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Detection of Fraud in Financial Statements Based on Managerial Tone Analysis, Financial Reporting Complexity, and Anomaly Detection Algorithms

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ABSTRACT

The present study aimed to identify fraudulent financial reporting based on managerial tone analysis, financial reporting complexity, and anomaly detection algorithms among companies listed on the Tehran Stock Exchange. This study was conducted using a quantitative applied research design with a correlational and explanatory approach based on machine learning and textual analysis techniques. The statistical population consisted of companies listed on the Tehran Stock Exchange between 2018 and 2024, from which 186 firms were selected using purposive screening criteria, resulting in 1302 firm-year observations. Data were collected from audited annual reports, financial statements, explanatory notes, and management discussion sections. Managerial tone was measured through sentiment analysis using natural language processing methods, while financial reporting complexity was assessed through readability indicators, report length, and disclosure structure measures. Fraudulent reporting risk was identified using abnormal accrual indicators and anomaly detection techniques including Isolation Forest, Local Outlier Factor, One-Class Support Vector Machine, Random Forest, and Autoencoder Neural Networks. Data analysis was conducted using Python, SPSS-27, and RapidMiner software through descriptive statistics, correlation analysis, logistic regression, ROC curve analysis, and machine learning model evaluation indicators including accuracy, precision, recall, F1-score, and AUC. The findings demonstrated that positive managerial tone ($\beta = 0.31$, $p < 0.001$), negative managerial tone ($\beta = 0.36$, $p < 0.001$), financial reporting complexity ($\beta = 0.39$, $p < 0.001$), Fog readability index ($\beta = 0.28$, $p < 0.001$), abnormal accruals ($\beta = 0.47$, $p < 0.001$), and Isolation Forest anomaly scores ($\beta = 0.51$, $p < 0.001$) significantly predicted fraudulent financial reporting. Correlation analysis revealed significant positive relationships among fraud risk, reporting complexity, abnormal accruals, and anomaly detection indicators ($p < 0.01$). Among the evaluated algorithms, the Autoencoder Neural Network demonstrated the highest predictive performance with an accuracy of 0.93 and AUC of 0.96, followed by Isolation Forest with an accuracy of 0.91 and AUC of 0.94. Machine learning-based anomaly detection techniques significantly outperformed traditional logistic regression models in identifying suspicious financial reporting patterns. The results indicate that integrating managerial tone analysis, financial reporting complexity indicators, and anomaly detection algorithms substantially improves the identification of fraudulent financial statements. The findings highlight the importance of combining textual analysis, artificial intelligence, and forensic accounting techniques within modern auditing and financial supervision systems. Furthermore, the superior performance of deep learning and anomaly detection models suggests that advanced computational technologies can significantly enhance fraud detection accuracy and support auditors and regulators in identifying hidden manipulation patterns within corporate financial disclosures.

Keywords: Financial Statement Fraud, Managerial Tone Analysis, Financial Reporting Complexity, Anomaly Detection, Machine Learning, Sentiment Analysis, Artificial Intelligence, Forensic Accounting

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Introduction

Financial statement fraud has become one of the most critical challenges confronting modern financial systems, capital markets, regulatory institutions, and auditing professions. The increasing complexity of corporate structures, digital financial transactions, and managerial reporting practices has significantly intensified the difficulty of detecting fraudulent activities within organizations. Fraudulent financial reporting not only undermines the credibility of financial markets but also erodes investor confidence, distorts resource allocation, and creates substantial economic and social consequences for stakeholders. The collapse of major corporations and the occurrence of accounting scandals across international markets have highlighted the urgent necessity for more sophisticated and technology-oriented fraud detection frameworks capable of identifying hidden manipulation patterns in financial statements (1, 2). Traditional auditing approaches and rule-based fraud identification systems often struggle to detect complex and strategically concealed manipulation schemes because fraudulent activities have evolved from simple accounting irregularities into multidimensional patterns involving narrative disclosures, managerial communication, and technological manipulation (3, 4). Consequently, researchers and practitioners have increasingly emphasized the integration of artificial intelligence, machine learning, forensic analytics, and natural language processing techniques into accounting and auditing systems to improve fraud detection effectiveness (5, 6).

In recent years, the emergence of advanced computational methods has transformed the landscape of accounting fraud detection. Artificial intelligence technologies have demonstrated considerable capability in identifying abnormal financial behaviors, extracting hidden relationships from large datasets, and predicting suspicious reporting patterns more effectively than traditional statistical models (5, 7). Machine learning algorithms, particularly anomaly detection techniques, enable researchers to identify irregular observations without relying solely on predefined fraud rules or deterministic assumptions. Such approaches are especially important because fraudulent reporting often evolves dynamically and may not follow stable behavioral patterns over time (8, 9). The integration of anomaly detection algorithms into financial auditing environments has therefore become an important direction within forensic accounting research. Prior studies have shown that data analytics and artificial intelligence significantly improve the accuracy and efficiency of fraud identification systems by uncovering complex nonlinear relationships among financial variables (6, 10). Furthermore, technological forensic auditing systems have increasingly been recognized as effective mechanisms for combating financial crimes and enhancing audit quality within modern organizations (9, 11).

