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Identifying Factors Affecting on Managers' Fraudulent Reporting and Providing a Model for its Prediction by Using of Artificial Intelligence Algorithms

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ABSTRACT

The present study has analyzed the identification of factors affecting fraudulent reporting by managers and providing a model for its prediction using artificial intelligence algorithms. In terms of approach, this research is exploratory in the qualitative part and descriptive-causal in the quantitative part. In order to achieve the research objectives, first, using theoretical foundations and opinions of experts in the field, the dimensions, components, and indicators affecting fraudulent reporting by managers were extracted and, using the Delphi method, 7 dimensions (including organizational factors, weak corporate governance, inappropriate information disclosure, poor earnings information content, poor financial performance, inefficient board of directors, and high risk-taking) and 26 components were identified and agreed upon. The statistical population of this study was all certified public accountants in Iran, and the required data were collected by distributing a researcher-made questionnaire among 338 people. After that, Inferential statistical methods such as t-test and structural equation modeling using SmartPLS were used to analyze the data. The first result of this research is the identification of dimensions and components affecting managers' fraudulent reporting, which was achieved by using theoretical studies, summarizing the opinions of accounting and auditing experts, analyzing the opinions of the statistical community, and receiving the opinions of experts in fields related to the research. The findings related to artificial intelligence algorithms stated that in general, Bayesian network algorithms, SVM algorithm, and RBF kernel algorithm have the ability to predict fraudulent reporting. Also, based on the findings of the Bayesian network algorithm; the variable of not using modern criteria has the highest predictive power and the variable of increasing capital cost has the lowest predictive power of managers' fraudulent reporting. The findings of the SVM algorithm; It was stated that lack of attention to employee productivity management has the highest power and low stock liquidity has the lowest power to predict fraudulent reporting by managers. Based on the RBF kernel algorithm, risk-based factors have the highest power and organizational factors have the lowest power to predict fraudulent reporting by managers.

Keywords: fraud, financial reporting, fraudulent financial reporting, artificial intelligence, Bayesian network algorithm, SVM algorithm, RBF kernel algorithm

1. Introduction

Today, given the increasing need of managers for accurate financial information to make management decisions about the long-term horizon of the company and the need to attract domestic and foreign investors to provide capital and compete on this issue; financial reports have become particularly important. Sometimes, financial reporting may not provide individuals with accurate information, which can be due to accountants' mistakes or fraudulent reporting by managers. One of the basic goals of establishing accounting standards is that users can make relatively relevant and correct decisions based on financial statements (Jingyu et al., 2024). Therefore, the accounting profession needs a type of reporting method that meets the interests of all users in a desirable manner; but as can be seen from the definition of fraudulent reporting, managers report earningss in a way that is inconsistent with the aim of meeting the general interests of users in order to achieve specific goals that logically serve the interests of certain groups. Several studies show that the amount of compensation creates a greater incentive for board members to manipulate earnings, and the model presented in such studies shows fraudulent reporting as a function of the amount of compensation (Kaveh et al., 1403). On the other hand, some other studies have shown that managers use fraudulent reporting tools to obtain the maximum amount of their incentive compensation, which is determined by the reported earnings. The interpretation of these researchers based on the results of the research suggests that managers, through their freedom of action, manage reported earnings and thus increase their compensation (Chen et al., 2024). In recent years, due to the financial crises in companies, fraud in financial reporting and accounting has grown significantly; Fraud has become a political and economic issue, and today, legislative bodies have paid special attention to the accounting and management professions due to the creation of fraud and ways to deal with fraudulent behavior in financial reports. Fraud has broad legal implications; but it is generally a deliberate action to obtain unfair and illegal benefits. Violation is also misconduct that is referred to as violating laws, regulations, internal procedures of the organization and disregarding market expectations of ethical behavior in business (Jonathan, 2024).

Research Problem Statement

Fraudulent reporting by managers in financial reports is a major threat to investors. However, in practice; there is no method for immediately detecting fraudulent reporting by managers. Therefore, it is very necessary to pay attention to the criteria that directly affect fraud in financial reporting. Theoretically, in addition to traditional criteria for identifying the possibility of fraud, which are generally quantitative criteria; Qualitative criteria can also be useful in detecting the possibility of fraud (Babaei et al., 1400). In order to show the importance of earnings as one of the most important performance evaluation criteria and determinant of company value, researchers and practitioners in the accounting profession inevitably evaluate the earnings reported by economic units. A concept called financial reporting quality is used to evaluate this earnings. In various articles, in defining the concept of financial reporting quality, two characteristics have been mentioned to determine the quality of financial reporting: one of them is decision-making usefulness and the other is reporting reliability. In other words, financial reporting quality is the honest statement of reported earnings, earnings (Sheikhzadeh Abkenar, 1403). That is, high financial reporting quality indicates the usefulness of earnings information for users' decision-making and also its greater compliance with Hicks' economic earnings. However, because people use information in different decisions, it is not possible to provide a comprehensive definition of earnings (Norouzi, 2015). Some financial analysts consider the quality of financial reporting as a regular and continuous earnings, repeatable and generating cash flow from operations. They believe that the quality of financial reporting is a figure between reported net earnings and cash flow from operations minus non-recurring figures. So far, financial experts have not been able to achieve an independent calculation of earnings that they consider to have the necessary quality. In this case, financial experts can achieve a range that more accurately reflects the quality of financial reporting than reported net earnings by making appropriate adjustments. Therefore, the concept of financial reporting quality is not a fixed definition that can be achieved. Rather, it is a relative concept that depends on its relationship with views and attitudes. More generally, the quality of financial reporting is of interest to those who use financial reports for investment decisions and the conclusion of various contracts. In addition, it can be said that from the perspective of standard setters, the quality of financial reports indirectly reflects the quality of financial reporting standards (Hashemi-Behrman et al., 1403).

