Identifying Causal, Contextual, and Intervening Factors Influencing the Likelihood of Financial Fraud in Companies

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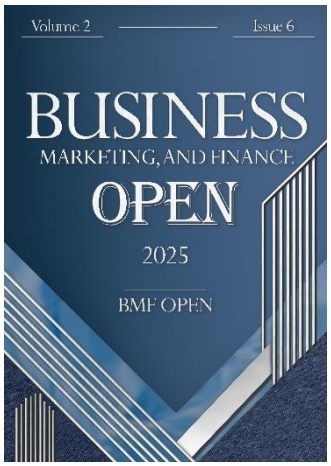

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Abstract: Today, given the increasing need of managers for accurate financial information to make managerial decisions regarding the long-term prospects of companies, and the need to attract domestic and foreign investors for capital funding and competition in this domain, financial reporting has gained special importance. At times, financial reporting may fail to provide accurate information to stakeholders, which can result either from accountants' mistakes or from fraudulent reporting by managers. Fraudulent managerial reporting in financial statements poses a significant threat to investors. However, in practice, there is no immediate method to detect such fraudulent managerial reporting. Therefore, paying attention to direct indicators affecting the likelihood of fraud in financial reporting is essential. Accordingly, this study aimed to identify the causal, contextual, and intervening factors that influence the likelihood of financial fraud in companies listed on the Tehran Stock Exchange. The present research adopts a qualitative and exploratory approach. According to the research methodology, dimensions, components, and indicators affecting the likelihood of financial fraud in companies were first extracted through interviews. Using the Delphi method, eight dimensions and 39 indicators were identified and agreed upon by experts. The results of this study showed that the dimensions of weak earnings-based characteristics, weaknesses in financial reporting, weaknesses in board characteristics, weaknesses in internal controls, weaknesses in corporate governance systems, weaknesses in financial features, and corporate characteristics affect the likelihood of financial fraud in companies. These dimensions were derived through theoretical studies, synthesizing expert opinions in the field of accounting and auditing, analyzing the views of the statistical population, and gathering insights from specialists in related research domains.

Keywords: Fraud, Financial Reporting, Fraudulent Financial Reporting.

1. Introduction

In the contemporary landscape of financial and corporate management, accurate and transparent financial reporting serves as a cornerstone for informed economic decision-making. Financial statements provide critical insights into a firm's financial health, performance, and future prospects, making them a key source of information for stakeholders including investors, creditors, and regulatory agencies. However, despite the regulatory frameworks and audit mechanisms in place, the prevalence of fraudulent financial reporting continues to be a significant threat to the integrity of capital markets and corporate governance systems. The increasing complexity of financial transactions, combined with managerial incentives and opportunities to manipulate reports, has

prompted scholars and practitioners alike to explore the underlying drivers and mechanisms of financial fraud more systematically [1].

The motivations for fraudulent reporting often stem from intense pressure to meet performance targets, maintain investor confidence, or avoid negative market reactions. Such pressures can lead managers to exploit discretionary accounting practices, manipulate accruals, or engage in more overt misstatements. According to the fraud diamond model, four dimensions—pressure, opportunity, rationalization, and capability—interact to create a conducive environment for fraud [2]. This multidimensionality of fraud risk complicates the detection process and underscores the need for deeper analytical approaches in understanding how and why financial fraud occurs. It is particularly important in the context of emerging and developing markets, where regulatory oversight may be weaker or inconsistently enforced [3].

Numerous high-profile corporate scandals in the early 2000s, including Enron and WorldCom, have revealed not only the devastating economic consequences of fraudulent reporting but also the failure of traditional audit systems to detect and prevent it. These cases have led to widespread concern about the *quality* and *transparency* of accounting information and have prompted an increase in academic investigations into both detection techniques and the socio-organizational factors underlying fraud [4]. As noted by [5], even when enforcement actions are taken, the lack of initial detection undermines investor trust and corporate valuation, contributing to systemic instability in financial markets.

