose and quantitative-empirical in method. It uses econometric and intelligent analytical models to evaluate audit report quality. The data were extracted from the financial statements and audit reports of companies listed on the Tehran Stock Exchange. The general research procedure consisted of data collection, variable calculation, preprocessing, model training, performance evaluation, and comparison between intelligent analytical models and a traditional statistical model.

2.2. Population and Sample

The statistical population consisted of all companies listed on the Tehran Stock Exchange. The sample was selected using systematic elimination. Companies were retained if they were active during the study period, had a fiscal year ending in March, had available financial statements and audit reports, and did not belong to financial, banking, or insurance industries because of their different operational and regulatory structures. After applying these criteria, 150 companies over the period 2017–2023 were included in the study.

2.3. Variables

The dependent variable was audit report quality (AQ), measured as a binary variable based on audit opinion type. AQ was coded as 1 when the company received a modified audit opinion and 0 when it received an unmodified opinion. This operationalization is consistent with audit-reporting research that treats modified opinions as direct indicators of audit reporting outcomes (Geiger & Raghunandan, 2002).

The independent variables included financial leverage (LEV), firm size (SIZE), profitability (ROA), auditor tenure (TENURE), audit fee (FEE), and operating cash flow ratio (CFO). Financial leverage was calculated as total debt divided by total assets. Firm size was measured as the natural logarithm of total assets. Profitability was calculated as net income divided by total assets. Auditor tenure was measured as the number of consecutive years in which the same auditor audited the company. Audit fee was measured as the natural logarithm of the disclosed audit fee. Operating cash flow was calculated as operating cash flow divided by total assets.

Table 1

Operational Definition of Research Variables

Variable	Measurement	Symbol	Source
Audit report quality	1 = modified audit opinion; 0 = unmodified opinion	AQ	Audit report
Financial leverage	Total debt / Total assets	LEV	Financial statements
Firm size	Natural logarithm of total assets	SIZE	Financial statements
Profitability	Net income / Total assets	ROA	Financial statements
Auditor tenure	Consecutive years of cooperation with the auditor	TENURE	Audit report
Audit fee	Natural logarithm of audit fee	FEE	Explanatory notes
Operating cash flow	Operating cash flow / Total assets	CFO	Statement of cash flows

2.4. Analytical Models

Four models were used to predict audit report quality: logistic regression, decision tree, random forest, and gradient boosting. Logistic regression was used as the traditional baseline model because AQ was binary. The model estimated the probability of receiving a modified audit opinion based on the explanatory variables. Decision tree, random forest, and gradient boosting models were used as intelligent analytical models. Decision trees classify observations by recursively splitting the data based on criteria such as Gini index or entropy. Random forest combines multiple decision trees and produces final classification by majority voting, which improves predictive stability (Breiman, 2001). Gradient boosting constructs models sequentially so that each new learner reduces the residual error of previous learners (Friedman, 2001; Hastie et al., 2009).

The logistic regression model was specified as follows: $AQ = \beta0 + \beta1LEV + \beta2SIZE + \beta3ROA + \beta4TENURE + \beta5FEE + \beta6CFO + \varepsilon$. Model performance was evaluated using accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (ROC-AUC). These criteria provide a broader assessment of classification performance than accuracy alone, especially when the distribution of modified and unmodified audit opinions is not perfectly balanced.

To reduce optimistic model evaluation, the same training and testing workflow was applied to all predictive models. Model performance was evaluated using the holdout testing data, and the reported metrics were used only for comparative assessment rather than causal interpretation.

3. Findings and Results

3.1. Descriptive Statistics

Table 2 presents descriptive statistics for the research variables. The mean of AQ was 0.27, indicating that approximately 27% of the audit reports in the sample were modified. The mean financial leverage was 0.58, suggesting a relatively high level of debt usage among the sampled companies. The mean firm size was 14.21, and the mean auditor tenure was 3.7 years.