In this direction; Financial reporting is considered an important source of information for economic decision-making, the purpose of which is to represent summarized and classified information about the financial position, financial performance and financial flexibility of the business unit. Fraud in financial reporting and accounting has grown significantly in recent years. With the emergence of financial crises in companies such as Enron, Global Crossing and WorldCom, the issue of fraud in financial reporting has also entered the political arena. Today, legislative bodies, the accounting profession and management have paid special attention to the causes of fraud and ways to prevent fraudulent behavior in financial reporting. Distortion of financial statements includes the manipulation of their constituent elements by overstating assets, sales and earningss or understating liabilities, expenses and losses. Detecting fraud in financial statements is not an easy task, because fraud is caused by many factors and can be applied in different ways. It should be noted that a series of corporate scandals around the world have damaged confidence in financial statements and left doubts in the minds of investors, which has led to a loss of investor confidence in various companies. For example, Enron, WorldCom, and Xerox in developed countries sought to attract investors due to lack of capital (Chen et al., 2024). Based on the design of these theoretical foundations, the question arises: what factors affect fraudulent reporting by managers?

Financial statement information must be useful in the decision-making process, and usefulness requires having two characteristics: relevance and reliability. Since this information is prepared with the opinion and responsibility of the company's management, it cannot meet the needs of various users with impartiality and acceptable reliability, and many estimates, judgments, and personal opinions are also applied in the process of identifying, measuring, and reporting information (Asha and Suresh, 2021).

Therefore, these statements cannot be free from errors or intentional distortions. In recent years, after the financial and accounting scandals of large Western companies such as Enron, WorldCom, Xerox, and Merck were revealed, it became clear that the managers of these companies had been painting better pictures of the company for many years, which has raised fundamental doubts about the "quality" and "transparency" of accounting and auditing information (Richard, 2020). In the current era, technological advances and widespread changes in the business environment have caused an increasing acceleration in the economy, and due to the increasing competition of institutions, achieving expected income has also been limited, so the scope for fraud is increasing day by day. Financial reporting is an important source of information for economic decision-making, and managers, investors, creditors, and other users use it to meet their information needs. However, over the past few decades, fraud discovered in corporate financial reports has caused severe fluctuations in the capital markets of different countries (Sheikhzadeh Abkenar et al., 1403).

These frauds have had a negative impact on capital markets and have caused the loss of public confidence in investment. Fraud in financial reports can have a destructive effect on corporate financial reports to the point that the nature of the companies is at risk. In defining fraud; Duffield and Grabowski in an article titled "The Psychology of Fraud", have defined fraud as obtaining something of value or avoiding an obligation by deception and trickery. Therefore, the common thread of all frauds is the intention to deceive in order to achieve personal gain. In this regard, fraud is different from "mistake" due to "intent to deceive". Also, according to the Fraud Statement in England and Wales in 2006; fraud basically involves the use of deception for personal gain or harm to another. In the financial field, various forms of fraud can be observed, including fraudulent financial statements, employee, vendor, customer fraud, investment fraud, bankruptcy fraud, and similar examples (Jonathan, 2024). Continuing the path, accounting fraud can also be defined as intentional deceptive acts in the process of producing company accounting information in order to gain illegal or unfair earnings. Fraud is considered a very important issue because it is covert in nature, undermines public trust, is a pervasive and global issue, and will have many negative financial and non-financial consequences. Today, many efforts have been made to measure the true extent of fraud in the world; but it is not easy to collect acceptable statistics on fraud. The majority of frauds are not detected, and even when fraud is detected, it may not be reported. The reason for this is that a company that is a victim of fraud may not want to have a tarnished image among the public (Yuezhen et al., 2019).

In the field of predicting factors affecting fraud in financial reporting; more accurate prediction of the risk of fraud in financial reporting will increase the ability to prevent and detect it. The issue of fraud, bankruptcy and failure of companies has always been a complex and noteworthy issue. In today's world where unlimited human desires and demands are faced with limited economic resources, the rise and fall of any phenomenon is rooted in the real and logical needs of human societies. The emergence of fraud in the field of professional accounting services cannot be an exception to this rule (Kavah et al., 1403). The increase in the number of frauds, distortions and restatements, which are often combined with the bankruptcy of large companies, has raised concerns about the quality of financial statements. For this reason, preventing or detecting significant errors and distortions in financial statements has always been the focus of attention of investors, legislators, managers and auditors, and accordingly, numerous standards and guidelines have been established regarding the responsibility of auditors in detecting fraud and distortions in financial statements. What has brought fraud and misconduct to everyone's attention is the costs that fraud imposes on society (Stijnkomp, 2018). Hence; identifying the factors affecting fraudulent reporting by managers shows its importance and necessity.