To address these challenges, researchers have increasingly turned to forensic accounting frameworks and data-driven techniques that go beyond traditional audit methods. For example, [6] highlights the role of deep learning algorithms in detecting financial anomalies that are indicative of manipulation or fraud. The integration of artificial intelligence (AI) and machine learning into auditing and fraud detection processes has demonstrated promising results, especially in improving the precision and recall of fraud identification models [7, 8]. These innovations are instrumental in moving from reactive to proactive fraud prevention strategies.

Furthermore, scholars have emphasized the need to identify causal, contextual, and intervening variables that influence the likelihood of fraud. [9] argue that while machine learning tools are efficient in flagging anomalies, understanding the human and institutional factors—such as managerial overconfidence, weak governance structures, and inadequate internal controls—is essential for holistic fraud prevention. These internal behavioral and structural weaknesses often create fertile ground for fraudulent financial reporting, particularly in companies under financial or reputational stress [10].

Among these factors, the role of corporate governance has attracted significant attention. Weak boards of directors, concentrated ownership structures, and role conflicts between the CEO and board chair have been repeatedly identified as enablers of fraudulent activity [11]. Additionally, ineffective internal audit mechanisms, lack of transparency, and poor regulatory enforcement further amplify the risk of misreporting [12]. These findings suggest that preventing financial fraud requires a systemic approach that integrates governance reform, financial oversight, and technological advancement.

In this context, financial data analysis has emerged as a key tool in the early detection and prevention of fraud. [13] employed data mining methods to identify patterns associated with financial misreporting, demonstrating that predictive analytics can significantly reduce the time and cost associated with traditional auditing. Likewise, the use of big data analytics, as discussed by [14], enables auditors to process massive volumes of structured and unstructured financial information, thereby increasing their ability to detect irregularities that may otherwise go unnoticed.

Nevertheless, while technology provides valuable support, it cannot substitute for structural and ethical safeguards. [15] emphasize that fraud detection must be embedded within a broader culture of accountability and compliance, supported by institutional mechanisms such as whistleblower protections, audit committee independence, and professional skepticism among auditors. The effectiveness of these institutional safeguards is often contingent upon the broader socio-economic environment and organizational culture [16].

In the Iranian context, fraudulent financial reporting has been associated with both internal and external pressures. According to [17], financial fraud in Iran is often facilitated by the opacity of organizational operations, the lack of forensic accounting standards, and the limited application of preventive monitoring mechanisms. These structural challenges are compounded by behavioral factors, such as executive narcissism and managerial opportunism, which create conditions ripe for manipulation and concealment [18].

To improve detection and prevention in such environments, hybrid models that combine qualitative and quantitative methods have proven effective. For example, [19] optimized the Beneish M-score model using neural networks and genetic algorithms, significantly enhancing the model's ability to predict financial restatements. Similarly, [20] identified the most influential financial indicators contributing to fraud risk using statistical feature selection, thereby streamlining the detection process.

These findings point to the necessity of a multidimensional approach to studying financial fraud. Integrating behavioral, structural, technological, and regulatory perspectives can help researchers and practitioners understand not only how fraud is committed, but also how it can be systematically mitigated. The current study contributes to this body of knowledge by adopting a qualitative, exploratory approach to identify causal, contextual, and intervening factors affecting the probability of financial fraud in companies listed on the Tehran Stock Exchange. Using in-depth interviews with financial executives, auditors, and academic experts, followed by a systematic coding process, this research seeks to map the complex interplay of variables that contribute to financial misreporting and propose a conceptual framework for proactive fraud risk management.

Ultimately, by drawing on both theoretical insights and practical experiences, the present study aims to support policymakers, auditors, and corporate leaders in designing more robust mechanisms for early fraud detection and ethical financial governance.

2. Methodology

The present study is exploratory in nature regarding its research approach. Data collection in this study was conducted in multiple steps.

In the first step, in-depth semi-structured interviews were conducted with professional experts.

