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The Role of Media in Identifying and Predicting Financial Fraud in Companies Listed on the Tehran Stock Exchange

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ABSTRACT

The aim of this study was to evaluate the role of media in identifying and predicting financial fraud in companies listed on the Tehran Stock Exchange using machine learning algorithms. In the first stage, text-mining analysis of official news websites, together with content screening of studies relevant to the research objective, was employed to identify effective media-related criteria for predicting the likelihood of financial fraud. After assessing the validity and reliability of the identified dimensions, machine learning algorithms were used to evaluate the effectiveness of these criteria in identifying and predicting corporate financial fraud. For this purpose, data on companies listed on the Tehran Stock Exchange covering the period from 2019 to 2025 were collected. Following initial preprocessing, data from 95 companies were classified, based on the Modified Beneish Model, into non-fraudulent samples and samples with a likelihood of financial fraud. Given the class imbalance and considerable overlap between the non-fraudulent observations and those indicating a likelihood of financial fraud, the Synthetic Minority Over-sampling Technique (SMOTE) was applied exclusively to the training dataset to prevent data leakage. Subsequently, to ensure a fair assessment and evaluate the robustness of machine learning models encompassing both supervised and unsupervised approaches, and with the objective of identifying an effective preliminary algorithm for detecting signals derived from analytical media in predicting the likelihood of fraud among companies listed on the Tehran Stock Exchange, a systematic approach based on grid search and repeated five-fold cross-validation with five repetitions (R5FCV) was employed. The results indicated that, among the various supervised and unsupervised learning models examined, supervised learning models—particularly logistic regression—achieved superior performance metrics and demonstrated greater accuracy and discriminatory power in predicting the likelihood of financial fraud based on operational and process-related measures derived from media functions among companies listed on the Tehran Stock Exchange. These findings confirm that the extracted measures possess meaningful analytical capacity for predicting financial fraud and may serve as complementary tools for capital market analysts and regulatory authorities.

Keywords: Financial Media, Accurate Fraud Detection, Confusion Matrix Evaluation

Introduction

Financial fraud constitutes one of the most persistent threats to the integrity, efficiency, and credibility of capital markets. Fraudulent financial reporting, earnings manipulation, concealment of adverse information, and other forms of corporate misconduct distort the information environment in which investors, creditors, regulators, auditors, and other stakeholders make decisions. When financial information no longer faithfully reflects the economic condition of a firm, market participants may misallocate resources, securities may be incorrectly priced, and



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confidence in the mechanisms of corporate reporting and market supervision may deteriorate. These consequences are particularly important in emerging capital markets, where information asymmetry, variations in disclosure quality, and heterogeneous governance structures may intensify the adverse effects of misleading corporate information. Internal control mechanisms have traditionally been considered a primary defense against fraudulent behavior, yet empirical evidence has shown that weaknesses in internal controls remain closely associated with the occurrence and persistence of fraud (1). In addition, abnormal reporting patterns, financial red flags, and managerial incentives may provide early indications of financial-statement manipulation before formal enforcement actions occur (2). Consequently, the timely identification of fraud risk has become an important objective not only for auditors and regulators but also for capital-market analysts seeking to distinguish financially sound companies from firms exhibiting potentially deceptive reporting behavior.

The problem of financial fraud is fundamentally connected with information asymmetry. Corporate insiders normally possess substantially more information about the firm's financial condition, operating risks, contractual obligations, and future prospects than outside investors. When managers strategically disclose, delay, frame, or conceal information, this informational advantage can facilitate opportunistic reporting. The development of sustainable capital markets therefore requires mechanisms capable of reducing information asymmetry and identifying irregular reporting patterns at an early stage (3). Changes in financial disclosure trajectories themselves may provide evidence of emerging manipulation, because shifts in language, reporting emphasis, and disclosure behavior can precede or accompany fraudulent activity (4). Similarly, textual characteristics and topics embedded in corporate communication may reveal patterns associated with financial misreporting that cannot be captured solely through conventional accounting ratios (5). These findings indicate that financial fraud should not be viewed exclusively as an accounting-number problem; rather, it is an information-environment problem in which quantitative, qualitative, managerial, and communicative signals interact.

Within this broader information environment, the media have acquired an increasingly important monitoring and disciplinary role. Traditional financial news outlets, online news platforms, social media, and specialized capital-market channels can disseminate information more rapidly than conventional annual and interim reporting mechanisms. Through reporting, interpretation, criticism, and repeated exposure of corporate events, the media can draw market attention to unusual transactions, governance weaknesses, performance deterioration, regulatory concerns, or inconsistencies in corporate disclosures. Prior research has documented the corporate-governance role of media attention in the context of financial fraud, suggesting that media scrutiny may increase the visibility of irregularities and impose reputational and market pressures on firms (6). Media supervision has also been associated with corporate earnings-management behavior and auditing-related outcomes, indicating that external information intermediaries can influence managerial reporting incentives (7). Furthermore, the monitoring role of the media has been demonstrated in relation to earnings management, where increased media attention can contribute to the external oversight of managerial reporting behavior (8). These studies collectively support the view that media content can function as an alternative or complementary source of fraud-related information.

The development of digital communication has expanded this monitoring capacity substantially. Social media platforms allow market participants, analysts, journalists, employees, customers, and other stakeholders to generate and circulate information concerning companies at unprecedented speed and scale. Social media adoption has consequently changed the structure of corporate disclosure and the channels through which firm-specific information becomes publicly available (9). The use of web-based financial reporting and social media may

reduce information asymmetry by increasing accessibility to financial and non-financial information, although the effects depend on the quality, credibility, and transparency of the content being distributed (10). Social media may also constrain corporate violations by increasing public visibility and scrutiny, while in some settings it may create new informational dynamics that influence managerial behavior (11). A case-study approach has further demonstrated that social media content can contain observable signals useful for detecting corporate fraud (12). More recent accounting research has therefore increasingly treated social media not merely as a communication channel, but as a potentially valuable data source for accounting, auditing, governance, and fraud-detection research (13).

The relationship between media information and financial risk is especially relevant when media signals are transformed into measurable analytical variables. Evidence from capital markets suggests that social-media information can improve the prediction of financial risk by capturing market-relevant information that may not yet be fully reflected in formal accounting statements (14). Similarly, machine-learning analysis of media reports has shown that news content can be used to detect and forecast corporate fraud by systematically extracting and combining predictive signals from large volumes of textual information (15). Social-media transparency may also interact with established fraud frameworks such as the fraud diamond, thereby affecting the detection of fraudulent financial reporting (16). These developments are important because they shift the role of media from a purely descriptive or reputational mechanism toward a measurable predictive mechanism capable of being incorporated into formal fraud-detection models.

Nevertheless, media information does not automatically provide objective or unbiased evidence of fraud. Media framing can shape how corporate scandals are interpreted and can amplify, minimize, or redirect attention toward particular actors and explanations. Research on the Wirecard scandal, for example, has illustrated how media narratives may simultaneously reveal facts, reproduce failures, and construct competing interpretations of fraudulent behavior (17). Political and institutional contexts can also influence the interpretation of fraud and corruption, while media bias may introduce moral ambiguity into public assessments of misconduct (18). Moreover, media exposure itself may intensify around firms experiencing business failure or delisting risk, making it difficult to determine whether negative coverage is merely reacting to deteriorating performance or independently providing predictive information (19). Accordingly, effective use of media signals for fraud prediction requires systematic extraction, screening, validation, and integration of media-derived indicators rather than reliance on isolated news items or subjective interpretations.

This requirement has increased interest in computational approaches capable of processing complex financial and media data. Machine learning is particularly suitable for fraud detection because fraudulent observations are often rare, multidimensional, nonlinear, and difficult to identify through conventional parametric techniques. Supervised machine-learning algorithms use labeled observations to learn associations between predictor variables and known outcomes, allowing them to classify new observations according to patterns learned from training data (20). Contemporary reviews have shown that supervised methods encompass a wide range of algorithms with different assumptions and decision structures, making model selection an empirical rather than purely theoretical issue (21). In financial applications, supervised algorithms have demonstrated substantial utility in detecting fraudulent transactions, including credit-card fraud, where models can learn complex combinations of attributes associated with minority-class events (22). Machine-learning methods have also been compared for fraud detection

in blockchain-related settings, reinforcing the importance of evaluating multiple classifiers rather than assuming the superiority of a single algorithm (23).

Unsupervised learning provides a different analytical perspective. Rather than relying on predetermined class labels, unsupervised algorithms identify latent clusters, anomalous observations, and structural similarities in the data. Such methods are valuable when labels are unavailable, incomplete, or unreliable and when the primary objective is to detect unusual patterns that may warrant further investigation (24). Comparative research has therefore increasingly examined supervised and unsupervised approaches together in financial-fraud detection (25). Although reinforcement learning represents another important branch of machine learning and has been applied across diverse decision environments, its logic differs from supervised classification and unsupervised pattern discovery because it is based on sequential learning through reward structures (26). For the present fraud-prediction context, comparing supervised and unsupervised algorithms is particularly relevant because the study seeks both to determine whether labeled information improves predictive performance and to identify which baseline method can most effectively discriminate between firms with and without a likelihood of fraud.