Although numerical financial indicators remain important predictors of fraudulent reporting, contemporary research increasingly argues that qualitative disclosures and managerial narratives contain substantial informational value regarding organizational behavior and reporting integrity. Corporate narratives, especially those included in annual reports and management discussion sections, reflect managerial intentions, strategic framing, and disclosure motivations that may reveal signals of manipulation or concealment (12, 13). Managers often attempt to influence stakeholder perceptions through optimistic, defensive, ambiguous, or excessively technical language when organizations experience financial pressure or engage in reporting manipulation. Consequently, textual analysis and sentiment analysis methods have emerged as influential tools in accounting and financial fraud research (12, 14). Natural language processing technologies now allow researchers to analyze large volumes of textual financial disclosures and identify linguistic patterns associated with fraud risk, deception, and abnormal

managerial behavior (15, 16). The growing application of large language models and deep learning techniques in accounting research has further expanded the ability to detect hidden textual signals related to fraudulent reporting practices (15, 16).

Managerial tone analysis has attracted considerable scholarly attention because the emotional and semantic characteristics of corporate disclosures may reveal strategic communication behaviors intended to influence investor perceptions. Positive managerial tone, excessive optimism, and exaggerated confidence within annual reports may function as mechanisms for masking financial difficulties or concealing fraudulent activities (17, 18). At the same time, abnormal use of uncertainty-related, defensive, or risk-oriented language may indicate managerial attempts to justify weak performance or prepare stakeholders for negative outcomes (19, 20). Research has shown that tone-related disclosures significantly influence market reactions, analyst recommendations, investor behavior, and perceptions of organizational legitimacy (18, 21). Studies have also demonstrated that deceptive managerial communication may generate misleading informational environments capable of obscuring the actual financial condition of organizations (17, 22). Therefore, the analysis of managerial tone represents an important dimension in the development of modern fraud detection frameworks.

The relationship between textual sentiment and financial reporting quality has become increasingly prominent within accounting literature. Sentiment analysis methods enable researchers to quantify positive, negative, uncertain, and litigious expressions embedded within corporate reports and evaluate their association with financial outcomes and reporting reliability (14, 23). Prior research has shown that firms engaging in earnings management or deceptive reporting frequently display abnormal linguistic patterns characterized by excessive optimism, complex terminology, and strategic ambiguity (19, 24). Moreover, textual risk disclosures have demonstrated strong predictive capability for identifying accounting fraud and financial distress (23, 25). Advances in deep learning and natural language processing have further improved the ability of researchers to analyze contextual meanings, semantic structures, and emotional dimensions within financial narratives (15, 16). Consequently, textual analysis has evolved into a critical component of contemporary forensic accounting and fraud analytics research.

Another important factor associated with fraudulent financial reporting is financial reporting complexity. Complex reporting structures often reduce transparency, increase information asymmetry, and limit stakeholders' ability to interpret financial disclosures effectively. Organizations engaged in manipulation may intentionally increase the complexity of annual reports to obscure unfavorable information and reduce the detectability of irregularities (26, 27). Readability difficulties, excessive report length, dense technical terminology, and complicated disclosure structures may function as strategic tools for concealing earnings management practices or masking fraudulent activities (13, 26). Prior studies have shown that firms with lower readability and more complex disclosures are more likely to exhibit accounting irregularities and financial manipulation (24, 27). Furthermore, changes in disclosure trajectories and narrative structures over time may provide important indicators of fraudulent behavior (27). Therefore, financial reporting complexity constitutes a critical dimension in understanding how organizations strategically manage informational environments.

The increasing complexity of financial reporting has also created significant challenges for auditors, regulators, and enforcement institutions. Conventional auditing procedures often depend heavily on sampling methods, manual reviews, and predefined analytical procedures that may be insufficient for identifying sophisticated manipulation schemes hidden within large and multidimensional datasets (2, 28). Consequently, regulatory authorities and audit institutions have increasingly emphasized the necessity of integrating advanced analytical technologies into fraud

prevention and detection systems (28, 29). Technological auditing systems, forensic analytics, and AI-driven auditing procedures enable auditors to process large amounts of structured and unstructured data more efficiently while identifying suspicious patterns that may not be visible through traditional approaches (10, 11). Research has further demonstrated that information technology utilization significantly improves auditors' skepticism, judgment quality, and fraud detection capability (29, 30).

Recent developments in deep learning and natural language processing have opened new opportunities for integrating textual and numerical analysis within unified fraud detection models. Advanced machine learning architectures can simultaneously process financial ratios, disclosure narratives, sentiment indicators, and anomaly scores to generate more accurate predictions regarding fraudulent behavior (7, 15). Studies focusing on manual journal entry testing, textual risk disclosures, and disclosure trajectory analysis have shown that combining structured financial data with unstructured textual information substantially improves fraud detection performance (15, 25). Similarly, stacking algorithms and ensemble learning techniques have demonstrated considerable effectiveness in identifying complex fraud patterns within listed companies (7, 8). These developments indicate that modern fraud detection frameworks increasingly depend on interdisciplinary integration among accounting, artificial intelligence, computational linguistics, and forensic analytics.