In the second step, a three-stage coding process was applied:

1. **Open Coding**: This stage involves the process of breaking down, comparing, conceptualizing, and categorizing data.
2. **Axial Coding**: This stage includes a set of procedures performed after open coding to establish connections among categories by relating them to each other in new ways.
3. **Selective Coding**: This stage involves the process of systematically selecting the core category, relating it to other categories, validating the relationships, and filling in gaps with categories that need refinement or expansion.

After identifying the factors affecting the likelihood of financial fraud in companies from different perspectives and establishing relationships between categories at different levels using conditional path mapping, the axial coding stage was concluded.

The statistical population includes a group of individuals or elements that share at least one common characteristic and may be studied for research purposes. The scope of any target population is defined by the researcher according to the objective of the study. Clearly, the definition of the population is based on the research objective, by selecting one or more key shared characteristics among its members. The population studied in the interview section of this study included company managers, auditing firm managers, and academic experts with professional backgrounds related to financial accounting and auditing.

Sampling in this study began using purposive sampling, as per the process in qualitative research, and continued through theoretical sampling. Accordingly, we initially selected individuals who were rich in relevant information about financial fraud and could contribute to understanding the research problem and central phenomenon. Sampling continued until theoretical saturation was achieved—when no new information emerged that added to the identified categories or the emerging theory.

In this study, theoretical saturation was approximately confirmed after interviewing 25 participants. However, to ensure greater confidence and to fill conceptual gaps in the proposed model, interviews were conducted with 7 additional experts. Thus, the total number of participants reached 32.

3. Findings and Results

The results of the coding process are presented in Table (1).

Table 1. Results of Coding in the Form of Identified Causal, Contextual, and Intervening Factors

Condition	Category	Variable
Causal	Managerial Behavioral Tendencies	Overconfidence of Managers
		Managerial Short-sightedness
		Managerial Narcissism
	Weakness in Earnings-Based Attributes	Earnings Management
		Income Smoothing
		Earnings Predictability
		Accrual Quality
	Weakness in Financial Reporting	Ambiguity in Financial Reporting
		Low Financial Reporting Quality
		Inadequate Disclosure of Information
		High Information Asymmetry
		Budgeting Goals Beyond Growth/Profit Capacity
Contextual	Weakness in Board Characteristics	Insufficient Use of Non-Executive Members
		Inadequate Use of Financially Literate Members
		Lack of Separation Between CEO and Chair Roles
	Weakness in Internal Controls	Noncompliance with Internal Controls
		Lack of Internal Audit Unit
		Inefficiency and Ineffectiveness of Controls
		Noncompliance with Laws and Regulations
		Lack of Asset Protection
		Weak Independent Auditing
Intervening	Weakness in Corporate Governance	Related Party Transactions
		CEO Tenure
		Ownership Concentration

	CEO Dominance
	Agency Problems
	Management-Ownership Conflict
	Lack of Information Transparency
	Lack of Managerial Accountability
	Lack of Managerial Responsibility
	Lack of Stakeholder Participation in Decision-Making
Weakness in Financial Characteristics	Excessive Use of Assets to Repay Liabilities
	High Operating Leverage
	Capital Structure
	Low Asset Growth Rate
	Low Asset Liquidity
Corporate Characteristics	Ambiguity in Going Concern
	Lack of Preventive and Punitive Regulations
	Likelihood of Financial Distress

The results of the coding process revealed several causal conditions that contribute to the likelihood of financial fraud in companies. Key among these were behavioral tendencies of managers, including overconfidence, short-sightedness, and narcissism, which can lead to unethical decision-making. In addition, weaknesses in earnings-based characteristics were identified, such as earnings management, income smoothing, low predictability of earnings, and poor accrual quality—all of which distort financial realities. Furthermore, deficiencies in financial reporting practices, including ambiguity, low-quality reporting, inadequate disclosure, high information asymmetry, and unrealistic budgeting targets, were found to increase the risk of fraudulent behavior.