Table 2

Descriptive Statistics of Research Variables

Variable	Mean	Median	Minimum	Maximum	Standard deviation
AQ	0.27	0	0	1	0.44
LEV	0.58	0.55	0.12	0.91	0.19
SIZE	14.21	14.08	12.30	17.95	1.12
ROA	0.084	0.072	-0.23	0.41	0.11
TENURE	3.7	3	1	10	2.4
FEE	20.45	20.30	17.10	23.90	1.14
CFO	0.09	0.07	-0.19	0.39	0.12

3.2. Correlation Analysis

The Pearson correlation matrix indicated a positive association between financial leverage and modified audit opinion. Firm size showed a negative correlation with modified audit opinion, suggesting that larger firms were less likely to receive modified audit reports in the sample. The correlation coefficients did not indicate severe multicollinearity among the main predictors.

Table 3

Pearson Correlation Matrix

Variable	AQ	LEV	SIZE	ROA	TENURE
AQ	1				
LEV	0.31	1			
SIZE	-0.28	-0.12	1		
ROA	-0.34	-0.21	0.26	1	
TENURE	-0.19	0.08	0.11	0.07	1

3.3. Logistic Regression Results

The logistic regression results showed that financial leverage had a positive and significant effect on the probability of receiving a modified audit opinion. Firm size, profitability, auditor tenure, and operating cash flow were negatively associated with modified audit opinions. These findings are consistent with the view that financial risk increases the likelihood of modified reporting, while stronger firm characteristics may reduce audit-reporting risk (DeFond & Zhang, 2014; Geiger & Raghunandan, 2002; Myers et al., 2003).

Table 4

Logistic Regression Results

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Variable	Coefficient	z statistic	p value
LEV	1.87	3.41	0.001
SIZE	-0.64	-2.58	0.010
ROA	-2.21	-3.02	0.003
TENURE	-0.17	-2.14	0.032
FEE	-0.11	-1.76	0.079
CFO	-0.92	-2.33	0.020
Pseudo R^2	0.31		

3.4. Predictive Model Performance

Table 5 compares the performance of logistic regression, decision tree, random forest, and gradient boosting. Random forest produced the highest predictive performance across the reported metrics, with accuracy = 0.83 and ROC-AUC = 0.88. Gradient boosting also performed well, while logistic regression had the lowest predictive performance among the four models. These findings answer the prediction-oriented research question and are consistent with prior evidence that machine-learning models can improve prediction in audit and fraud-detection contexts (Breiman, 2001; Friedman, 2001; Perols, 2011). Figure 1 visualizes the comparative advantage of ensemble-based models in accuracy and ROC-AUC.