Despite the growing body of international literature regarding fraud detection technologies, several important research gaps remain unresolved. First, many previous studies have primarily focused on numerical accounting indicators while paying limited attention to the combined effects of managerial tone, reporting complexity, and anomaly detection algorithms. Second, although textual analysis methods have become increasingly popular, relatively few studies have simultaneously integrated sentiment analysis and machine learning-based anomaly detection within a unified predictive framework. Third, much of the existing evidence has been generated in developed financial markets, whereas emerging economies and developing capital markets continue to receive limited empirical attention (1, 8). Additionally, the rapid advancement of artificial intelligence technologies has created the need for updated empirical evidence regarding the effectiveness of deep learning and natural language processing systems in accounting fraud detection (5, 16). Addressing these gaps is especially important because emerging markets often exhibit weaker regulatory systems, lower transparency, and higher informational asymmetry, thereby increasing the importance of sophisticated fraud detection mechanisms.

Furthermore, the interaction between managerial communication behavior and technological fraud analytics remains insufficiently explored in accounting literature. While prior studies have separately examined managerial tone, reporting readability, and forensic technologies, limited attention has been devoted to understanding how these dimensions jointly contribute to the prediction of fraudulent financial reporting (12, 14). The integration of textual sentiment analysis with anomaly detection algorithms may provide a more comprehensive understanding of how deceptive managerial communication aligns with abnormal financial behavior. Such integration is particularly relevant in modern financial environments where managers increasingly use strategic narratives and disclosure manipulation to influence stakeholders and conceal organizational risks (17, 18). Therefore, combining linguistic analysis, reporting complexity measures, and machine learning-based anomaly detection may substantially improve the predictive capability of fraud identification systems.

Accordingly, the present study aims to identify fraud in financial statements based on managerial tone analysis, financial reporting complexity, and anomaly detection algorithms among companies listed on the Tehran Stock Exchange.

Methods and Materials

This study was conducted using a quantitative applied research design with a correlational and explanatory approach based on machine learning techniques and financial text analysis. In terms of temporal orientation, the study was retrospective and utilized archival financial data extracted from the annual reports and audited financial statements of companies listed on the Tehran Stock Exchange. The statistical population consisted of all firms listed on the Tehran Stock Exchange between 2018 and 2024. After applying the screening criteria, including continuous stock market activity during the study period, availability of complete annual reports and financial statements, accessibility of management discussion and analysis sections, non-membership in financial intermediary industries such as banks and insurance companies due to differences in reporting structures, and the absence of missing financial data, a final sample of 186 companies was selected. Considering the seven-year period under investigation, the final dataset included 1302 firm-year observations. The sampling procedure was conducted using a purposive screening method to ensure data consistency and comparability across firms and periods. The dependent variable of the study was the probability of fraud occurrence in financial statements, while managerial tone indicators, financial reporting complexity measures, and anomaly detection outputs served as the primary independent and predictive variables. Fraudulent financial reporting cases were identified using modified Beneish indicators, abnormal accrual behavior, auditor remarks, financial restatements, and warning signs disclosed by supervisory authorities. The unit of analysis was the firm-year observation, and all data were extracted from audited annual reports, board reports, explanatory notes, and official databases associated with the Tehran Stock Exchange.

Data collection in this study was based on a combination of financial statement indicators, textual analysis instruments, and machine learning-based anomaly detection techniques. To measure managerial tone, textual content from the management discussion and analysis section, board reports, and explanatory disclosures was analyzed using sentiment analysis methods grounded in financial linguistics. The managerial tone analysis framework was adapted from the financial textual analysis models developed by Loughran and McDonald (2011), which classify positive, negative, uncertain, litigious, and constraining financial terms. The textual data were first standardized and cleaned through preprocessing stages including tokenization, stop-word elimination, stemming, and normalization. Subsequently, sentiment polarity scores and tone imbalance indices were extracted using Python-based natural language processing libraries. Positive managerial tone was operationalized as the ratio of optimistic and confidence-related expressions to the total number of meaningful words, whereas negative tone represented the frequency of pessimistic, risk-oriented, and uncertainty-related expressions. The validity of the managerial tone indicators has been confirmed extensively in previous accounting and financial reporting studies, and their reliability has been demonstrated through repeated textual classification procedures and inter-method consistency assessments.

Financial reporting complexity was assessed using several structural and linguistic indicators derived from annual financial reports. These indicators included report length, readability difficulty, number of explanatory notes, syntactic density, average sentence length, frequency of technical accounting terminology, and the Fog readability index. The Fog index was employed because it is one of the most widely accepted measures of textual complexity in accounting research and evaluates the cognitive difficulty associated with understanding corporate reports. Higher Fog index scores reflected lower readability and greater reporting complexity. In addition, the total number

of pages in annual reports and the ratio of complex sentences to total sentences were incorporated as supplementary indicators of reporting complexity. The extracted complexity measures were standardized before entry into the predictive models to ensure comparability among variables with different scales. Prior studies in financial reporting literature have confirmed the construct validity and predictive capability of these complexity indicators in identifying information asymmetry, earnings manipulation, and fraudulent reporting behavior.