Research Questions

- What are the causal factors affecting fraudulent reporting by managers?
- What are the intervening factors affecting fraudulent reporting by managers?
- What are the contextual factors affecting fraudulent reporting by managers?
- What are the strategies for employing fraudulent reporting by managers?
- What are the consequences of fraudulent reporting by managers?
- Does the model presented in the qualitative section have sufficient validity to reflect the identification of factors affecting fraudulent reporting by managers?
- Does the Bayesian network algorithm have the ability to predict fraudulent reporting by managers?
- Does the SVM algorithm have the ability to predict fraudulent reporting by managers?
- Does the RBF kernel algorithm have the ability to predict fraudulent reporting by managers?

Research Method

The present research is exploratory in terms of approach in the qualitative section and descriptive-causal research in the quantitative section. Since the main purpose of this research is exploratory and fundamental and is in line with the development of a desirable framework, the appropriate type of research strategy for examining and researching this research is a hybrid or mixed research strategy. In the meantime, qualitative methods such as grounded theory are used. In general, the general research design in this research, considering the objectives, subject, and research approach; It is a combination of a sequential qualitative-quantitative approach in which qualitative data are collected and analyzed first, followed by quantitative data. The qualitative phase is usually given priority, and quantitative data is used to reinforce qualitative data.

Grounded data analysis and its research methods are one of the qualitative methodological approaches used in generating new theories. Grounded data analysis, or sometimes used interchangeably by researchers, is a qualitative method that enables the researcher to study a specific phenomenon or process and discover new theories based on this method, so that these theories are based on the analysis of real-world data. Grounded data research has an inductive approach in which new theories are extracted from the data. In this approach, data collection and analysis and theory development occur in a back-and-forth process, this process continues until more data does not add any more insight to generate a new theory (theoretical saturation).

Methods and tools for collecting information and data

Methods and tools for collecting information

In the present study, information is collected in several steps. In the first step, in order to examine the validity of the questionnaires, a semi-structured in-depth interview method will be used with professional elites. It should be noted that in a semi-structured interview; although the researcher has previously prepared the topics and titles necessary to cover the information; not all questions have been prepared in advance and the interview process relies largely on questions that arise spontaneously in the interaction between the interviewer and the interviewee. After the interview, the final questions will be designed and completed. All interviews will be conducted after necessary coordination with the eligible participants, at a place of their choice and by setting a time in advance in an environment of their choice. At the beginning and before the interview begins, the researcher will clarify the benefits of conducting this research. Then, according to the determined research objectives, the researcher will pose various types of possible questions based on the interview guide.

Data Collection Methods and Tools

In this step; coding will be done in three stages.

1) Open-Coding: It is the process of breaking down, comparing, conceptualizing, and categorizing data. The open-coding method not only leads to the discovery of categories but also clarifies their characteristics and dimensions.
2) Axial-Coding: It is a series of procedures that are carried out after open coding to establish links between categories and relate information to each other in new ways.
3) Selective-Coding: This is the process of systematically selecting a core category and relating it to other categories, validating the relationships, and filling in the gaps with categories that need to be refined and expanded.

The results of the coding are shown in Table 1.

Table (1): Results of the coding in the form of identifying causal, contextual and intervening factors

Variable	Category	Conditions
Lack of attention to employee talent management	Organizational factors	Causal
Lack of attention to employee productivity management		
Disregard for employee performance		
Ignoring the importance of human resource management		
Low reliability	Corporate Governance	
Existence of annual adjustments		
Transactions with related parties		
Ambiguity in financial reporting	Disclosure of information	
High information asymmetry		
Increased capital cost		
Low stock liquidity		
Low financial stability	Content of earnings information	Field
Low earnings quality		
High earnings smoothing		
High earnings management		
Lack of attention to innovative activities	Financial performance	
Not using new standards		
Low financial ratios		
Low use of financially literate members	Inefficient board of directors	Interventionist
Low use of non-commissioned members		
Not separating the role of the CEO from the role of the chairman of the board of directors		
Excessive CEO stability		
Discontinuity of activity	Risk - taking	
High capital structure		
High volatility of earningsability		
Environmental uncertainty		

Statistical population

The statistical population includes a set of members and elements that have at least one common characteristic and may be used for study and research, and the researcher tends to infer it within the scope of his research. The scope of each research community is also defined by the researcher based on the definition of the community. Obviously, the definition of the community is based on the purpose of the research, by selecting one or more important common characteristics that the members of that community have.

The importance of selecting these individuals is because only the most skilled and best accountants in the country can be members of the Society of Certified Public Accountants. The ability of certified public accountants as an expert and skilled financial officer has also been proven.

Statistical population in the qualitative section

In this study, the study community in the qualitative section includes experts related to the research topic. In this direction, the selected experts must meet the following conditions:

- Have at least 15 years of experience in accounting, auditing or management.
- Their field of study must be accounting or auditing at all levels of education.
- Be members of the Society of Certified Public Accountants.