The growing sophistication of computational fraud detection is also evident in the increasing use of deep learning, neural networks, transformers, and cross-platform analytical systems. Deep learning has been used to identify financial-statement fraud under conditions of information asymmetry, demonstrating its capacity to model complex nonlinear relationships among financial indicators (3). Artificial neural-network utility algorithms have similarly been proposed for financial-fraud detection in capital-market settings (27). Cross-platform fraud-detection systems based on machine-learning algorithms further show the potential of integrating heterogeneous information sources within a unified predictive framework (28). In digital environments, hybrid deep-transformer models and hyperparameter optimization have been applied to fraudulent-account detection, highlighting the broader movement toward high-dimensional, automated fraud analytics (29). At the same time, the use of more complex algorithms does not eliminate the need for interpretable and statistically robust baseline models. In many applied contexts, simpler classifiers may provide comparable or superior performance while offering greater transparency to auditors, regulators, and market practitioners.

Model evaluation is therefore as important as model construction. Financial-fraud datasets are typically characterized by pronounced class imbalance because fraudulent observations represent only a small proportion of the total sample. Under such conditions, overall accuracy can be misleading: a model may correctly classify nearly all non-fraudulent observations while failing to detect most fraudulent cases. Appropriate evaluation consequently requires measures such as precision, recall, F1-score, receiver operating characteristic analysis, and area under the curve (30). Cross-validation procedures are also essential for obtaining more stable estimates of classification performance and reducing the risk that model selection reflects a particular random split of the data (31). This is particularly important when the minority class is small and the analytical objective emphasizes the cost of missed fraud cases. Therefore, robust fraud-detection research should combine class-balancing strategies, repeated cross-validation, hyperparameter tuning, and evaluation metrics that are sensitive to minority-class identification.

In addition to technological advances, the selection of theoretically meaningful input variables remains critical. Financial fraud can be associated with liquidity pressures, leverage, declining profitability, unusual accruals, related-party transactions, managerial compensation, customer concentration, auditor characteristics, and other financial and governance indicators. Empirical research on public companies has shown that combining financial and non-

financial criteria within a machine-learning framework can improve financial-fraud detection (32). Data-driven clustering approaches have also been used to identify drivers of creative accounting and reveal combinations of characteristics that may not be evident through conventional linear analysis (33). Sustainability-reporting functions, information structures, and related corporate disclosure mechanisms may further affect how capital-market participants interpret firm performance and risk (34). Thus, a theoretically informed machine-learning model should not rely solely on algorithmic complexity; it should incorporate variables that reflect operational, reporting, governance, and information-process mechanisms associated with fraudulent behavior.

These issues have particular relevance for the Iranian capital market. The Tehran Stock Exchange operates within an economic and institutional environment in which macroeconomic instability, regulatory developments, exchange-rate dynamics, sanctions, and market-specific information structures can influence firm behavior and investor expectations. The relationship between exchange-rate regimes and the Iranian capital market illustrates the importance of contextual economic conditions in understanding market performance and risk (35). Recent research on Iranian capital-market behavior has likewise emphasized the importance of information type and market symmetry in shaping investor and market responses (36). In such an environment, financial news websites, specialized analytical channels, and social-media platforms may provide a substantial volume of information beyond formal corporate disclosures. These media signals can potentially reveal changes in operational conditions, governance concerns, managerial incentives, liquidity pressures, related-party relationships, customer concentration, and other warning signs relevant to fraud risk before they are fully recognized through conventional financial-analysis procedures.

The integration of media-derived signals with machine-learning methods therefore represents a potentially important development for fraud prediction in the Tehran Stock Exchange. Existing research has separately documented the monitoring role of media, the relationship between social media and information asymmetry, the predictive value of media reports, and the effectiveness of machine-learning algorithms in financial-fraud detection (8, 10, 15, 32). However, fewer studies have systematically combined media mining, structured screening of the scientific literature, expert validation of media-related indicators, and comparative evaluation of supervised and unsupervised machine-learning algorithms within a single framework. This gap is particularly evident in the Iranian capital market, where the informational role of analytical media and its potential integration with algorithmic fraud prediction remain underexplored.

A further methodological challenge concerns the distinction between correlation, classification, and meaningful fraud signals. A model may produce high predictive accuracy without providing a robust understanding of which media-related indicators contribute most consistently to discrimination between potentially fraudulent and non-fraudulent firms. Therefore, candidate variables should first be identified through a structured process and validated before entering the algorithmic stage. The combined use of systematic media analysis, literature screening, expert consensus, and machine-learning evaluation can reduce the risk of introducing arbitrary or weakly justified predictors. This approach also responds to concerns that financial-fraud detection should incorporate both quantitative red flags and qualitative indicators embedded in public information environments (2, 5). Moreover, by comparing multiple supervised and unsupervised algorithms, it becomes possible to determine whether the informational value of media-derived criteria is strong enough to support reliable classification across different computational approaches.

The practical relevance of such an integrated framework is substantial. Regulatory authorities may use media-derived risk indicators as complementary early-warning signals for prioritizing investigations. Auditors may incorporate unusual media patterns into fraud-risk assessment procedures. Investors and financial analysts may use predictive outputs to identify firms requiring more intensive fundamental analysis. Listed companies themselves may benefit from understanding which reporting, governance, and operational characteristics are interpreted by external information intermediaries as potential fraud signals. Importantly, the objective is not to treat media coverage as definitive evidence of misconduct, but to evaluate whether systematically extracted and empirically validated media-related measures contain sufficient information to improve the prediction of financial-fraud likelihood. When combined with suitable classification algorithms and robust evaluation procedures, these measures may strengthen the informational infrastructure of capital-market surveillance.

Accordingly, building on prior evidence concerning media monitoring, social-media disclosure, fraud-related red flags, information asymmetry, and machine-learning-based classification (6, 9, 12-14), the present study seeks to connect the informational role of analytical media with a systematic machine-learning framework specifically tailored to the Tehran Stock Exchange. It addresses both the identification of media-derived fraud indicators and the comparative predictive performance of alternative algorithms, while accounting for the methodological problems associated with class imbalance and model evaluation. Such an approach may provide a more comprehensive understanding of how external information signals can be transformed into measurable inputs for corporate-fraud prediction and may contribute to the development of more responsive monitoring mechanisms in emerging capital markets.

Therefore, the aim of this study was to evaluate the role of analytical-media signals in identifying and predicting the likelihood of financial fraud among companies listed on the Tehran Stock Exchange by identifying and validating relevant media-based criteria and comparing the performance of supervised and unsupervised machine-learning algorithms.

Methods and Materials

The nature of this study can be classified as quasi-experimental because, through the combined collection of data, it examines a relatively homogeneous set of documentary data, or so-called ex post facto data, to develop applied inferences from the operational realities of companies listed on the Tehran Stock Exchange. Accordingly, from a methodological perspective, the outcomes of this study are applied in nature, because by evaluating media-related drivers for detecting the likelihood of financial fraud in companies, decision-makers can benefit from a more informed basis for distinguishing fraudulent companies from other firms. In terms of purpose, this study is descriptive because it examines a continuum extending from theoretical functions to their analysis among the sample companies, with the aim of providing a better understanding of operational realities in the capital market and thereby guiding financial decision-makers toward a more coherent understanding. Finally, with respect to methodological reasoning from a philosophical perspective, this study falls within the category of inductive-deductive research, commonly referred to as a two-phase mixed-methods study. In the inductive phase, the study first explores events reported by official capital market media, on the one hand, and relevant studies concerned with identifying criteria for assessing the likelihood of fraud, on the other, in order to integrate and systematize previously unidentified aspects arising from the absence of an established theoretical framework in this area. Subsequently, after identifying media-related criteria relevant to fraud detection and assessing them in terms of validity and reliability

indicators, the study seeks to extend these criteria to the empirical context by applying algorithmic machine learning techniques. This constitutes the deductive phase of the study and serves to address the analytical objectives, research questions, and hypotheses. Regarding the analytical procedures and techniques employed, it should be noted that two principal methods were used in the qualitative phase: text mining and content screening. In the text-mining stage, official news websites available through designated Tehran Stock Exchange platforms were examined over the study period to identify criteria with analytical applicability in the quantitative phase and suitability for algorithm-based analysis. These criteria generally represent reference indicators that may serve as informative signals for financial decision-making in capital market analysis. Once these criteria had been identified, the study proceeded to the content-screening process using research literature similar to the present study, because the identified criteria required an adequate analytical foundation for implementation. By integrating the criteria derived from text mining and content screening, the measurement framework for the analytical objectives was established. Following assessment of their validity and reliability for generalization to the study context, the quantitative phase evaluated the predictive effectiveness of the identified criteria through the implementation of a set of procedures specifically designed for analytical algorithms.