To identify anomalies and suspicious reporting patterns, several machine learning algorithms were utilized. These included Isolation Forest, Local Outlier Factor, One-Class Support Vector Machine, and Autoencoder Neural Networks. The algorithms were selected because of their widespread application in anomaly detection within financial fraud analytics and their capability to detect non-linear and hidden irregularities in multidimensional datasets. Financial ratios related to profitability, liquidity, leverage, accruals, operational efficiency, earnings persistence, and cash flow quality were used as input variables for anomaly detection. Before model implementation, all financial variables were normalized using z-score transformation to reduce scale-related distortions. The Isolation Forest algorithm identified abnormal observations through random partitioning of multidimensional data, whereas the Local Outlier Factor algorithm evaluated the local density deviation of each observation relative to neighboring points. The One-Class Support Vector Machine established a boundary around normal reporting patterns and classified deviations as anomalous observations. In addition, Autoencoder Neural Networks were trained to reconstruct normal financial patterns, and observations with high reconstruction error were classified as potential fraud cases. The reliability and predictive stability of these algorithms were assessed using repeated cross-validation procedures and performance consistency across training and testing datasets.

The data analysis process was conducted in several stages using Python, SPSS version 27, and RapidMiner software environments. Initially, descriptive statistics including means, standard deviations, skewness, kurtosis, and correlation coefficients were calculated for all study variables. Subsequently, feature engineering and dimensionality reduction procedures were performed to improve model efficiency and reduce multicollinearity among predictors. Principal Component Analysis was employed to extract the most informative features from high-dimensional financial and textual variables. In the predictive modeling stage, the dataset was divided into training and testing subsets using a 70-to-30 ratio. Model performance was evaluated based on accuracy, precision, recall, F1-score, Area Under the ROC Curve (AUC), and confusion matrix indicators. To compare the predictive power of different algorithms, cross-validation with ten iterations was implemented. Logistic regression analysis was also conducted as a benchmark statistical model to compare traditional econometric prediction performance with machine learning approaches. Finally, variable importance analysis was carried out to determine the relative contribution of managerial tone indicators, reporting complexity measures, and anomaly detection outputs in predicting fraudulent financial reporting.

Findings and Results

The final dataset consisted of 1302 firm-year observations related to 186 companies listed on the Tehran Stock Exchange during the period from 2018 to 2024. The companies represented a wide range of industries, including manufacturing, petrochemical, pharmaceutical, automotive, food products, metals, mining, and technology-related sectors. Among the selected firms, 28.11% belonged to manufacturing industries, 17.84% operated in petrochemical and chemical industries, 14.67% were active in metal and mineral sectors, 11.52% were related to automotive and machinery industries, and the remaining firms represented diversified sectors. The average firm

age was 17.46 years, with a minimum of 6 years and a maximum of 42 years. The mean total assets of firms were 48,362.74 billion IRR, indicating substantial variation in organizational size across the sample. Based on the fraud classification criteria, 19.43% of the firm-year observations were categorized as high-risk or potentially fraudulent cases, whereas 80.57% were classified as normal reporting observations. Preliminary analyses also indicated that firms identified as suspicious generally exhibited higher managerial optimism scores, greater reporting complexity, and significantly abnormal accrual patterns compared with non-fraudulent firms.

Table 1. Descriptive Statistics of the Main Research Variables

Variables	Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis
Fraud Risk Score	0.38	0.21	0.04	0.93	1.14	1.87
Positive Managerial Tone	0.61	0.13	0.28	0.89	-0.48	0.72
Negative Managerial Tone	0.34	0.11	0.09	0.67	0.56	0.43
Financial Reporting Complexity	17.92	4.38	9.41	31.86	0.73	1.26
Fog Readability Index	21.47	3.95	12.83	34.51	0.81	1.63
Report Length (Pages)	126.58	37.42	48.00	267.00	1.09	1.94
Abnormal Accruals	0.19	0.10	-0.08	0.51	0.68	0.91
Isolation Forest Score	0.57	0.18	0.11	0.97	-0.24	-0.11
Local Outlier Factor Score	1.36	0.42	0.71	3.14	1.28	2.03
Autoencoder Reconstruction Error	0.29	0.12	0.04	0.71	0.96	1.37

The descriptive statistics presented in Table 1 indicate substantial variability among the analyzed firms in terms of managerial tone, reporting complexity, and anomaly detection outputs. The mean fraud risk score was 0.38 with a standard deviation of 0.21, suggesting moderate dispersion across firm-year observations. Positive managerial tone demonstrated a relatively high average value (M = 0.61, SD = 0.13), indicating that optimistic language was dominant in management disclosures across most firms. However, the simultaneous presence of a considerable negative managerial tone score (M = 0.34, SD = 0.11) suggests that firms also employed uncertainty-oriented and risk-related expressions in financial narratives. Financial reporting complexity exhibited relatively high levels, with an average complexity score of 17.92 and an average Fog readability index of 21.47, reflecting the technical and cognitively demanding nature of many annual reports. Furthermore, report length varied substantially among firms, ranging from 48 to 267 pages, which demonstrates notable heterogeneity in disclosure practices. The anomaly detection indicators also revealed significant variation across firms. The average Isolation Forest score was 0.57, while the Local Outlier Factor mean reached 1.36, indicating the existence of multiple suspicious observations with abnormal financial characteristics. In addition, the relatively high skewness values observed for fraud risk, report length, and anomaly detection scores suggest that a subset of firms demonstrated substantially higher abnormality levels than the majority of the sample.