Furthermore, the sampling of this study was started based on the qualitative research process or purposive sampling and continued with theoretical sampling. In this way, we first targeted individuals who were rich in information related to fraudulent reporting in relation to the current research topic and were able to be effective in understanding the research problem and the central phenomenon; then, sampling continued until theoretical saturation was reached (i.e., when the next sample did not add any new items to the emerging categories and emerging theory). In this study, after referring to 18 participants, theoretical saturation was somewhat confirmed for the researcher; but in order to achieve greater confidence and complete the conceptual gaps in the developed model; referring to 5 other elites was on the agenda and finally the total number of participants reached 23.

After determining the number of experts and conducting interviews regarding the identification of possible factors affecting managers' fraudulent reporting; The information and data required to prove the research hypotheses were extracted through the study of distributional questionnaires and SMARTPLS software was used to analyze them.

Statistical population in the quantitative section

In the quantitative section; the statistical population of this study included all certified auditors in the country and the statistical sample was selected using the random sampling method and the Cochran method. The Cochran formula is one of the statistical methods that is usually used in connection with the study of qualitative variables to determine the sample size. The sample size in this method is calculated as follows:

$$n = \frac{\frac{z^2 + pq}{d^2}}{1 + \frac{1}{n}} \left(\frac{z^2 + pq}{d^2} - 1\right)$$

In this formula:

N The size of the population includes all certified accountants in the country, 2819 people.

Statistic: p is the percentage of the distribution of the trait in the population, that is, the proportion of people who have the trait under study (0.5)

Statistic: q is the percentage of people who do not have the trait under study (0.5)

If the values of p and q are not known, their maximum value, that is, 0.5, should be used.

The statistic z=t and there is no problem if t is used instead of z. At a 5% error level, the value of z is 1.96 and Z2 is 3.8416.

The value of d is the difference between the actual proportion of the trait in the population and the researcher's estimate of the presence of that trait in the population. The accuracy of sampling depends on this factor and if the researcher's intention is to have the most accurate sampling, the maximum value of d is 5%. Accordingly, we will have:

$$n = \frac{2819 * 1.96^2 * (0.5 * 0.5)}{8293140 * 0.05^2 + 1.96^2(0.5 * 0.5)} \approx 338$$

Accordingly, 338 people were selected as a statistical sample and the required data was collected by distributing a researcher-made questionnaire among 338 people.

Research findings

Delphi analysis

According to the Delphi technique; First, each member of the group was given a questionnaire containing the desired sub-criteria. Then, 23 experts who were selected and familiar with all matters examined each indicator according to the Delphi method. For the initial screening of the identified indicators, the assigned scores ranged from 1 to 10, and indicators with a score of less than 7 were eliminated. The Delphi technique continued in 3 stages and was stopped in the third stage when a final agreement was reached.

The first stage of the fuzzy Delphi technique

The first stage in examining the experts' views is that the experts' views have been explained in the first round.

To summarize the data obtained from the first stage of the fuzzy Delphi, A¬m, which represents the average of the experts' views, is calculated.

$$A_m = (a^i_{m_1}, a^i_{m_2}, a^i_{m_3}) = (\frac{1}{n}\sum a_1^{[i]}, \frac{1}{n}\sum a_2^{[i]}, \frac{1}{n}\sum a_3^{[i]})$$

In the above relation, Am represents the average of the experts' views. The next step of defuzzification is the method of converting a fuzzy set into non-fuzzy values. In this research, the mean value method is used. The defuzzification value by the mean value method is equal to:

$$S(A)=1/2(S_L(A)+S_R(A))=1/2\left[(a_{2i}-\int_{a_{1i}}^{a_{2i}} f_{\tilde{A}}(x)) + (a_{2i}-\int_{a_{2i}}^{a_{3i}} f_{\tilde{A}}(x))\right] = \frac{a_{1i}+a_{2i}+a_{3i}}{4}$$

According to the collective agreement of the experts; no factor was eliminated and all these indicators have an average fuzzy score higher than 7 or in other words, they are indicators that the experts have a strong tendency to influence.

The second stage of the Fuzzy Delphi Technique

The first stage in examining the experts' views is shown as follows. The average of the experts' views and defuzzification in the second stage are given in Table (3).

Table (2): Average of experts' views and defuzzification in the first stage

Defuzzification	a1	a2	a3	Sub-criteria	Criteria
8.242	7.909	7.909	8.909	Lack of attention to employee talent management	Organizational factors
7.697	7.364	7.364	8.364	Lack of attention to employee productivity management	
8.060	7.727	7.727	8.727	Disregard for employee performance	
7.182	7.182	7.182	7.182	Ignoring the importance of human resource management	Corporate Governance
7.969	7.636	7.636	8.636	Low reliability	
7.969	7.636	7.636	8.636	Existence of annual adjustments	
7.515	7.727	7.727	7.091	Transactions with related parties	
8.060	7.727	7.727	8.727	Ambiguity in financial reporting	Disclosure of information
7.788	7.455	7.455	8.455	High information asymmetry	
7.771	7.351	7.451	8.512	Increased capital cost	
7.736	7.645	7.542	8.021	Low stock liquidity	
7.612	7.582	7.114	8.141	Low financial stability	Content of earnings information
7.655	7.110	7.625	8.231	Low earnings quality	
7.955	7.252	8.032	8.582	High earnings smoothing	
8.177	7.322	8.551	8.659	High earnings management	
8.208	7.988	8.978	7.658	Lack of attention to innovative activities	Financial performance
7.437	7.025	7.285	8.001	Not using new standards	
7.470	7.366	7.119	7.925	Low financial ratios	
7.857	8.015	8.006	7.551	Low use of financially literate members	Inefficient board of directors
8.320	8.978	8.812	7.171	Low use of non-commissioned members	
7.577	8.051	7.029	7.652	Not separating the role of the CEO from the role of the chairman of the board of directors	