Consistent with the inductive-deductive nature of the study and its combined data-collection approach, the statistical population can be differentiated into qualitative and quantitative components in terms of participant selection and data selection within the study context. As previously explained, two approaches were used in the qualitative phase to identify the measurement criteria. The first involved searching news-evaluation texts published by official media outlets and extracting keywords from such reports that indirectly reflected dimensions associated with the likelihood of fraud. The second approach involved content screening of research studies adopting an approach similar to that of the present study, particularly studies integrating media functions with the likelihood of financial fraud among companies listed on the Tehran Stock Exchange. After identifying and integrating the criteria obtained through both approaches as media-related functions relevant to financial fraud prediction, it was necessary to identify those criteria demonstrating the highest frequency of occurrence across comparable studies. Structuring this process required the use of an instrument such as a critical appraisal tool so that, through the participation of a group of research experts, these procedures could be examined while maintaining the effectiveness of the study in selecting the most appropriate criteria. Therefore, the experts selected for participation needed to possess adequate analytical and professional competencies. Accordingly, individuals considered knowledgeable informants were selected based on the following criteria.

First, one group of experts had to include individuals whose research records contained studies addressing financial fraud. The inclusion of this criterion was expected to enhance the synergy and effectiveness of differentiated evaluations of criteria relevant to the present research.

Second, participants were required to have sufficient experience teaching doctoral-level accounting courses related to financial theories and advanced financial risk management, and these courses had to constitute part of their principal university teaching assignments.

Third, participants had to agree with the qualitative implementation approach of the study, including the allocation of sufficient time to score the critical appraisal checklists, and they were required to demonstrate adequate motivation to participate.

These criteria helped strengthen the implementation effectiveness of the study during the distribution and collection of the appraisal checklists. In addition, the selection of participants for the qualitative phase was based

on homogeneous sampling. To achieve an appropriate level of competence among the selected experts, participants who met the predefined criteria were further assessed using the approach proposed by Henwood and Pidgeon (1992), with particular emphasis on relevance, discriminatory capacity, awareness of the research context, and, specifically, interpretive explanatory ability. Accordingly, based on the specified criteria, invitations were initially sent to 23 individuals to determine their willingness or unwillingness to participate. Of these 23 individuals, 17 expressed their willingness to participate. The initially selected 17 experts were subsequently screened again based on their sensitivity to the study context. A brochure outlining the objectives and nature of the study was provided to them, and their responses were evaluated in terms of discriminatory capacity, awareness of the research context, and explanatory interpretation of the research topic. Ultimately, considering both the availability of sufficient time for participation and the adequacy of their cognitive perspectives, 14 individuals were selected as participants in the qualitative phase. These participants demonstrated the required level of motivation and awareness regarding the phenomenon under investigation. Furthermore, because the implementation of systematic content screening required text mining, relevant studies were retrieved from databases including the Scientific Information Database (SID) in Iran, Magiran in Iran, the Computer Research Center of Islamic Sciences (Noorsoft) in Iran, ScienceDirect, Emerald Insight, and Online Library. These sources were used to identify studies comparable to the present research so that the criteria derived from the text-mining processes could be integrated and the most important criteria suitable for extension to the quantitative phase could be determined.

Because, following identification of the dimensions of the central phenomenon, the study sought to evaluate companies listed on the Tehran Stock Exchange in terms of the influence of media functions on the likelihood of predicting financial fraud using secondary data, it was necessary to define a specific time period for data collection and select the sample companies accordingly. Therefore, the required data were collected for the period from 2019 to 2025. However, during this process, an appropriate procedure was required for selecting listed companies in order to obtain a more homogeneous dataset for analysis. Accordingly, systematic sampling was used, and the sample companies were selected according to the following criteria.

1. Companies had to have been listed on the Tehran Stock Exchange before the beginning of the study period and had to remain listed through the end of the period under investigation.
2. The fiscal year of eligible companies had to end on March 20 of each year.
3. During the study period, the companies must not have changed the nature of their business activities or industry classification.
4. The selected companies must not have been investment companies, pension funds, or insurance companies.
5. Eligible companies must not have experienced a suspension of trading lasting more than six months during the period under investigation.

After applying the aforementioned criteria through a systematic elimination screening procedure, 95 companies, representing 570 firm-year observations across 25 different industries, were selected as the screened study population.

Findings and Results

The primary objective of this study was to evaluate the influence of analytical-media signals on predicting the likelihood of financial fraud among companies listed on the Tehran Stock Exchange (TSE). Before conducting the

machine-learning analyses that constituted the quantitative analytical basis of the study, the relevant predictive criteria were reconstructed in the qualitative phase through a systematic review process. Two complementary sources of evidence were used: analytical-media content and previous empirical studies. The criteria identified through these two procedures were subsequently integrated to determine the factors most suitable for predicting the likelihood of financial fraud and for use as algorithmic input variables.

The first research question addressed in the qualitative phase was as follows: What factors derived from media signals can be used to predict the likelihood of financial fraud among companies listed on the Tehran Stock Exchange? To answer this question, factors emphasized by analytical media in reports disseminated through financial news channels were first identified. Accordingly, media outlets related to the Iranian capital market were classified, and their reports were examined to determine which indicators were repeatedly associated with increased concern regarding the likelihood of corporate financial fraud. Subsequently, comparable empirical studies examining the role of mass-media functions in fraud prediction were systematically screened. The criteria obtained from both procedures were then integrated, and those displaying the greatest convergence were retained as candidate inputs for the machine-learning algorithms.

The principal objective of the media-mining stage was to collect financial news from news websites and Telegram channels over the specified study period in relation to selected firms and stock symbols. Several Python-based programming tools, including Scrapy, Telethon, and Streamlit, were employed. Scrapy was used to retrieve news articles from financial news websites. Because of its flexibility and capability to manage multiple concurrent requests, this framework was considered appropriate for web crawling. For each website, the browser's Network panel was initially inspected to determine how data were loaded. Where available, fetch or XMLHttpRequest (XHR) requests were examined to identify the website's internal application programming interfaces (APIs). When an API was unavailable, the website's search URLs were used to retrieve relevant news. This procedure enabled systematic extraction of news associated with the target companies and stock symbols.

For Telegram-based data, the Telethon Python library was employed to access relevant messages from selected official financial channels. Its search functionality was used to retrieve textual messages based on keywords associated with company names and stock symbols. A specific time interval corresponding to the study period was defined for each stock symbol so that only messages published within the relevant period were retained. This temporal restriction reduced irrelevant observations and increased the analytical focus of the resulting dataset.

General capital-market news disseminated through financial-media channels was also considered when it incorporated expert financial analyses or research-based assessments of market conditions. Search terms included concepts such as *fraud*, *sanctions*, *risk*, and *crisis*, together with company-specific terms. This procedure enhanced the identification of media content directly or indirectly associated with financial-fraud risk and facilitated more targeted subsequent analysis.

Streamlit was subsequently used to construct a simple interactive graphical interface for the preliminary examination and organization of the extracted data. The interface functioned as a categorized information dashboard and facilitated the classification of media content according to its relevance to the likelihood of fraud. News items retrieved from websites and Telegram channels were displayed in tabular form, while pagination was used to manage the large volume of observations and reduce difficulties in identifying relevant records.

The combined application of Scrapy, Telethon, and Streamlit resulted in the identification of 23 media-related criteria. Five financial news websites—Eghtesad Online, Bourse24, Donya-e-Eqtesad, SENA, and Eghtesad News—were examined. Table 1 presents the frequency with which each criterion appeared across these sources.

Table 1. Media-Based Criteria for Predicting the Likelihood of Financial Fraud in the Iranian Capital Market

No.	Media-Based Criterion	Eghtesad Online	Bourse24	Donya-e-Eqtesad	SENA	Eghtesad News	Frequency
1	Asset accumulation	✓	✓	—	✓	—	3
2	Decline in the firm's bargaining power	—	✓	—	—	✓	2
3	Going-concern uncertainty	✓	—	—	✓	—	2
4	Failure to revalue assets	✓	✓	—	✓	—	3
5	Failure to calculate fair value	✓	✓	—	✓	—	3
6	Accumulated losses	✓	—	✓	—	✓	3
7	Major customers	✓	✓	✓	✓	—	4
8	Asset depreciation	✓	✓	—	✓	—	3
9	Managerial ownership	—	—	✓	✓	✓	3
10	Executive compensation	✓	✓	✓	✓	✓	5
11	Auditor reputation	—	✓	—	—	—	1
12	Auditor tenure	✓	—	—	✓	—	2
13	Asset impairment	✓	✓	—	✓	—	3
14	Board size	✓	✓	✓	—	✓	4
15	Related-party transactions	✓	—	✓	✓	—	3
16	Issuance of sukuk, participation bonds, or lease securities	—	✓	—	✓	—	2
17	Fictitious transactions	✓	—	—	—	✓	2
18	Accruals	—	—	—	✓	✓	2
19	Internal-control weakness	—	—	—	✓	✓	2
20	Asset revaluation	—	—	—	✓	✓	2
21	Information-processing delay	—	—	—	✓	✓	2
22	Artificial price-to-earnings-per-share indicator	—	✓	—	✓	—	2
23	Export restrictions	—	✓	✓	—	—	2

As shown in Table 1, 23 recurring indicators associated with media discussions of factors potentially signaling financial fraud were identified. Based on their frequency of occurrence across the five financial news sources, 11 media-related indicators that were repeatedly emphasized in a substantial proportion of the sources were provisionally retained. These indicators were subsequently compared with criteria identified through systematic screening of the scientific literature to determine the variables most appropriate for algorithmic analysis.