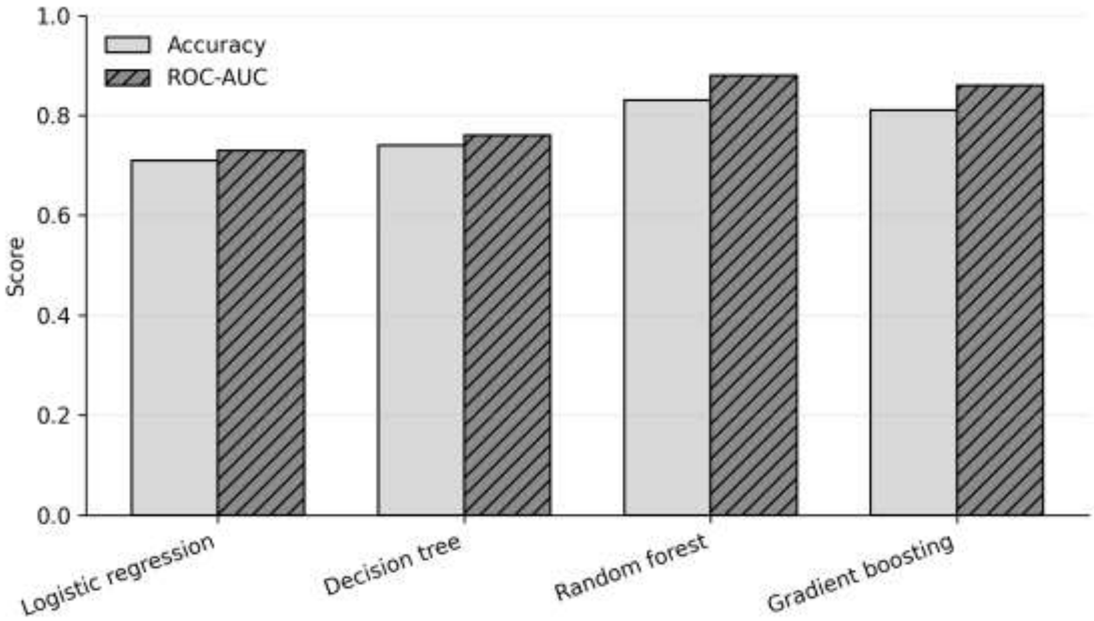
Table 5

Predictive Performance of Analytical Models

Model	Accuracy	Precision	Recall	ROC-AUC
Logistic regression	0.71	0.69	0.64	0.73
Decision tree	0.74	0.72	0.70	0.76
Random forest	0.83	0.81	0.79	0.88
Gradient boosting	0.81	0.80	0.76	0.86

Figure 1

Comparison of model performance based on accuracy and ROC-AUC.



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3.5. Variable Importance

Variable-importance analysis in the random forest model showed that financial leverage, firm size, auditor tenure, and profitability were the most important predictors of modified audit opinions. The importance of leverage supports the role of financial risk in audit reporting, while the importance of firm size and auditor tenure is consistent with prior audit-quality research (Francis & Yu, 2009; Geiger & Raghunandan, 2002; Myers et al., 2003). Figure 2 presents the same ranking graphically.

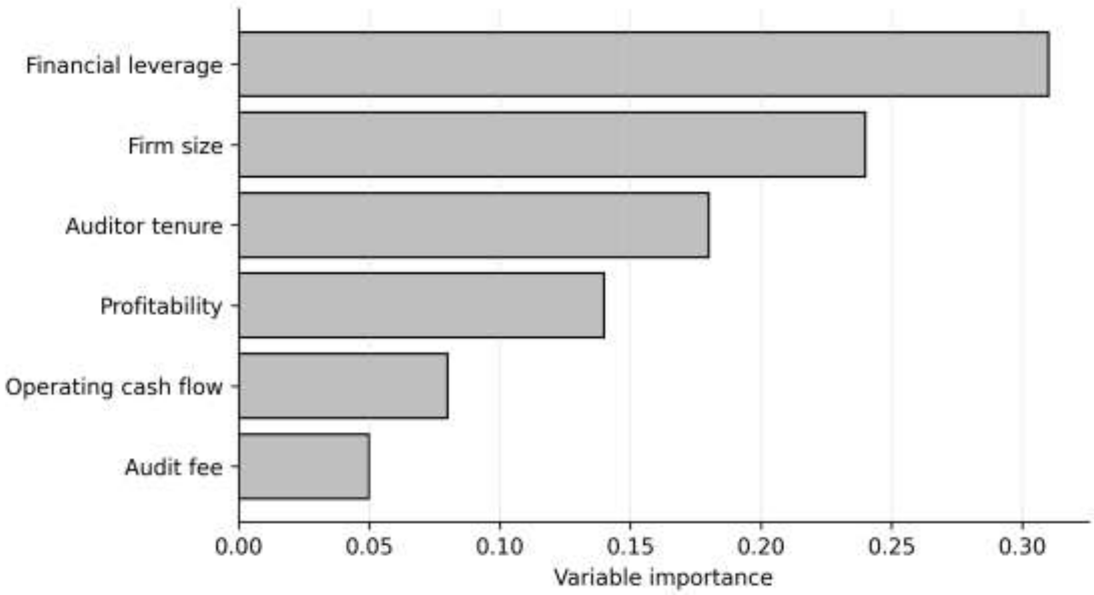
Table 6

Variable Importance in the Random Forest Model

Variable	Importance
Financial leverage	0.31
Firm size	0.24
Auditor tenure	0.18
Profitability	0.14
Operating cash flow	0.08
Audit fee	0.05

Figure 2

Variable-importance ranking in the random forest model.