In terms of contextual conditions, structural weaknesses within organizations were prominent. Specifically, deficiencies in board characteristics—such as insufficient non-executive or financially literate members and lack of role separation between CEO and board chair—contributed to ineffective oversight. Similarly, internal control failures, such as noncompliance with internal control procedures, absence of internal audit units, inefficiency in control execution, regulatory noncompliance, asset protection failures, and weak independent auditing, were cited as significant enablers of fraud. These contextual vulnerabilities create an environment where fraudulent reporting becomes more feasible due to lack of checks and balances.

The analysis also identified critical intervening conditions related to systemic and financial governance weaknesses. Poor corporate governance practices, including excessive related-party transactions, long CEO tenure, ownership concentration, CEO dominance, agency conflicts, management-ownership frictions, lack of transparency, managerial unaccountability, and low stakeholder participation, were found to exacerbate fraud risk. Additionally, weak financial characteristics—such as excessive use of assets to settle debts, high operational leverage, unstable capital structure, low asset growth, and liquidity challenges—create financial pressures that may motivate fraudulent reporting. Finally, general corporate conditions like ambiguity about going concern status, absence of deterrent regulations, and heightened likelihood of financial distress were also found to significantly increase the risk of financial fraud.

4. Discussion and Conclusion

The findings of this study provide a comprehensive framework for understanding the multifaceted nature of financial fraud risk in publicly listed companies by identifying causal, contextual, and intervening factors influencing its occurrence. Through semi-structured interviews and systematic coding, the results revealed that

behavioral traits of managers, such as overconfidence, short-sightedness, and narcissism, significantly contribute to financial misreporting. These behavioral inclinations often drive aggressive earnings management, income smoothing, and other manipulative accounting practices. These observations are consistent with prior studies highlighting managerial behavioral traits as root causes of fraudulent behavior. For instance, [2] emphasized that capability and rationalization, as part of the fraud diamond model, enable managers to justify unethical practices, especially under performance pressure. Similarly, [3] identified executive personality and opportunistic tendencies as strong predictors of fraudulent financial behavior in organizations lacking oversight.

Weaknesses in earnings-based characteristics—particularly aggressive earnings management, low predictability of profits, and poor quality of accruals—were also confirmed as key causal drivers of fraud. These findings align with [20], who demonstrated that volatility in earnings indicators is highly correlated with financial fraud detection. In parallel, [19] advanced these insights by refining fraud detection models based on anomalies in earnings data, further validating the significance of profit-based indicators. Furthermore, the study identified ambiguities and deficiencies in financial reporting practices—such as low-quality disclosure, information asymmetry, and unrealistic budgeting targets—as strong enablers of manipulation. These mirror the insights of [13], who concluded that such distortions often arise from managerial manipulation in the absence of strong deterrents and accurate monitoring tools.

From a contextual perspective, structural and procedural weaknesses within organizations were revealed to be pivotal in enabling fraudulent reporting. Weaknesses in board composition—such as lack of independent members and insufficient financial expertise—were repeatedly noted by participants. These align with the findings of [11], who stressed that a weak board is less capable of monitoring executives, thereby increasing the risk of fraud. Similarly, ineffective internal control systems were highlighted, including the absence of internal audit units, lack of regulatory compliance, and inefficient safeguarding of assets. This is in line with [14], who argued that without robust internal control frameworks and evidence-gathering mechanisms, auditors are often unable to detect or deter fraud in real-time.

Intervening conditions such as weak corporate governance, concentrated ownership, and executive dominance were also shown to significantly influence the likelihood of fraudulent financial reporting. Respondents emphasized that a long CEO tenure, role duality, and low stakeholder participation in decision-making often erode transparency and accountability. These findings are reinforced by [12], whose meta-analysis confirmed that discretionary accruals and fraudulent behavior increase in firms with entrenched leadership and poor governance practices. In addition, this study found that financial stress indicators—including excessive use of assets for debt settlement, high leverage, and poor liquidity—were associated with greater fraud risk. This supports the work of [17], who utilized fuzzy ANP methods to prioritize financial constraints as catalysts for fraudulent decision-making, particularly in times of economic uncertainty.