Defuzzification	a1	a2	a3	Sub-criteria	Criteria
7.686	7.992	7.573	7.493	Stability over the operating range	
8.338	8.332	8.652	8.032	Discontinuity of activity	Risk - taking
8.395	8.525	8.199	8.462	High capital structure	
8.291	8.112	8.211	8.551	High volatility of earningsability	
8.272	8.633	8.009	8.174	Environmental uncertainty	

Table (3): Average of the experts' views and defuzzification in the second stage

Defuzzification	a1	a2	a3	Sub-criteria	Criteria
8.182	7.182	8.182	9.182	Lack of attention to employee talent management	Organizational factors
7.909	6.909	7.909	8.909	Lack of attention to employee productivity management	
7.909	6.909	7.909	8.909	Disregard for employee performance	
7.818	6.818	7.818	8.818	Ignoring the importance of human resource management	Corporate Governance
8.000	7.000	8.000	9.000	Low reliability	
8.182	7.182	8.182	9.182	Existence of annual adjustments	
7.909	6.909	7.909	8.909	Transactions with related parties	
7.428	6.621	7.541	8.121	Ambiguity in financial reporting	Disclosure of information
7.051	6.321	7.251	7.582	High information asymmetry	
7.061	6.002	7.641	7.541	Increased capital cost	
7.182	7.182	7.182	7.182	Low stock liquidity	
7.969	7.636	7.636	8.636	Low financial stability	Content of earnings information
7.969	7.636	7.636	8.636	Low earnings quality	
7.515	7.727	7.727	7.091	High earnings smoothing	
8.060	7.727	7.727	8.727	High earnings management	
7.788	7.455	7.455	8.455	Lack of attention to innovative activities	Financial performance
7.771	7.351	7.451	8.512	Not using new standards	
7.736	7.645	7.542	8.021	Low financial ratios	
7.612	7.582	7.114	8.141	Low use of financially literate members	Inefficient board of directors
7.655	7.110	7.625	8.231	Low use of non-commissioned members	
7.955	7.252	8.032	8.582	Not separating the role of the CEO from the role of the chairman of the board of directors	
8.048	8.110	8.036	7.998	Stability over the operating range	
8.177	7.322	8.551	8.659	Discontinuity of activity	Risk - taking
8.151	8.223	8.109	8.111	High capital structure	
8.208	7.988	8.978	7.658	High volatility of earningsability	
7.437	7.025	7.285	8.001	Environmental uncertainty	

Table (4): The degree of difference in expert opinions in the first and second phase of the survey

Difference between the first and second stages	Second stage	First stage	Sub-criteria	Criteria
0.060	8.182	8.242	Lack of attention to employee talent management	Organizational factors
0.212	7.909	7.697	Lack of attention to employee productivity management	
0.151	7.909	8.060	Disregard for employee performance	
0.636	7.818	7.182	Ignoring the importance of human resource management	Corporate Governance
0.031	8.000	7.969	Low reliability	
0.213	8.182	7.969	Existence of annual adjustments	
0.394	7.909	7.515	Transactions with related parties	
0.633	7.428	8.060	Ambiguity in financial reporting	Disclosure of information
0.737	7.051	7.788	High information asymmetry	

Difference between the first and second stages	Second stage	First stage	Sub-criteria	Criteria
0.710	7.061	7.771	Increased capital cost	
0.554	7.182	7.736	Low stock liquidity	
0.357	7.969	7.612	Low financial stability	Content of earnings information
0.314	7.969	7.655	Low earnings quality	
0.440	7.515	7.955	High earnings smoothing	
0.117	8.060	8.177	High earnings management	
0.420	7.788	8.208	Lack of attention to innovative activities	Financial performance
0.334	7.771	7.437	Not using new standards	
0.266	7.736	7.470	Low financial ratios	
0.245	7.612	7.857	Low use of financially literate members	Inefficient board of directors
0.665	7.655	8.320	Low use of non-commissioned members	
0.378	7.955	7.577	Not separating the role of the CEO from the role of the chairman of the board of directors	
0.362	8.048	7.686	Stability over the operating range	
0.221	8.177	8.338	Discontinuity of activity	Risk - taking
0.244	8.395	8.151	High capital structure	
0.83	8.208	8.291	High volatility of earningsability	
0.835	7.437	8.272	Environmental uncertainty	

The third stage of the fuzzy Delphi technique

The third stage in examining the experts' views is as follows: in this stage, while making the necessary changes to the model indicators, a third questionnaire was prepared and sent back to the members of the expert group along with each person's previous point of view and the extent of their difference with the views of other experts. The average views of the experts and defuzzification in the third round are given in Table 5.