A systematic content screening (SCS) procedure was subsequently conducted to identify the criteria most frequently documented in studies with objectives comparable to those of the present research. The critical appraisal instrument proposed by Irwin et al. (2011) was employed to evaluate the methodological appropriateness of candidate studies. International publications from 2020 to 2025 and domestic scientific publications from 2021 to 2026 were considered. The literature-selection process involved three primary stages: title screening, content screening, and analytical-method screening.

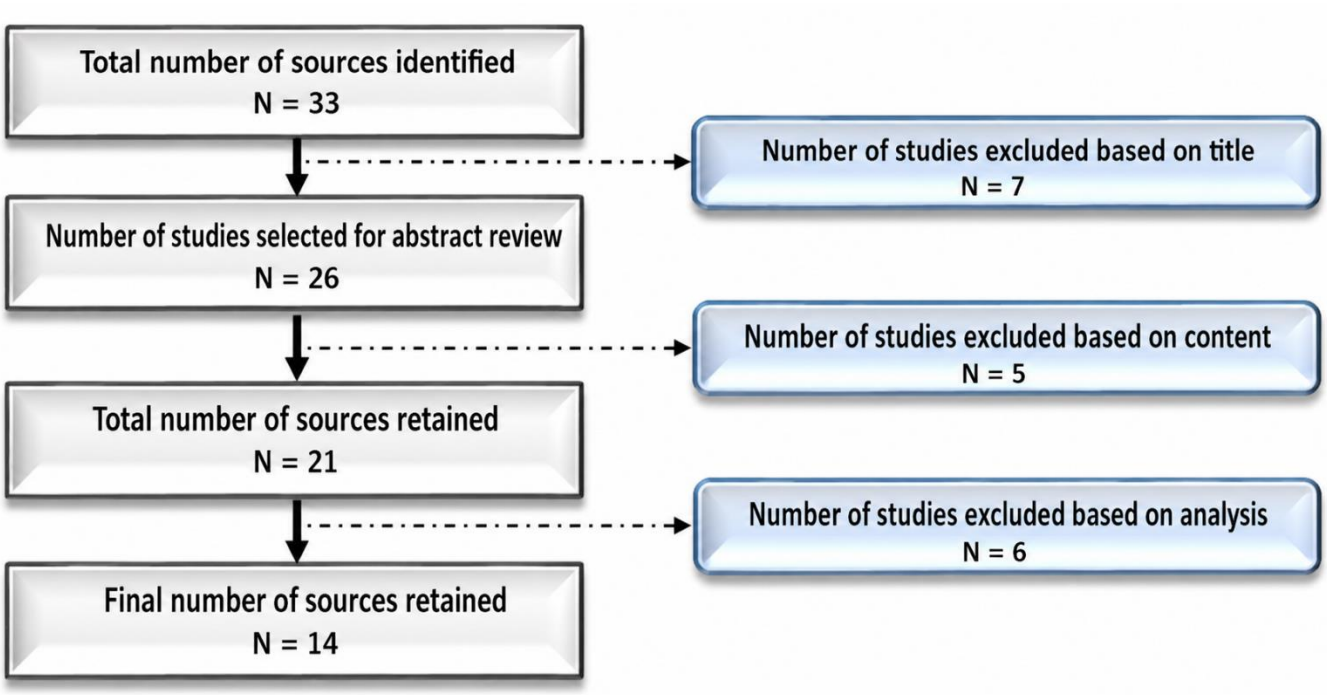


Figure 1. Flowchart of the Identification, Screening, and Final Selection of Studies Included in the Systematic Content Review

A total of 33 potentially relevant records were initially identified. Following the sequential screening of titles, substantive content, and analytical procedures, 14 studies were retained for critical appraisal. Each study was evaluated by the participating experts using 10 criteria scored on a five-point scale. These criteria concerned research objectives, research method, study design, sampling procedure, data-collection procedure, generalizability of findings, ethical considerations, statistical analysis, theoretical contribution, and overall research value. The modal expert score was used because it represented the most frequently assigned rating for each criterion. A total critical-appraisal score of 30 or higher was established as the threshold for retention.

The total appraisal scores for the 14 studies were 32 for Coyle and West (2025), 35 for Shaokala et al. (2025), 33 for Juanda et al. (2024), 26 for Ullrich and Seibold (2024), 35 for Trangoda et al. (2024), 34 for De Twit (2024), 31 for Liu et al. (2023), 33 for Qiu and Liu (2023), 25 for Li et al. (2023), 33 for Wang et al. (2022), 31 for Zhang et al. (2021), 21 for John (2021), 35 for Khalifi (2021), and 22 for Chen et al. (2021). Consequently, Ullrich and Seibold (2024), Li et al. (2023), John (2021), and Chen et al. (2021) were excluded because their scores were below 30. The remaining 10 studies were used to identify recurrent fraud-related indicators. Table 2 presents the frequencies of the criteria identified across these studies.

Table 2. Criteria Identified Through the Systematic Review as Factors Associated With Media-Based Financial-Fraud Prediction

No.	Criterion	Coyle & West (2025)	Shaokala et al. (2025)	Juanda et al. (2024)	Trangoda et al. (2024)	De Twit (2024)	Liu et al. (2023)	Qiu & Liu (2023)	Wang et al. (2022)	Zhang et al. (2021)	Khalifi (2021)	Frequency
1	Operating cash flow to net income	✓	—	—	✓	—	✓	✓	—	✓	✓	6
2	Borrowed funds to non-	—	—	✓	—	—	—	—	✓	—	—	2

	current assets											
3	Retained earnings to total assets	—	✓	✓	—	✓	—	✓	✓	—	✓	6
4	Gross profit to sales	—	✓	—	—	✓	✓	—	—	—	—	3
5	Debt to assets	✓	✓	—	✓	—	✓	—	—	✓	—	5
6	Cash flow to current/short -term debt	—	—	✓	✓	✓	—	✓	✓	—	—	5
7	Return on assets	✓	—	✓	—	—	✓	—	✓	—	—	4
8	Short-term debt to operating cash flow	✓	—	—	✓	—	✓	—	✓	—	✓	5
9	Current assets to total assets	—	✓	—	—	—	—	✓	—	—	—	2
10	Long-term debt to equity	—	✓	✓	—	✓	—	✓	—	✓	—	5
11	Working capital to total assets	✓	—	—	—	—	✓	—	—	—	✓	3
12	Operating cash flow to total assets	—	—	✓	✓	✓	—	✓	✓	—	—	5
13	Executive compensatio n	✓	✓	—	—	—	✓	—	—	✓	✓	5
14	Fixed assets to total assets	—	—	✓	✓	—	—	—	—	—	—	2
15	Related-party transactions	—	✓	✓	✓	—	✓	—	✓	✓	—	6
16	Cash holdings to total assets	—	✓	—	✓	—	—	✓	—	—	—	3
17	Fixed-asset turnover	✓	—	—	—	—	✓	—	—	✓	—	3
18	Accounts receivable to sales	—	✓	—	✓	—	—	—	—	—	✓	2
19	Capital flexibility ratio	—	✓	—	—	—	—	—	✓	—	—	2

Among the 19 criteria identified through the systematic review, nine demonstrated frequencies at or above the median frequency of the retained studies and were therefore considered sufficiently recurrent to be operationalized as inputs to the quantitative algorithmic analyses. These indicators were subsequently integrated with the media-derived factors identified in the preceding stage. This synthesis produced 11 final criteria, comprising seven operational financial indicators and four process-related indicators, as reported in Table 3.

Table 3. **Final Media-Related Criteria for Predicting Financial Fraud in the Capital Market**

Category	Criterion	Operational Definition
Operational	Operating cash flow to net income	(CFtoNI_{it}=\frac{Cash\ Flow_{it}}{Net\ Income_{it}})
Operational	Retained earnings to total assets	(REtoTA_{it}=\frac{Retained\ Earnings_{it}}{Total\ Assets_{it}})

Operational	Debt to assets	(DtoA_{it}=\frac{Total\ Debt_{it}}{Total\ Assets_{it}})
Operational	Cash flow to current/short-term debt	(CFtoShD_{it}=\frac{Cash\ Flow_{it}}{Short\text{-}Term\ Debt_{it}})
Operational	Short-term debt to operating cash flow	(ShDtoCFO_{it}=\frac{Short\text{-}Term\ Debt_{it}}{Operating\ Cash\ Flow_{it}})
Operational	Long-term debt to equity	(LTD to EQ_{it}=\frac{Long\text{-}Term\ Debt_{it}}{Equity_{it}})
Operational	Operating cash flow to total assets	(CFOtoTA_{it}=\frac{Operating\ Cash\ Flow_{it}}{Total\ Assets_{it}})
Process-related	Related-party transactions	(RPT_{it}=\frac{Related\text{-}Party\ Transactions_{it}}{Total\ Assets_{it}})
Process-related	Major customers/customer concentration	(CC_{it}=\sum_{j=1}^{J}\frac{Sales_{ijt}}{Sales_{it}})
Process-related	Executive compensation	(Compensation\ Change_{it}=CEO\ Compensation_{it}-CEO\ Compensation_{it-1})
Process-related	Audit-firm size	Determined from the notes accompanying the financial statements and disclosures concerning the company's audit firm

Following the integration of these criteria as media-related drivers of financial-fraud prediction, a fuzzy Delphi analysis was conducted to assess their reliability and determine whether sufficient expert consensus existed to justify their extension to the quantitative phase. Each of the 11 criteria was assessed by the 14 experts using a five-category linguistic scale. The categories were *very high*, *high*, *moderate*, *low*, and *very low*, corresponding respectively to scores of 9, 7, 5, 3, and 1. Their associated triangular fuzzy numbers were (7, 9, 10), (5, 7, 9), (3, 5, 7), (1, 3, 5), and (0, 1, 3), respectively.