The inclusion of corporate characteristics such as ambiguity in going concern assumptions and the absence of deterrent legal frameworks was a novel contribution of this study. These findings underscore that systemic issues—such as regulatory inefficiencies and judicial gaps—are integral to understanding fraud risk. As [16] observed, systemic corruption or weak institutional enforcement creates conditions where unethical behavior becomes normalized. Similarly, [10] cautioned that fraud is no longer limited to isolated behavior but is embedded in wider organizational cultures where managerial impunity is prevalent.

Importantly, the qualitative approach adopted in this study added depth to the understanding of how these factors interrelate in practice. Theoretical saturation was reached through interviews with a diverse group of

experts including corporate executives, auditors, and academics, providing a triangulated view of fraud dynamics. This methodological rigor complements the more data-driven approaches of previous studies. For example, [6] demonstrated how deep learning models can predict fraud based on patterns, while [7] emphasized the transformative power of AI in detecting financial anomalies. However, our findings affirm that such tools must be complemented by organizational reforms and behavioral safeguards to be truly effective.

Another insight that emerged was the dynamic interaction between human behavior and structural enablers. Overconfident or narcissistic executives are not inherently fraudulent, but in environments with poor governance, high performance pressure, and weak accountability, the probability of misreporting increases. This interaction echoes [9], who found that psychological and institutional variables jointly influence fraudulent outcomes. Moreover, [15] stressed that unless fraud prevention is embedded within a culture of compliance and transparency, technological tools alone will be insufficient.

Furthermore, the findings of this study underscore the limitations of relying solely on conventional audits to detect fraud. [5] showed that enforcement actions often come after substantial damage is done, and even then, firms may obscure the extent of wrongdoing. Our respondents echoed this concern, noting that auditors often lack the authority, data access, or independence required to identify subtle but impactful manipulations. Hence, echoing [8], this research advocates for proactive, real-time fraud detection systems backed by integrated data platforms and ethical governance models.

The study also holds practical implications for regulatory bodies and audit committees. By mapping the pathways through which causal, contextual, and intervening variables influence fraudulent outcomes, it provides a framework for designing targeted interventions. For example, enhancing the independence of boards, mandating internal audit functions, and instituting whistleblower protections could directly reduce the enabling conditions for fraud. These measures, as advocated by [18], are particularly vital in high-risk environments where external oversight is weak or compromised.

Lastly, the research contributes to forensic accounting by offering a model that identifies and categorizes key risk indicators through qualitative inquiry. As noted by [1], forensic frameworks that integrate behavioral cues with structural red flags enhance the predictive power of fraud detection efforts. By offering such a layered understanding, this study not only complements but also extends prior quantitative research, paving the way for hybrid models that can better capture the complexity of financial fraud in practice.

This study is not without limitations. First, the reliance on qualitative interviews, while providing in-depth insights, limits the generalizability of the findings. The results are shaped by the experiences and perceptions of 32 participants within a specific national and regulatory context (i.e., the Tehran Stock Exchange), which may not be entirely transferable to other settings. Second, there may be biases in expert selection and respondent recall, as some participants might underreport or overemphasize certain factors based on professional or institutional perspectives. Finally, while efforts were made to achieve theoretical saturation, there remains a possibility that additional variables could emerge in other contexts or industries.

Future research could build on the current findings by adopting a mixed-methods approach that integrates qualitative insights with quantitative validation. Large-scale surveys or structural equation modeling could help test the relationships among the identified variables across industries and jurisdictions. Additionally, longitudinal studies would provide insights into how fraud risk factors evolve over time, particularly in response to regulatory reforms or macroeconomic changes. Researchers should also consider exploring the psychological and ethical training of corporate leaders as a mitigating factor in fraud prevention.

Practitioners should prioritize establishing comprehensive fraud risk management frameworks that incorporate behavioral, structural, and technological dimensions. Audit committees must be equipped with advanced analytical tools and training to identify red flags early. Regulatory bodies should strengthen oversight mechanisms, ensure board independence, and promote transparency in financial reporting. Moreover, firms should foster a culture of ethics and accountability through leadership development programs, internal audits, and active stakeholder engagement to reduce the risk of financial misreporting.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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