The difference between the second and third stages is shown in Table 6.

According to Table 6 and calculating the difference in the means of steps 2 and 3, the experts reached a consensus on the indicators of: organizational factors, corporate governance, information disclosure, earnings information content, financial performance, ineffective board of directors and risk-taking.

Robust structural equations and resampling In the results obtained from structural equations, some research hypotheses were not confirmed, and also in the validity study using the confirmatory factor analysis method, some questions were eliminated in the process of estimating latent variables. Therefore, to ensure the accuracy of the results, we use the robust maximum likelihood method with resampling in the tests. For fitting, the regression method was used. To control the effect of environmental conditions on the relationships between the third-level latent variables (variables related to the research hypotheses), the variables of gender, membership in the society of certified public accountants, position, work experience and education were converted into third-level equations as artificial variables. The definition of artificial variables is given in Table 7.

Table (5): Average views of the experts and defuzzification in the third stage

Defuzzification	a1	a2	a3	Sub-criteria	Criteria
8.273	7.273	8.273	9.273	Lack of attention to employee talent management	Organizational factors
8	7.000	8.000	9.000	Lack of attention to employee productivity management	
8	7.000	8.000	9.000	Disregard for employee performance	
7.909	6.909	7.909	8.909	Ignoring the importance of human resource management	Corporate Governance
8.091	7.091	8.091	9.091	Low reliability	
8.182	7.182	8.182	9.182	Existence of annual adjustments	
8	7.000	8.000	9.000	Transactions with related parties	
7.66 4	7.215	7.541	8.235	Ambiguity in financial reporting	Disclosure of information

Defuzzification	a1	a2	a3	Sub-criteria	Criteria
7.838	7.632	7.251	8.632	High information asymmetry	
8	7.000	8.000	9.000	Increased capital cost	
7.061	6.002	7.641	7.541	Low stock liquidity	
7.182	7.182	7.182	7.182	Low financial stability	Content of earnings information
7.969	7.636	7.636	8.636	Low earnings quality	
7.969	7.636	7.636	8.636	High earnings smoothing	
7.515	7.727	7.727	7.091	High earnings management	
8.060	7.727	7.727	8.727	Lack of attention to innovative activities	Financial performance
7.788	7.455	7.455	8.455	Not using new standards	
7.771	7.351	7.451	8.512	Low financial ratios	
7.736	7.645	7.542	8.021	Low use of financially literate members	Inefficient board of directors
7.788	7.455	7.455	8.455	Low use of non-commissioned members	
8.958	8.961	8.963	8.950	Not separating the role of the CEO from the role of the chairman of the board of directors	
8.140	8.140	8.136	8.144	Stability over the operating range	
7.736	7.645	7.542	8.021	Discontinuity of activity	Risk - taking
8.550	8.549	8.553	8.551	High capital structure	
7.706	7.708	8.704	8.706	High volatility of earningsability	
7.655	7.110	7.625	8.231	Environmental uncertainty	

Table (6): The extent of the difference in the experts' views in the second and third stage survey

The difference between the second and third stages	Third stage	Second stage	Sub-criteria	Criteria
0.091	8.273	8.182	Lack of attention to employee talent management	Organizational factors
0.091	8	7.909	Lack of attention to employee productivity management	
0.572	8	7.428	Disregard for employee performance	
0.858	7.909	7.051	Ignoring the importance of human resource management	Corporate Governance
1.03	8.091	7.061	Low reliability	
1	8.182	7.182	Existence of annual adjustments	
0.039	8	7.969	Transactions with related parties	
0.305	7.66 4	7.969	Ambiguity in financial reporting	Disclosure of information
0.323	7.838	7.515	High information asymmetry	
0.160	8	8. 1 60	Increased capital cost	
0.188	7.061	7.788	Low stock liquidity	
0.589	7.182	7.771	Low financial stability	Content of earnings information
0.233	7.969	7.736	Low earnings quality	
0.357	7.969	7.612	High earnings smoothing	
0.14	7.515	7.655	High earnings management	
0.105	8.060	7.955	Lack of attention to innovative activities	Financial performance
0.260	7.788	8.048	Not using new standards	
0.406	7.771	8.177	Low financial ratios	
0.659	7.736	8.395	Low use of financially literate members	Inefficient board of directors
0.420	7.788	8.208	Low use of non-commissioned members	
1.521	8.958	7.437	Not separating the role of the CEO from the role of the chairman of the board of directors	
0.092	8.140	8.048	Stability over the operating range	
0.441	7.736	8.177	Discontinuity of activity	Risk - taking
0.155	8.550	8.395	High capital requirement	
0.502	7.706	8.208	High volatility of earningsability	
0.218	7.655	7.437	Environmental uncertainty	