A difference threshold of **less than 0.20** between consecutive Delphi rounds was used as the criterion for consensus. Although such thresholds may vary according to research design and investigator judgment, a value below 0.20 was considered sufficient evidence that expert opinions had stabilized.

Table 4 summarizes the two-round fuzzy Delphi results. For each criterion, the first and second sets of frequencies correspond to the first and second Delphi rounds, respectively.

Table 4. Second-Round Fuzzy Delphi Analysis of the Final Fraud-Prediction Criteria

No.	Criterion	Round	Very High	High	Moderate	Low	Very Low	Defuzzified Mean	Difference
1	Operating cash flow to net income	1	8	2	4	0	0	7.38	0.02
		2	7	4	3	0	0	7.40	
2	Retained earnings to total assets	1	9	3	2	0	0	7.79	0.12
		2	10	2	2	0	0	7.90	
3	Debt to assets	1	9	4	1	0	0	7.93	0.14
		2	9	5	0	0	0	8.07	
4	Cash flow to short-term debt	1	11	3	0	0	0	8.31	0.12
		2	12	2	0	0	0	8.43	
5	Short-term debt to operating cash flow	1	12	2	0	0	0	8.43	0.12
		2	13	1	0	0	0	8.55	
6	Long-term debt to equity	1	11	2	1	0	0	8.17	0.14
		2	11	3	0	0	0	8.31	
7	Operating cash flow to total assets	1	10	1	3	0	0	7.76	0.02
		2	9	3	2	0	0	7.79	
8	Related-party transactions	1	8	5	1	0	0	7.81	0.12
		2	9	4	1	0	0	7.93	
9	Major customers	1	11	2	1	0	0	8.17	0.02
		2	10	4	0	0	0	8.19	
10	Executive compensation	1	12	2	0	0	0	8.43	0.00
		2	12	2	0	0	0	8.43	

11	Audit-firm size	1	10	1	3	0	0	7.76	0.17
		2	9	4	1	0	0	7.93	

The results presented in Table 4 show that the differences between the two Delphi rounds ranged from 0.00 to 0.17 and were therefore below the predefined threshold of 0.20 for all 11 criteria. Consequently, all criteria met the expert-consensus requirement and were retained. These results established the reliability and theoretical consensus required to use the 11 indicators as media-related predictors of financial-fraud likelihood among TSE-listed companies.

After completion of the qualitative phase, the study proceeded to the quantitative machine-learning phase. The 11 validated criteria constituted the algorithmic inputs. The second research question was therefore formulated as follows: Which baseline machine-learning algorithm provides the strongest performance for detecting analytical-media signals in predicting the likelihood of financial fraud among companies listed on the Tehran Stock Exchange?

All stages of data preprocessing, computational analysis, model training, and performance evaluation were implemented using the Python programming language. Two broad classes of machine-learning algorithms were evaluated: supervised and unsupervised learning. Supervised algorithms learn mappings between labeled inputs and outputs and can be applied to regression or classification tasks. In the present study, the classification setting was used to estimate the probability that an observation belonged to the potential-fraud class (Tuche Tchio et al., 2024). In contrast, unsupervised algorithms identify latent clusters, anomalous structures, or natural groupings without using target labels during training (Rolf et al., 2025).

Prior to model estimation, the target variable was constructed using the modified Beneish model (Beneish, 2020). The observations were divided into two classes: non-fraudulent and potential fraud. Examination of the target distribution showed pronounced class imbalance: 96.9% of observations belonged to the non-fraudulent class, whereas only 3.1% were categorized as potential fraud.

Because this imbalance could strongly bias a classifier toward the majority class, the Synthetic Minority Over-sampling Technique (SMOTE) was applied exclusively to the training data. SMOTE generates synthetic minority-class observations through linear interpolation between neighboring minority observations and thereby increases representation of the minority class without simply duplicating existing observations. Importantly, the test dataset remained unchanged, thereby preventing information leakage and preserving a realistic evaluation environment.

The pronounced class imbalance also demonstrated why overall accuracy alone was not an appropriate criterion for model selection. A naïve classifier assigning every observation to the non-fraudulent class would achieve approximately 96.9% accuracy while failing to identify any potential fraudulent observations. Consequently, model assessment emphasized metrics sensitive to minority-class detection, specifically recall, precision, F1-score, the receiver operating characteristic (ROC) curve, and the area under the ROC curve (AUC).

To visually examine the structure and separability of the two classes, principal component analysis (PCA) and t-distributed stochastic neighbor embedding (t-SNE) were applied to the training data. PCA provided a linear two-dimensional representation maximizing retained variance, whereas t-SNE was used as a nonlinear dimensionality-reduction approach capable of revealing more complex local neighborhood structures.

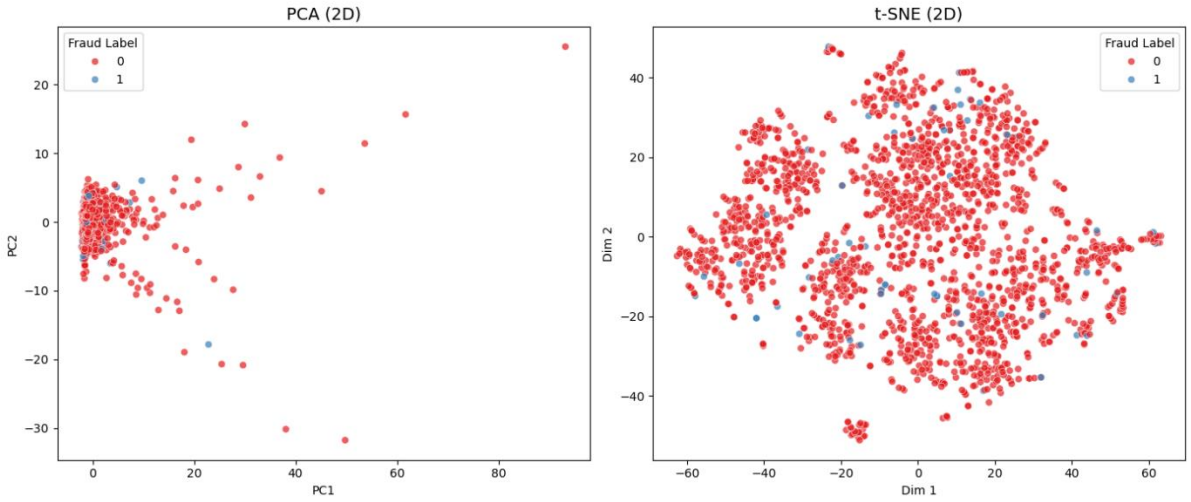


Figure 2. Comparison of Potential-Fraud and Non-Fraud Observations in Two-Dimensional PCA and t-SNE Space Before and After Data Balancing

Visual examination showed substantial overlap between potential-fraud and non-fraud observations. The overlap was evident in both PCA and t-SNE representations and indicated that the two classes could not be separated by a simple linear decision boundary in the existing feature space. This result confirmed the intrinsic difficulty of the fraud-detection problem and supported the use of machine-learning models capable of capturing complex relationships. It also reinforced the need for class-balancing procedures such as SMOTE and minority-sensitive evaluation measures such as the F1-score.

Following model implementation and hyperparameter tuning, supervised and unsupervised algorithms were evaluated using a systematic procedure based on grid search and five-times repeated five-fold cross-validation (R5FCV). For every model and each hyperparameter combination, the algorithm was trained on the relevant folds and evaluated on the corresponding validation fold. Performance statistics were then averaged across folds. The primary model-selection criterion was the mean F1-score because it simultaneously incorporates precision and recall and is particularly appropriate for imbalanced classification problems. Recall, precision, ROC/AUC, and accuracy were also calculated.

Table 5 presents the comparative performance of the supervised and unsupervised models.