Table 2. Pearson Correlation Matrix among the Research Variables

Variables	1	2	3	4	5	6	7
1. Fraud Risk Score	1						
2. Positive Managerial Tone	0.49**	1					
3. Negative Managerial Tone	0.53**	0.31**	1				
4. Financial Reporting Complexity	0.61**	0.38**	0.42**	1			
5. Fog Readability Index	0.57**	0.33**	0.39**	0.74**	1		
6. Abnormal Accruals	0.66**	0.41**	0.48**	0.52**	0.46**	1	
7. Isolation Forest Score	0.71**	0.44**	0.51**	0.58**	0.49**	0.69**	1

The results presented in Table 2 demonstrate statistically significant positive relationships among all primary research variables. Fraud risk score exhibited the strongest correlation with the Isolation Forest anomaly score (r =

0.71, $p < 0.01$), indicating that machine learning-based anomaly detection was highly effective in identifying suspicious financial reporting patterns. Fraud risk also showed a strong positive association with abnormal accruals ($r = 0.66$, $p < 0.01$) and financial reporting complexity ($r = 0.61$, $p < 0.01$), suggesting that firms engaging in potentially fraudulent reporting tended to produce more complex and less transparent financial disclosures. Positive managerial tone was moderately associated with fraud risk ($r = 0.49$, $p < 0.01$), indicating that excessively optimistic managerial narratives may serve as an important warning signal for financial manipulation. Similarly, negative managerial tone exhibited a significant positive relationship with fraud risk ($r = 0.53$, $p < 0.01$), implying that firms with greater uncertainty-oriented language also displayed elevated levels of suspicious reporting behavior. The strong correlation between reporting complexity and readability difficulty ($r = 0.74$, $p < 0.01$) confirms the conceptual overlap between these measures while remaining below critical multicollinearity thresholds. Overall, the correlation matrix provides preliminary empirical evidence supporting the theoretical relationships proposed in the study.

Table 3. Performance Comparison of Fraud Detection Algorithms

Algorithms	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	0.78	0.73	0.69	0.71	0.81
Decision Tree	0.83	0.79	0.76	0.77	0.85
Random Forest	0.89	0.86	0.84	0.85	0.92
Isolation Forest	0.91	0.88	0.87	0.87	0.94
Local Outlier Factor	0.87	0.84	0.82	0.83	0.90
One-Class SVM	0.85	0.81	0.80	0.80	0.88
Autoencoder Neural Network	0.93	0.91	0.89	0.90	0.96

The comparative performance results shown in Table 3 indicate that machine learning-based anomaly detection algorithms substantially outperformed traditional statistical models in detecting fraudulent financial reporting. Among all evaluated techniques, the Autoencoder Neural Network achieved the highest predictive performance, with an accuracy rate of 0.93, precision of 0.91, recall of 0.89, F1-score of 0.90, and an AUC value of 0.96. These findings suggest that deep learning approaches were highly effective in identifying hidden and nonlinear fraudulent patterns within multidimensional financial data. The Isolation Forest algorithm also demonstrated strong performance, achieving an accuracy of 0.91 and an AUC of 0.94, confirming its effectiveness in detecting anomalous observations through unsupervised learning mechanisms. In contrast, the traditional logistic regression model showed comparatively lower predictive capability, with an accuracy of 0.78 and an AUC of 0.81, indicating that linear econometric approaches may not adequately capture the complexity of fraudulent financial behavior. Random Forest algorithms also performed strongly, producing an accuracy rate of 0.89 and an F1-score of 0.85. Overall, the results demonstrate that anomaly detection algorithms combined with textual and financial indicators provide substantial improvements in fraud detection accuracy compared with conventional statistical techniques.

Table 4. Results of Logistic Regression Analysis for Predicting Fraudulent Financial Reporting

Predictor Variables	B	Standard Error	Beta	Wald	p-value
Positive Managerial Tone	1.42	0.27	0.31	27.64	0.001
Negative Managerial Tone	1.68	0.31	0.36	29.18	0.001
Financial Reporting Complexity	1.91	0.34	0.39	31.73	0.001
Fog Readability Index	1.26	0.24	0.28	25.11	0.001
Abnormal Accruals	2.37	0.41	0.47	36.82	0.001
Isolation Forest Score	2.54	0.38	0.51	41.29	0.001
Constant	-3.18	0.69	—	21.46	0.001