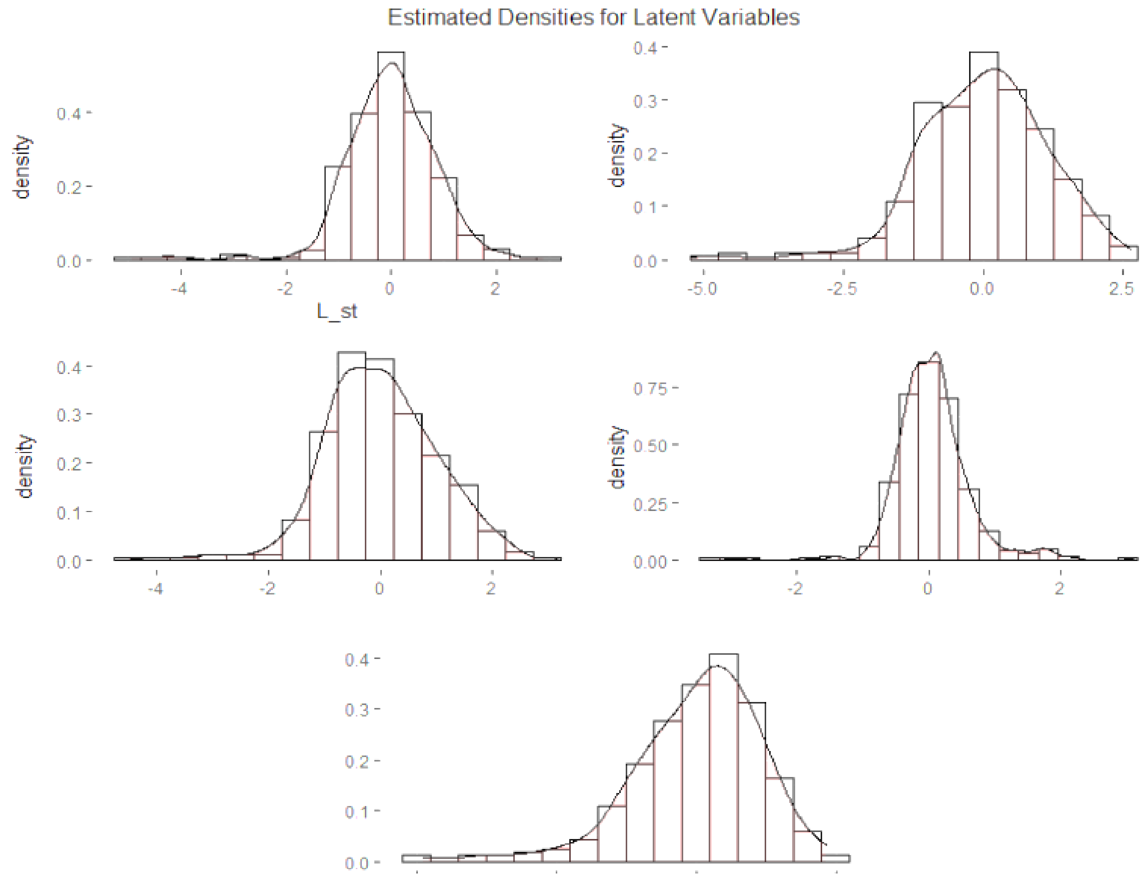
Table (7): Definitions of artificial variables

Definition	Artificial variable	Variable	Definition	Artificial variable	Variable
Less than 6 years	EXP1	Work experience	Man 0 Woman 1	GEN	Gender
Between and6 11 years old	6EXP2		Working member 1 Non-member 0	MEM	Membership in the Society of Certified Public Accountants
Between 11 and 15 years old	EXP3		Bachelor's degree	EDU1	Education
Over years old 15	EXP4		Master's degree	EDU2	
			PhD	EDU3	

Quantile Structural Equations

In the previous section, the causal relationship between research variables was examined using structural equations. In this section, the probability distribution of latent variables is first examined, and then the relationship between research variables is tested on each other's subgroups (quantiles). Table 8 shows the estimation of the distribution of second-level latent variables based on the kernel function method.

Table (8): Estimation of the distribution of research variables using the kernel function method



In each case, the plotted curve shows the estimated probability density function.

As can be seen in Figure 8, the estimated frequency curve is often skewed or stretched. To test the assumption of normality of the variables, we use the Shapiro-Wilk test. The results of the Shapiro-Wilk test are given in Table 9. Based on the results of this test, the assumption of normality is rejected for all research variables. Therefore, in addition to examining the effect of the variables on each other's means, the effect of the variables on each other's distributions should also be tested.

Table (9): Results of the Shapiro-Wilk test

Test probability	Test statistic	Symbol	Variable
0.000	160.669	GEN	Gender
0.000	337,774	EXP	Work experience
0.000	323,438	EDU	Education

Figures 10 and 11 show the path coefficients and estimated dummy coefficients and 95% confidence intervals in the percentile equations related to the dependent variable using the quantile structural equation model.

Based on the results presented in Figure 11, work experience and gender in some percentiles show a significant effect on managers' fraudulent reporting.