Table 5. Performance of Supervised and Unsupervised Machine-Learning Models

Model	Learning Type	Accuracy	Recall	Precision	F1-Score	ROC/AUC
K-means	Unsupervised	0.968	0.039	0.266	0.067	0.519
DBSCAN	Unsupervised	0.968	0.039	0.313	0.068	0.518
Agglomerative hierarchical clustering	Unsupervised	0.968	0.039	0.280	0.067	0.519
Gaussian mixture model	Unsupervised	0.969	0.007	0.080	0.013	0.503
Logistic regression	Supervised	0.968	0.767	0.509	0.604	0.871
Support vector classifier	Supervised	0.968	0.674	0.530	0.581	0.826
Decision tree	Supervised	0.934	0.360	0.241	0.267	0.656
Random forest	Supervised	0.969	0.344	0.551	0.417	0.667
Gradient boosting	Supervised	0.960	0.177	0.268	0.205	0.572
K-nearest neighbors	Supervised	0.972	0.295	0.636	0.039	0.644
Gaussian naïve Bayes	Supervised	0.891	0.452	0.137	0.209	0.679
Multilayer perceptron	Supervised	0.973	0.495	0.615	0.537	0.742

The results in Table 5 demonstrate that supervised methods substantially outperformed unsupervised methods on the minority-sensitive performance measures. Although accuracy was high for most algorithms and showed relatively limited variation, recall, F1-score, and ROC/AUC revealed substantial differences in genuine fraud-detection capability. Among all models, **logistic regression produced the strongest overall performance**, with a recall of approximately **0.768**, an F1-score of approximately **0.605**, and an AUC of **0.871**. The support vector classifier was the closest competitor, with an F1-score of approximately 0.582 and an AUC of 0.826.

By contrast, the unsupervised algorithms yielded F1-scores between approximately 0.013 and 0.068 and recall values no higher than approximately 0.039. Thus, despite their apparently high accuracy values, they identified very few minority-class observations correctly. This finding further demonstrates that accuracy is potentially misleading in highly imbalanced fraud-detection settings.

To formally test whether the two algorithmic families differed in performance, the first quantitative hypothesis was formulated as follows:

$H0_1$: There is no statistically significant difference between the F1-score performance of supervised and unsupervised machine-learning models in predicting financial fraud among companies listed on the Tehran Stock Exchange.

$H1_1$: There is a statistically significant difference between the F1-score performance of supervised and unsupervised machine-learning models in predicting financial fraud among companies listed on the Tehran Stock Exchange.

A Mann–Whitney U test was used to compare F1-score distributions between the supervised and unsupervised groups. The test indicated a statistically significant difference between the two groups ($p < .05$). Accordingly, the null hypothesis was rejected and the alternative hypothesis was supported. The results demonstrate that supervised algorithms, which use labeled observations during training, achieved significantly better performance than unsupervised approaches in predicting the likelihood of financial fraud among TSE-listed companies.

The second quantitative hypothesis examined whether all supervised models demonstrated equivalent predictive performance:

$H0_2$: The supervised machine-learning models exhibit equivalent performance in predicting financial fraud among companies listed on the Tehran Stock Exchange; therefore, the choice of supervised algorithm does not significantly affect predictive performance.

$H1_2$: At least one supervised machine-learning model exhibits significantly different and superior performance in predicting financial fraud among companies listed on the Tehran Stock Exchange; therefore, model choice significantly affects predictive performance.

A Friedman nonparametric test was conducted to compare the supervised models across the repeated evaluations. The results indicated a statistically significant overall difference in model performance ($p < .05$). Thus, the null hypothesis of equivalent performance was rejected. The relatively high Kendall's W further indicated substantial agreement and consistency in model rankings across the evaluations, suggesting that the relative pattern of stronger and weaker algorithms was stable. Because the Friedman test identifies only an overall difference and does not indicate which model pairs differ significantly, post hoc pairwise Wilcoxon signed-rank tests were performed.

Table 6. Pairwise Wilcoxon Comparisons of Machine-Learning Model F1-Scores

Model A	Model B	Mean A	Mean B	p	Significant at .05
K-means	DBSCAN	0.067033	0.068484	.877691	No
K-means	Agglomerative	0.067033	0.067912	.915583	No
K-means	Gaussian mixture	0.067033	0.013333	.041432	Yes
K-means	Logistic regression	0.067033	0.604794	1.226×10^{-5}	Yes
K-means	SVC	0.067033	0.581788	1.228×10^{-5}	Yes
K-means	Decision tree	0.067033	0.267804	.000126	Yes
K-means	Random forest	0.067033	0.417171	1.216×10^{-5}	Yes
K-means	Gradient boosting	0.067033	0.393238	1.384×10^{-5}	Yes
K-means	K-nearest neighbors	0.067033	0.186168	.003284	Yes
K-means	Gaussian NB	0.067033	0.209052	.000101	Yes
K-means	MLP	0.067033	0.537399	1.225×10^{-5}	Yes
DBSCAN	Agglomerative	0.068484	0.067912	.719918	No
DBSCAN	Gaussian mixture	0.068484	0.013333	.039650	Yes
DBSCAN	Logistic regression	0.068484	0.604794	1.225×10^{-5}	Yes
DBSCAN	SVC	0.068484	0.581788	5.960×10^{-8}	Yes
DBSCAN	Decision tree	0.068484	0.267804	1.568×10^{-5}	Yes
DBSCAN	Random forest	0.068484	0.417171	1.211×10^{-5}	Yes
DBSCAN	Gradient boosting	0.068484	0.393238	1.380×10^{-5}	Yes
DBSCAN	K-nearest neighbors	0.068484	0.186168	.005610	Yes
DBSCAN	Gaussian NB	0.068484	0.209052	5.752×10^{-5}	Yes
DBSCAN	MLP	0.068484	0.537399	1.217×10^{-5}	Yes
Agglomerative	Gaussian mixture	0.067912	0.013333	.037571	Yes
Agglomerative	Logistic regression	0.067912	0.604794	1.228×10^{-5}	Yes
Agglomerative	SVC	0.067912	0.581788	5.960×10^{-8}	Yes
Agglomerative	Decision tree	0.067912	0.267804	5.747×10^{-5}	Yes
Agglomerative	Random forest	0.067912	0.417171	1.219×10^{-5}	Yes
Agglomerative	Gradient boosting	0.067912	0.393238	1.381×10^{-5}	Yes
Agglomerative	K-nearest neighbors	0.067912	0.186168	.003244	Yes
Agglomerative	Gaussian NB	0.067912	0.209052	6.446×10^{-5}	Yes
Agglomerative	MLP	0.067912	0.537399	1.225×10^{-5}	Yes
Gaussian mixture	Logistic regression	0.013333	0.604794	1.220×10^{-5}	Yes
Gaussian mixture	SVC	0.013333	0.581788	1.225×10^{-5}	Yes
Gaussian mixture	Decision tree	0.013333	0.267804	1.226×10^{-5}	Yes
Gaussian mixture	Random forest	0.013333	0.417171	1.195×10^{-5}	Yes
Gaussian mixture	Gradient boosting	0.013333	0.393238	1.215×10^{-5}	Yes
Gaussian mixture	K-nearest neighbors	0.013333	0.186168	.000189	Yes
Gaussian mixture	Gaussian NB	0.013333	0.209052	1.382×10^{-5}	Yes
Gaussian mixture	MLP	0.013333	0.537399	1.217×10^{-5}	Yes
Logistic regression	SVC	0.604794	0.581788	.082980	No
Logistic regression	Decision tree	0.604794	0.267804	5.960×10^{-8}	Yes
Logistic regression	Random forest	0.604794	0.417171	1.132×10^{-6}	Yes
Logistic regression	Gradient boosting	0.604794	0.393238	3.278×10^{-6}	Yes
Logistic regression	K-nearest neighbors	0.604794	0.186168	1.227×10^{-5}	Yes
Logistic regression	Gaussian NB	0.604794	0.209052	1.228×10^{-5}	Yes
Logistic regression	MLP	0.604794	0.537399	.048262	Yes
SVC	Decision tree	0.581788	0.267804	5.960×10^{-8}	Yes
SVC	Random forest	0.581788	0.417171	3.621×10^{-5}	Yes
SVC	Gradient boosting	0.581788	0.393238	4.172×10^{-7}	Yes
SVC	K-nearest neighbors	0.581788	0.186168	1.228×10^{-5}	Yes
SVC	Gaussian NB	0.581788	0.209052	5.960×10^{-8}	Yes
SVC	MLP	0.581788	0.537399	.201201	No
Decision tree	Random forest	0.267804	0.417171	.000194	Yes
Decision tree	Gradient boosting	0.267804	0.393238	.000162	Yes
Decision tree	K-nearest neighbors	0.267804	0.186168	.026417	Yes
Decision tree	Gaussian NB	0.267804	0.209052	.002025	Yes

Decision tree	MLP	0.267804	0.537399	1.228×10^{-5}	Yes
Random forest	Gradient boosting	0.417171	0.393238	.391342	No
Random forest	K-nearest neighbors	0.417171	0.186168	3.215×10^{-5}	Yes
Random forest	Gaussian NB	0.417171	0.209052	5.960×10^{-8}	Yes
Random forest	MLP	0.417171	0.537399	.000112	Yes
Gradient boosting	K-nearest neighbors	0.393238	0.186168	1.770×10^{-5}	Yes
Gradient boosting	Gaussian NB	0.393238	0.209052	1.192×10^{-7}	Yes
Gradient boosting	MLP	0.393238	0.537399	8.345×10^{-7}	Yes
K-nearest neighbors	Gaussian NB	0.186168	0.209052	.395711	No
K-nearest neighbors	MLP	0.186168	0.537399	1.384×10^{-5}	Yes
Gaussian NB	MLP	0.209052	0.537399	5.960×10^{-8}	Yes

The pairwise comparisons showed that a substantial proportion of the observed differences were statistically significant. Of the 66 pairwise comparisons, 59 were significant at the .05 level, whereas only 7 comparisons were not statistically significant. Logistic regression achieved the highest mean F1 performance (M = 0.604794) and was therefore identified as the strongest overall model. It also demonstrated statistically significant superiority over most alternative algorithms. However, the difference between logistic regression and the support vector classifier was not statistically significant (p = .08298), indicating that the two approaches performed at relatively similar levels. Likewise, the difference between SVC and MLP was not significant (p = .20120), nor were the differences among several closely performing unsupervised approaches.