The logistic regression findings presented in Table 4 indicate that all explanatory variables exerted statistically significant positive effects on the probability of fraudulent financial reporting. Among the predictors, the Isolation Forest anomaly score demonstrated the strongest standardized effect (β = 0.51, p < 0.001), indicating that anomaly-based machine learning outputs represented the most influential predictor of fraud risk. Abnormal accruals also showed a substantial positive impact on fraudulent reporting probability (β = 0.47, p < 0.001), confirming the importance of accrual manipulation indicators in fraud identification models. Financial reporting complexity significantly increased the likelihood of fraud occurrence (β = 0.39, p < 0.001), suggesting that firms with more opaque and difficult-to-understand reports were more likely to engage in manipulative financial practices. Both positive managerial tone (β = 0.31, p < 0.001) and negative managerial tone (β = 0.36, p < 0.001) significantly predicted fraudulent reporting behavior, demonstrating that abnormal narrative characteristics in managerial disclosures can function as early warning signals for manipulation risk. The Fog readability index also exerted a significant positive influence (β = 0.28, p < 0.001), indicating that lower readability and greater textual ambiguity were associated with higher fraud probability. Collectively, the regression results confirm that the integration of textual analysis, reporting complexity measures, and anomaly detection algorithms substantially enhances the predictive capability of fraud detection frameworks.

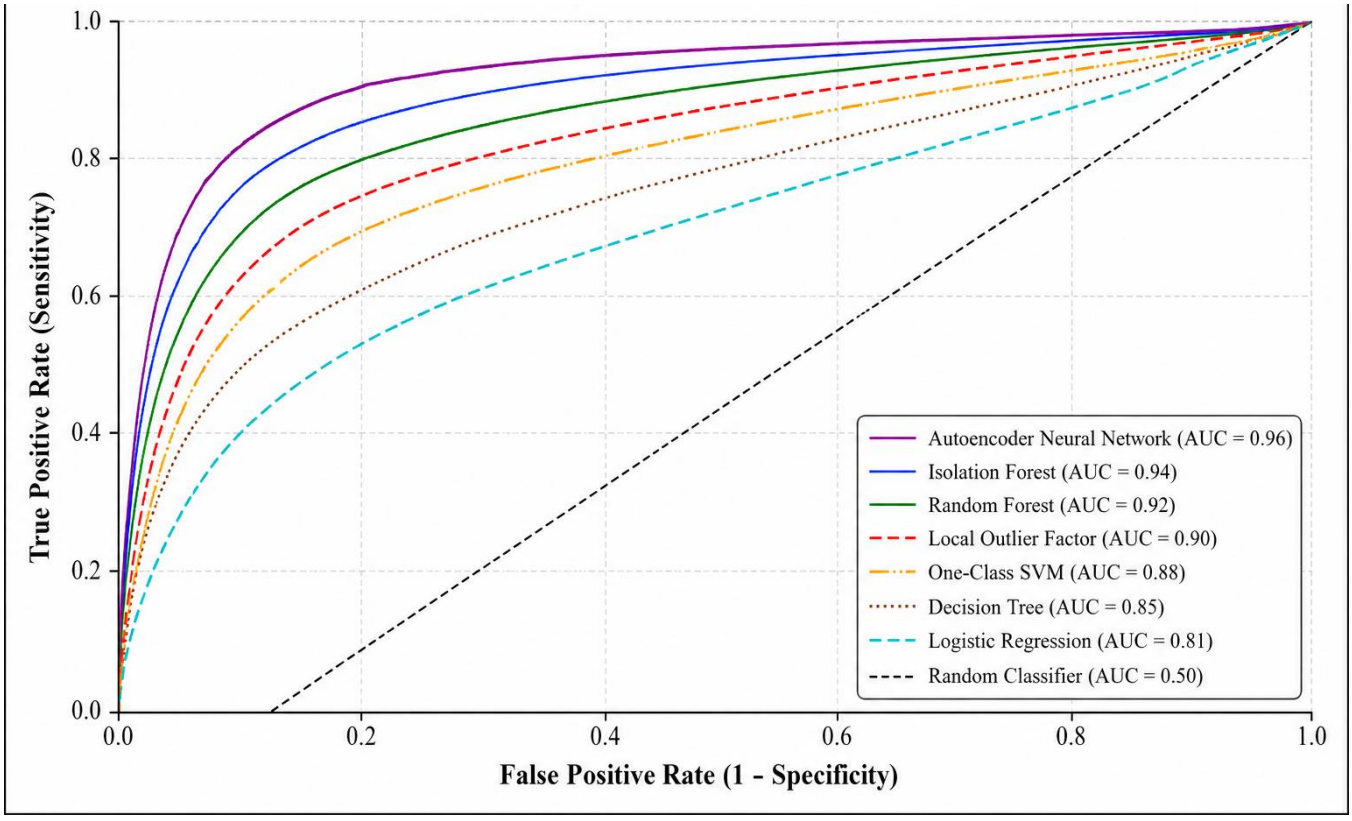

Figure 1. Comparative ROC Curves of Fraud Detection Algorithms in Predicting Fraudulent Financial Statements

The ROC curve analysis illustrated in Figure 1 demonstrates clear differences in predictive discrimination power among the evaluated fraud detection models. The Autoencoder Neural Network exhibited the largest area under the curve, followed closely by the Isolation Forest and Random Forest algorithms, indicating superior sensitivity and specificity in distinguishing fraudulent from non-fraudulent observations. In contrast, the logistic regression model displayed a noticeably lower curve trajectory, reflecting weaker classification performance relative to machine

learning-based approaches. The graphical comparison confirms that advanced anomaly detection algorithms provide more robust predictive capabilities when integrating managerial tone indicators and financial reporting complexity variables into fraud detection systems. Furthermore, the visual separation among the curves indicates that non-linear learning architectures are substantially more effective in capturing hidden irregularities and multidimensional interactions within financial reporting data.