4. Discussion

This study examined the application of artificial intelligence and intelligent analytical models in evaluating audit report quality among companies listed on the Tehran Stock Exchange. The results showed that the random forest model outperformed logistic regression, decision tree, and gradient boosting in predicting modified audit opinions. This finding suggests that audit report quality may depend on nonlinear and interactive relationships among financial and audit-related variables. Logistic regression remains useful for interpretation and hypothesis testing, but ensemble models may provide stronger prediction when relationships are complex (Breiman, 2001; Friedman, 2001; Hastie et al., 2009).

The positive effect of financial leverage on modified audit opinions is theoretically coherent. Highly leveraged firms are more exposed to financial distress, covenant pressure, and incentives for earnings management. Auditors may therefore be more likely to issue modified opinions

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when leverage is high. This result is consistent with audit-reporting studies linking financial risk and auditor reporting decisions (DeFond & Zhang, 2014; Geiger & Raghunandan, 2002).

The negative association between firm size and modified audit opinions suggests that larger firms in the sample may have stronger internal controls, greater regulatory visibility, and more developed reporting systems. This interpretation is compatible with research showing that audit quality is shaped by both client characteristics and auditor characteristics (Francis, 2004; Francis & Yu, 2009). However, the relationship between firm size and audit quality should be interpreted carefully because larger firms may also have more complex operations.

The significant role of auditor tenure indicates that client-specific knowledge and auditor independence are both relevant to audit report quality. Prior research has reported mixed theoretical expectations regarding auditor tenure. Longer tenure can improve auditor knowledge of the client, but it may also raise independence concerns (Myers et al., 2003). In the present study, auditor tenure was negatively associated with modified audit opinions, suggesting that longer auditor-client relationships may be linked to fewer modified reports.

The superior performance of random forest aligns with the growing literature on audit analytics and artificial intelligence. Big-data and machine-learning approaches can assist auditors by identifying patterns, anomalies, and risk indicators that traditional procedures may not capture (Appelbaum et al., 2017; Brown-Liburd et al., 2015; Kokina & Davenport, 2017; Sutton et al., 2016). However, these models should be interpreted as decision-support tools, not substitutes for professional skepticism and auditor judgment. Ethical, interpretability, and governance issues remain important when artificial intelligence is used in auditing.

From a practical perspective, the findings may help audit firms, regulators, and investors. Audit firms can use predictive models to identify high-risk clients and allocate audit resources more efficiently. Regulators may use such models as early-warning tools for monitoring financial-reporting risk. Investors may also benefit from predictive indicators that help assess the reliability of financial information. These applications are consistent with recent empirical evidence that artificial intelligence may improve audit quality and process efficiency when used appropriately (Fedyk et al., 2022).

5. Conclusion

This study examined the application of artificial intelligence and intelligent analytical models in evaluating audit report quality among companies listed on the Tehran Stock Exchange. The results show that random forest outperformed logistic regression, decision tree, and gradient boosting in predicting modified audit opinions. Financial leverage, firm size, auditor tenure, and profitability were identified as the most important predictors. Overall, the findings suggest that intelligent analytical models can support audit-risk assessment, regulatory monitoring, and investor decision-making in the Iranian capital market.

6. Limitations and Future Research

The study has several limitations. First, audit report quality was operationalized primarily through modified audit opinions. Because audit quality is multidimensional, future studies should also examine discretionary accruals, restatements, audit delays, going-concern opinions, and other quality indicators. Second, the sample was limited to 150 companies listed on the Tehran Stock Exchange during 2017–2023. Third, missing or incomplete disclosure of audit fees in some companies may affect the precision of the audit-fee variable. Fourth, machine-learning models require large and diverse datasets; therefore, larger samples may improve model generalizability.

Future studies may use textual data from audit reports and natural language processing methods, include board and corporate-governance variables, examine deep-learning models, and compare the performance of intelligent analytical models across different capital markets.

Authors' Contributions

All authors equally contributed to this study.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

This study used publicly available financial statements and audit reports of listed companies. No human participants were involved. Data were analyzed at the company level and no personal or confidential individual-level information was used.

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