After identifying logistic regression as the strongest baseline supervised algorithm, a confusion matrix was used to evaluate its classification performance in greater detail. A confusion matrix compares observed and predicted classes through four outcomes: true positive (TP), where a potential fraudulent observation is correctly identified; true negative (TN), where a non-fraudulent observation is correctly classified; false positive (FP), where a non-fraudulent observation is incorrectly classified as potential fraud; and false negative (FN), where a potential fraudulent observation is incorrectly classified as non-fraudulent. These components constitute the basis for deriving classification measures such as sensitivity, specificity, precision, and accuracy.

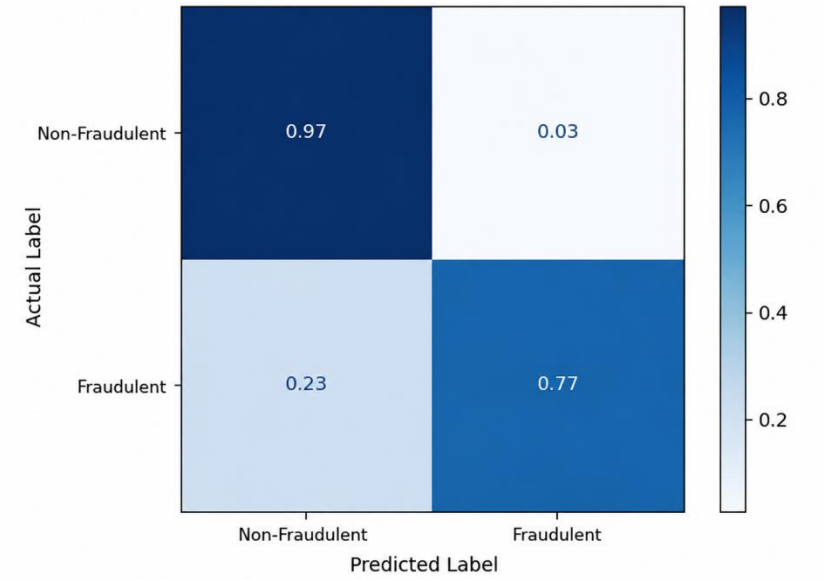


Figure 3. Confusion Matrix for the Best-Performing Supervised Model: Logistic Regression

Analysis of the confusion matrix showed that logistic regression correctly classified 97% of non-fraudulent observations as non-fraudulent and correctly identified 77% of potential fraudulent observations as potential fraud.

Conversely, only 3% of non-fraudulent observations were incorrectly classified as potential fraud, whereas 23% of potential fraudulent observations were incorrectly classified as non-fraudulent. These results indicate that logistic regression achieved a comparatively strong balance between correctly identifying the majority class and detecting the substantially smaller fraud-risk class.

Overall, the findings provide convergent evidence that the 11 operational and process-related criteria identified through analytical-media mining, systematic content screening, and fuzzy Delphi validation possess meaningful predictive capacity for financial-fraud risk. The quantitative analyses further demonstrate that supervised learning is substantially more effective than unsupervised learning for this purpose, and that logistic regression constitutes the most appropriate baseline model among the algorithms examined, with the support vector classifier providing the closest comparable performance. The confusion-matrix findings additionally confirm the practical discriminatory capability of logistic regression, particularly its ability to identify approximately three quarters of potential fraudulent observations despite the pronounced class imbalance in the dataset.

Discussion and Conclusion

The present study investigated the role of analytical-media signals in identifying and predicting the likelihood of financial fraud among companies listed on the Tehran Stock Exchange by integrating media-content analysis, systematic content screening, fuzzy Delphi validation, and comparative machine-learning modeling. The findings produced several important results. First, the qualitative phase identified a set of media-related indicators that could plausibly function as early warning signals of financial fraud. The initial media-mining process generated 23 indicators, which were subsequently refined through systematic examination of the scientific literature. After combining media-derived and literature-derived criteria, 11 indicators were retained, including operating cash flow to net income, retained earnings to total assets, debt to assets, cash flow to short-term debt, short-term debt to operating cash flow, long-term debt to equity, operating cash flow to total assets, related-party transactions, major customers, executive compensation, and audit-firm size. Second, fuzzy Delphi analysis demonstrated sufficient expert consensus regarding all 11 criteria, as the differences between Delphi rounds remained below the predefined threshold of 0.20. Third, the quantitative phase showed a pronounced class imbalance, with 96.9% of observations categorized as non-fraudulent and only 3.1% categorized as having a likelihood of fraud. Fourth, supervised machine-learning models substantially outperformed unsupervised approaches on fraud-sensitive metrics, particularly recall, F1-score, and AUC. Among the supervised methods, logistic regression achieved the strongest overall performance, with recall of approximately 0.768, an F1-score of approximately 0.605, and an AUC of 0.871. Finally, the confusion matrix showed that logistic regression correctly identified 97% of non-fraudulent observations and 77% of potential fraudulent observations, confirming its comparatively favorable discriminatory capacity.

The identification of financial and process-related indicators through media analysis is consistent with the growing body of research emphasizing the informational and monitoring role of financial media. The findings suggest that media outlets do not merely disseminate descriptive information but can also repeatedly highlight specific financial and governance conditions that may operate as warning signals of corporate misconduct. Previous studies have similarly shown that media attention can play an external governance role by drawing attention to suspicious reporting behavior and strengthening scrutiny of corporate actions (6, 8). The present findings also align with research demonstrating that social media and web-based reporting can reduce information asymmetry by expanding access to firm-specific information and increasing transparency (9, 10). Therefore, the convergence

between media-derived criteria and the indicators found in prior empirical studies reinforces the proposition that media content can contain analytically meaningful signals relevant to fraud detection.

The selection of related-party transactions, executive compensation, customer concentration, and audit-firm characteristics as important process-related indicators is also supported by prior literature. Financial fraud rarely emerges from one isolated accounting ratio; rather, it often reflects a combination of governance pressures, managerial incentives, reporting discretion, and transactional complexity. Studies examining fraud red flags have emphasized that unusual financial relationships and reporting structures may provide early indications of manipulation (2). Similarly, machine-learning research incorporating both financial and non-financial criteria has shown that models can benefit from the inclusion of governance and organizational variables alongside conventional financial ratios (32). The identification of executive compensation as one of the most frequently emphasized media indicators is especially important because compensation structures may create incentives for managers to influence reported performance. At the same time, the inclusion of audit-firm size and related-party transactions reflects the broader importance of monitoring quality and transaction transparency in limiting opportunities for manipulation.

The operational indicators retained in the final model also have strong theoretical and empirical relevance. Measures such as operating cash flow relative to net income, retained earnings relative to total assets, debt ratios, and operating cash flow relative to short-term liabilities capture several dimensions associated with liquidity pressure, earnings quality, capital structure, and financial distress. These conditions can provide incentives or opportunities for manipulation when firms attempt to preserve market expectations or maintain access to financing. The usefulness of financial ratios as fraud predictors has been repeatedly confirmed in computational fraud-detection research, especially when such variables are combined within multivariate and machine-learning frameworks (3, 27). Likewise, the use of both financial and non-financial characteristics has been shown to improve the ability of machine-learning models to differentiate fraudulent from non-fraudulent firms (32). The present study extends this perspective by showing that media repeatedly draw attention to many of the same indicators that are analytically useful in formal fraud-detection models.

The findings from the fuzzy Delphi stage also provide evidence of the robustness of the selected criteria. All 11 indicators achieved acceptable consensus across the two Delphi rounds, and no criterion exceeded the 0.20 difference threshold. This suggests that the identified variables were not merely frequent in media coverage or previous studies, but were also regarded by experts as sufficiently relevant to the specific context of the Tehran Stock Exchange. This is important because the validity of machine-learning models depends not only on algorithm selection but also on the substantive quality of the input variables. The integration of expert judgment with computational screening therefore strengthened the conceptual foundation of the model. This approach is compatible with research emphasizing the value of combining domain knowledge with data-driven analysis in complex financial-detection problems (33, 34).