Discussion and Conclusion

The present study aimed to identify fraudulent financial reporting based on managerial tone analysis, financial reporting complexity, and anomaly detection algorithms among companies listed on the Tehran Stock Exchange. The findings demonstrated that managerial tone variables, reporting complexity indicators, and machine learning-based anomaly detection outputs significantly contributed to the prediction of fraudulent financial statements. The results further revealed that advanced computational algorithms, particularly Autoencoder Neural Networks and Isolation Forest models, exhibited substantially higher predictive power compared with traditional statistical approaches such as logistic regression. In addition, the findings indicated that firms characterized by higher levels of reporting complexity, lower readability, abnormal accrual behavior, and excessive positive or negative managerial tone were significantly more likely to engage in suspicious or potentially fraudulent financial reporting practices.

One of the central findings of the study was the significant relationship between managerial tone and fraud risk. Both positive managerial tone and negative managerial tone positively predicted the probability of fraudulent financial reporting, indicating that abnormal linguistic characteristics within managerial disclosures may serve as important warning signals for manipulation. This finding is consistent with prior research suggesting that managers strategically employ language to shape stakeholder perceptions and conceal unfavorable organizational realities (17, 18). Excessively optimistic language may function as a mechanism for reducing market suspicion and strengthening investor confidence during periods of financial instability, whereas defensive or uncertainty-oriented language may reflect managerial attempts to justify poor performance or mitigate accountability risks. These results align closely with the findings of (20), who demonstrated that tone-related narratives significantly influence perceptions of organizational value and risk. Similarly, the findings support the arguments of (19), who showed that litigious and aggressive managerial tone is associated with elevated audit risk and greater concern among auditors regarding disclosure credibility.

The observed relationship between managerial tone and fraudulent reporting may also be interpreted within the framework of strategic disclosure theory. Managers engaged in manipulation often attempt to influence stakeholders through narrative impression management techniques, including selective optimism, ambiguity, and linguistic obfuscation. The current findings suggest that textual characteristics within annual reports contain hidden informational signals capable of revealing deceptive organizational behavior. These findings are strongly aligned with the studies of (14) and (12), both of whom emphasized the growing importance of natural language processing and sentiment analysis in evaluating accounting transparency and financial disclosure quality. Furthermore, the results support recent evidence provided by (25), who found that textual risk disclosures extracted from annual reports significantly improve accounting fraud detection capability. The consistency of the present findings with these studies reinforces the notion that managerial communication should not be interpreted merely as descriptive disclosure but rather as a strategic behavioral dimension reflecting managerial intentions and organizational conditions.

Another important finding of the study was the significant effect of financial reporting complexity and readability difficulty on fraud probability. Firms with higher reporting complexity scores and greater Fog readability index values exhibited significantly greater likelihood of fraudulent financial reporting. This finding suggests that organizations involved in manipulation may intentionally increase the complexity of financial disclosures to obscure irregularities and reduce transparency. Such results are fully consistent with prior literature emphasizing that difficult-to-read annual reports and excessive disclosure complexity are associated with accounting irregularities and lower informational transparency (13, 26). The findings also support the work of (27), who demonstrated that changes in disclosure trajectories and narrative complexity can function as important predictors of fraud occurrence.

The positive association between reporting complexity and fraud risk may be explained through information asymmetry theory. Complex reports increase cognitive processing costs for investors, auditors, and regulators, thereby limiting their ability to identify hidden irregularities or evaluate the actual economic condition of firms. Fraudulent organizations may exploit this informational burden by embedding manipulative disclosures within lengthy, highly technical, and difficult-to-interpret reports. The present findings therefore support the argument that reporting opacity constitutes a strategic concealment mechanism rather than merely a byproduct of organizational complexity. These findings are also aligned with the observations of (22), who emphasized the role of institutional language and accountability narratives in shaping stakeholder interpretation processes. Moreover, the findings are compatible with the conclusions of (24), who showed that earnings management practices significantly increase the probability of financial statement fraud.

The results further demonstrated that anomaly detection algorithms substantially outperformed traditional econometric methods in predicting fraudulent financial reporting. Among the evaluated models, Autoencoder Neural Networks achieved the highest classification accuracy and area under the ROC curve, followed closely by Isolation Forest and Random Forest algorithms. These findings indicate that deep learning and unsupervised anomaly detection techniques are highly effective in identifying hidden irregularities and nonlinear patterns embedded within multidimensional accounting datasets. This result strongly supports the emerging literature emphasizing the superiority of artificial intelligence systems in forensic accounting environments (7, 8). The findings are also highly consistent with the arguments of (5), who highlighted the transformative role of artificial intelligence technologies in accounting and finance.

The strong predictive performance of anomaly detection algorithms may be attributed to their ability to identify subtle deviations from normal reporting behavior without depending exclusively on predefined fraud assumptions. Traditional statistical models often rely on linear relationships and stable behavioral patterns, whereas fraudulent activities frequently involve dynamic and evolving manipulation strategies. In contrast, machine learning algorithms are capable of learning complex interactions among financial indicators, textual disclosures, and behavioral signals. This finding is consistent with the conclusions of (6), who found that artificial intelligence and data analytics significantly improve fraud detection automation and analytical efficiency. Similarly, the results align with the findings of (9) and (10), who demonstrated that technology-based forensic auditing systems substantially enhance financial crime detection capability within banking environments.

The superior performance of deep learning-based models also supports recent advancements in natural language processing and large language model applications within accounting research. The integration of textual analysis and anomaly detection appears to provide a more comprehensive understanding of fraudulent behavior than relying solely on numerical accounting variables. This finding is strongly supported by (15), who demonstrated

the effectiveness of combining deep learning and natural language processing in manual journal entry testing, as well as by (16), who emphasized the growing effectiveness of large language models in financial statement fraud detection. The present study therefore contributes to the expanding body of interdisciplinary research integrating accounting, forensic analytics, machine learning, and computational linguistics.

Another important implication of the findings relates to the role of abnormal accruals in fraud prediction. The results showed that abnormal accrual behavior significantly increased the likelihood of fraudulent reporting, confirming that earnings manipulation remains one of the strongest indicators of accounting fraud. This finding is consistent with the fraud triangle perspective proposed in prior accounting research, which suggests that financial pressure and opportunistic managerial incentives often motivate earnings manipulation and deceptive reporting behavior (3). The findings also support the conclusions of (24), who found that earnings management significantly increases fraud probability across firms. The persistence of abnormal accrual behavior among suspicious firms indicates that financial manipulation continues to represent a central mechanism through which organizations distort reported performance.

The present findings also highlight the growing importance of forensic auditing technologies and audit quality enhancement mechanisms in contemporary financial systems. The significant predictive capability of machine learning algorithms suggests that auditors and regulatory institutions should increasingly integrate artificial intelligence technologies into auditing and fraud examination procedures. These findings support the arguments of (11) and (29), both of whom emphasized that technological auditing systems and information technology utilization improve audit quality and strengthen fraud detection effectiveness. Moreover, the findings are compatible with the conclusions of (30), who demonstrated that effective governance and monitoring mechanisms significantly contribute to fraud prevention within organizations.

The findings of the study also contribute theoretically by demonstrating that fraudulent financial reporting should be understood as a multidimensional phenomenon involving financial manipulation, strategic communication behavior, disclosure complexity, and technological concealment mechanisms simultaneously. Many previous studies focused narrowly on numerical financial ratios or governance variables, whereas the current study demonstrates that integrating textual analysis, readability indicators, and anomaly detection algorithms provides a more comprehensive understanding of fraudulent behavior. This multidimensional perspective aligns with contemporary accounting research emphasizing the integration of structured and unstructured data within fraud analytics systems (12, 13). Furthermore, the findings reinforce the argument that future accounting research must increasingly adopt interdisciplinary and technology-oriented approaches to address the growing sophistication of financial crimes.

Despite the important contributions of the present study, several limitations should be acknowledged. First, the study was limited to companies listed on the Tehran Stock Exchange, which may reduce the generalizability of the findings to other institutional and regulatory environments. Second, the analysis relied primarily on publicly available annual reports and financial statements, while certain fraudulent activities may remain hidden within undisclosed managerial practices or internal organizational processes. Third, although advanced machine learning algorithms were utilized, the predictive performance of such models may still be influenced by data quality limitations and changing fraud patterns over time. Additionally, sentiment analysis methods may face challenges related to contextual interpretation, language ambiguity, and cultural differences in managerial communication styles.

Future research may extend the present study by examining fraud detection frameworks across different countries, industries, and regulatory environments to improve external validity and comparative understanding. Researchers may also integrate additional behavioral, governance, and macroeconomic variables into fraud prediction models to develop more comprehensive analytical frameworks. Future studies could further investigate the application of transformer-based language models, generative artificial intelligence systems, and real-time auditing technologies in detecting financial statement fraud. Moreover, longitudinal research designs examining the evolution of managerial tone and reporting complexity over extended periods may provide deeper insight into the dynamic nature of fraudulent reporting behavior.

From a practical perspective, the findings suggest that regulatory institutions, audit firms, and financial market supervisors should increasingly integrate artificial intelligence technologies, sentiment analysis systems, and anomaly detection algorithms into their monitoring and auditing procedures. Auditors should pay greater attention to textual disclosure characteristics, managerial narratives, and reporting readability when assessing fraud risk. Organizations should also strengthen internal governance systems, improve reporting transparency, and reduce unnecessary disclosure complexity to enhance stakeholder trust and financial reporting quality. Finally, policymakers and professional accounting institutions should invest in technological auditing infrastructure and provide specialized training programs to improve auditors' ability to utilize advanced forensic analytics and machine learning systems in modern auditing environments.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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