A particularly important quantitative finding was the severe imbalance between the non-fraudulent and potential-fraud classes. Only 3.1% of observations belonged to the minority class. This pattern is characteristic of many fraud-detection problems, where fraudulent events are comparatively rare but economically consequential. Under these circumstances, a model can achieve very high overall accuracy simply by predicting the majority class. The present study explicitly demonstrated this issue, as several models achieved accuracy levels above 0.96 despite performing poorly in identifying potential fraudulent observations. This finding strongly supports the argument that accuracy

alone is an inadequate evaluation criterion in imbalanced classification settings. Prior methodological research has similarly emphasized the importance of relying on precision, recall, F1-score, ROC, and AUC when the minority class is of central substantive interest (30, 31). Thus, the study's use of F1-score as the primary selection criterion was appropriate because it balanced sensitivity to fraud cases with the reliability of positive predictions.

The application of SMOTE only to the training dataset was another important methodological feature. By generating synthetic minority-class observations without modifying the test set, the study reduced majority-class bias while preserving an unbiased evaluation environment. This procedure is especially important because resampling before train-test separation can result in information leakage and artificially inflated performance estimates. The findings therefore provide a more realistic indication of how the algorithms might perform when applied to unseen company data. More broadly, the need to use balancing strategies confirms that fraud detection is not simply a conventional classification problem but an imbalanced-learning problem requiring specialized preprocessing and evaluation procedures.

The comparison between supervised and unsupervised learning provided one of the clearest findings of the study. Supervised algorithms significantly outperformed unsupervised methods, and the Mann–Whitney U test confirmed that the difference in F1-score performance between the two groups was statistically significant. This result is consistent with the conceptual distinction between these approaches. Supervised models use labeled observations during training and can therefore learn direct associations between known fraud status and the selected financial and media-related features (20, 21). By contrast, unsupervised methods identify clusters or anomalous structures without using target labels and may therefore be less effective when fraudulent and non-fraudulent observations overlap substantially in feature space (24). The current PCA and t-SNE visualizations showed exactly such overlap, providing a plausible explanation for the weak performance of the unsupervised models.

The results are also consistent with previous fraud-detection studies showing that supervised learning can provide strong discriminatory performance when labeled fraud cases are available. Research using supervised machine-learning methods for credit-card fraud has demonstrated that these algorithms can identify complex patterns associated with minority-class events (22). Similar comparisons of supervised and unsupervised models have also found that supervised approaches often perform better when reliable labeled examples exist (25). Moreover, comparative work in blockchain fraud detection has reinforced the value of supervised classification in distinguishing fraudulent transactions from legitimate observations (23). The present study extends this evidence from transaction-level fraud detection to firm-level financial-fraud prediction in a capital-market environment.

Among the supervised models, logistic regression emerged as the strongest overall classifier. Its recall of approximately 0.768 indicates that it correctly identified more than three quarters of potential fraudulent observations, while its AUC of 0.871 indicates strong overall class discrimination. Its F1-score also exceeded that of the other evaluated algorithms. This finding is important because logistic regression is relatively parsimonious and interpretable compared with more complex machine-learning approaches. In applications such as financial regulation and audit risk assessment, interpretability is highly valuable because decision-makers must often explain why a firm has been categorized as high risk. Although contemporary fraud research increasingly employs neural networks, deep learning, and hybrid models (3, 27-29), the present results show that algorithmic complexity does not necessarily guarantee superior performance.

The relatively strong performance of the support vector classifier also deserves attention. Pairwise Wilcoxon comparisons showed that the difference between logistic regression and the support vector classifier was not statistically significant. This indicates that the two models performed at broadly comparable levels, although logistic regression achieved the highest mean F1-score. The finding suggests that the predictive relationships among the selected variables may be captured effectively by both probabilistic linear classification and margin-based classification. At the same time, the comparatively weaker performance of decision trees, random forests, gradient boosting, K-nearest neighbors, Gaussian naïve Bayes, and the multilayer perceptron indicates that the structure of the current dataset may favor models capable of achieving stable decision boundaries under limited minority-class information.

The relatively poor results of the unsupervised models are also understandable in light of the visual overlap observed in PCA and t-SNE space. K-means, DBSCAN, agglomerative clustering, and Gaussian mixture modeling all produced very low recall and F1-scores. This suggests that the potential-fraud observations did not form a clearly distinct natural cluster that could be isolated without labels. This result is consistent with the general principle that unsupervised learning is most effective when meaningful latent structure or anomaly patterns are sufficiently distinct in the input space (24). In corporate fraud, however, fraudulent firms may intentionally mimic normal reporting behavior, making them difficult to separate through clustering alone. This interpretation also accords with evidence that fraud detection often requires subtle combinations of financial, textual, and governance indicators rather than reliance on simple structural outliers (4, 5).

The role of media-related information is particularly important in this context because such information can capture signals beyond the formal financial statements. Previous studies have shown that media reports can be used directly to detect and forecast corporate fraud (15), while social media can constrain corporate misconduct by increasing transparency and external scrutiny (11). Social-media information has also been found useful for financial-risk prediction (14). In addition, case-based research has shown that corporate fraud can sometimes be detected through patterns emerging from social-media content before conventional mechanisms fully identify the problem (12). The present findings therefore strengthen the argument that analytical media can function as part of a broader early-warning infrastructure in capital markets.

At the same time, media signals must be interpreted cautiously. Media coverage is influenced by framing, visibility, institutional context, and editorial judgment. Research on the Wirecard scandal has demonstrated that media narratives may both reveal and obscure aspects of corporate fraud (17). Similarly, political and institutional biases can affect the way fraud and corruption are framed publicly (18). Therefore, the value of the present model lies not in treating media attention itself as evidence of fraud, but in systematically extracting recurring, theoretically grounded indicators from media content and testing whether those indicators improve predictive discrimination. This distinction is crucial for avoiding false accusations and preserving the analytical rather than accusatory function of media-based fraud prediction.

The findings also have relevance for the Iranian capital-market environment, where information asymmetry and macroeconomic uncertainty may heighten the importance of supplementary information channels. Previous research has shown that market behavior in Iran is sensitive to information type, information symmetry, and broader economic conditions (35, 36). Therefore, integrating structured media signals with financial information may be particularly valuable in the Tehran Stock Exchange. In this setting, analytical-media reports can potentially

complement corporate disclosures by directing attention toward unusual changes in liquidity, leverage, customer dependence, managerial compensation, related-party dealings, or audit conditions.

Overall, the study demonstrates that media-related indicators can be systematically transformed into quantitative predictors of financial-fraud likelihood and that supervised machine-learning models are more effective than unsupervised alternatives in exploiting these signals. The superiority of logistic regression, together with the comparable performance of the support vector classifier, indicates that relatively interpretable supervised models may provide substantial practical value in highly imbalanced corporate fraud datasets. These findings contribute to the literature by linking media monitoring, financial red flags, expert validation, and algorithmic prediction within a single analytical framework.

This study has several limitations. First, the analysis was limited to companies listed on the Tehran Stock Exchange and therefore reflects the institutional, regulatory, economic, and information environment of a single capital market. Second, fraud status was operationalized as the likelihood of fraud based on the modified Beneish model rather than confirmed judicial or regulatory findings of fraud, meaning that the target variable represents a risk classification rather than definitive evidence of misconduct. Third, although data were collected from multiple official news websites and selected Telegram channels, some relevant information may have appeared in other digital platforms, informal networks, analyst reports, or restricted-access sources that were not included. Fourth, the extreme class imbalance reduced the number of observed potential-fraud cases available for training and evaluation. Although SMOTE and repeated cross-validation were used to address this issue, synthetic balancing cannot fully substitute for a larger number of genuine minority-class observations. Finally, the predictive criteria were operationalized at the firm-year level, and the study did not explicitly model the temporal sequence between media signals and subsequent changes in fraud risk.

Future studies should replicate the proposed framework in other stock exchanges and compare its performance across developed, emerging, and frontier markets. Longitudinal designs could also examine whether changes in media signals predict fraud risk several months or years before conventional accounting indicators become abnormal. Researchers should consider incorporating additional sources such as analyst reports, financial forums, corporate social-media accounts, regulatory announcements, and investor sentiment data. Future work may also test advanced natural language processing methods, transformer-based models, ensemble techniques, and hybrid architectures that integrate textual and numerical data directly rather than converting media content into predefined indicators. Larger datasets containing confirmed fraud cases would allow more precise comparison of sampling strategies and cost-sensitive learning techniques. In addition, future research could investigate feature importance, explainable artificial intelligence, calibration, and temporal validation to determine not only which model performs best but also why particular firms are classified as high risk.

Capital-market regulators, auditors, institutional investors, and financial analysts can use the validated media-related criteria as complementary early-warning indicators when prioritizing companies for closer examination. Regulatory bodies could develop monitoring dashboards that automatically collect and classify relevant financial-media content and combine these signals with accounting and governance data. Audit firms may incorporate media-derived risk indicators into preliminary fraud-risk assessments and client acceptance or continuance procedures. Investors and analysts can also use model outputs as screening tools rather than definitive judgments, directing more detailed fundamental analysis toward firms exhibiting elevated predicted risk. Because logistic regression provided the strongest and most interpretable overall performance, it may be especially suitable for initial

implementation in practical monitoring systems, while support vector classification can serve as a benchmark or complementary model for validating high-risk classifications.

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Authors' Contributions

All authors equally contributed to this study.

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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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