Table (10): Estimated path coefficients and 95% confidence intervals of percentile equations related to managers' fraudulent reporting

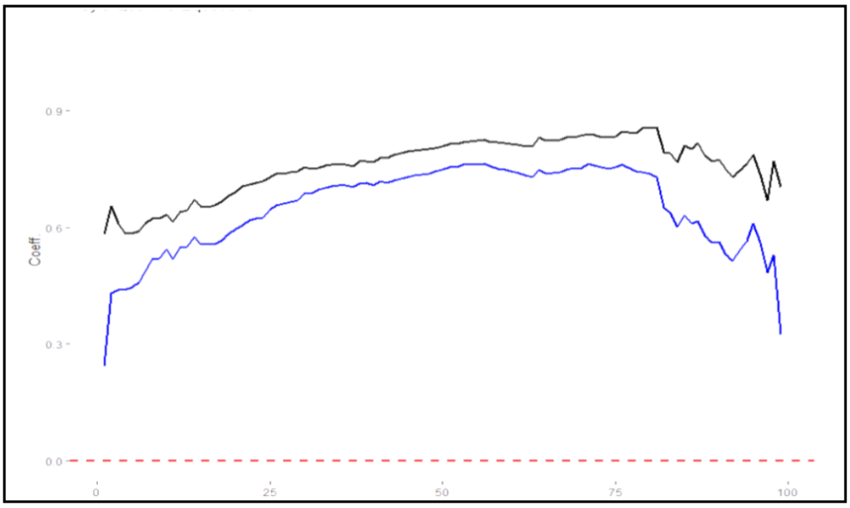
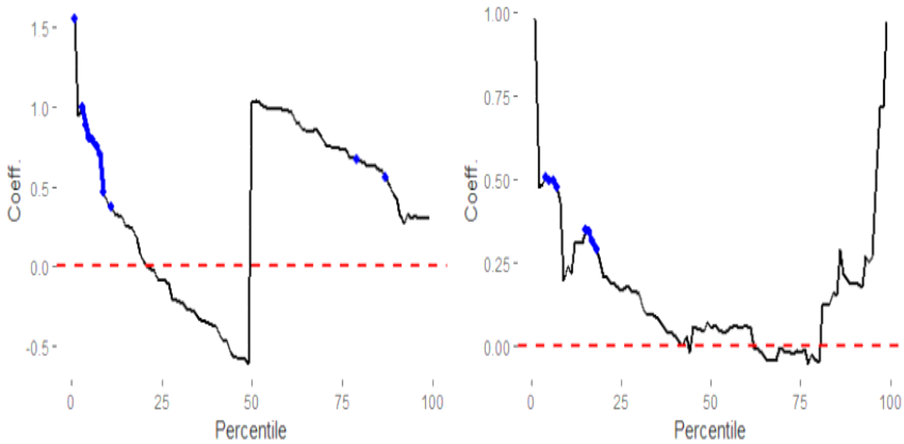


Table (11): Estimated coefficients of dummy variables in percentile equations related to fraudulent reporting by managers



Calculating the GOF goodness-of-fit index

This index has been developed as a general measure of model fit for partial least squares structural equation models. It is the square of the product of the average of the common values and the average of the coefficients of determination. However, since the GoF goodness-of-fit index cannot reliably distinguish valid from invalid models and since its application is limited to specific model settings, researchers should refrain from using it as an appropriate measure. GoF may be useful for multi-group analysis (PLS-MGA). Hensler and Sarstedt (2012) explain in detail that the GoF index is not a suitable measure for fitting partial least squares structural equation models and should not be used. However, Hensler and Sarstedt (2012) also show that GoF may be useful for multi-group analysis (PLS-MGA).

The GOF index is related to the general goodness of fit of structural equation models. This means that with this measure, the researcher can control the general goodness of fit after examining the measurement and structural parts of the overall research model. Its formula is given below.

$$GOF = \sqrt{0.812 * 0.87} = 0.70$$

Presentation of a conceptual model

In the supplementary stage of the research and in order to present the model; research literature and the results of quantitative data analysis were used. At this stage, in order to determine the degree of fit of the model; one-sample t-test and other statistical tests were used. The results of the tests used showed that the difference between the average of the presented model in all sections and the expected average; is less than the 5 percent error level. Therefore, the statistical model was approved with a 95 percent confidence level by experts and independent auditors. In the following; the conceptual model of the factors affecting fraudulent reporting by managers is defined.

The first result of this research is the identification of the dimensions and components affecting managers' fraudulent reporting, which was achieved by using theoretical studies, summarizing the opinions of accounting and auditing experts, analyzing the opinions of the statistical community, and receiving the opinions of experts in fields related to the research. The second result of this research showed that lack of attention to employee talent management, lack of attention to employee productivity management, transactions with related parties, ambiguity in financial reporting, low financial stability, high earnings management, lack of attention to innovative activities, low use of members with financial knowledge, excessive stability of the CEO, high volatility of earningsability, and environmental uncertainty have a positive and significant effect on managers' fraudulent reporting.

Findings related to artificial intelligence algorithms

Predicting managers' fraudulent financial reporting using Bayesian network algorithm

Bayesian network is a graphical model for displaying probabilities between the variables of interest. Bayesian networks, on the other hand, are a way to represent large continuous probability distributions in an exponential and compact way that allows for efficient probabilistic computations. They use the structure of a graphical model for independent criteria between random variables.

Bayesian classifiers in machine learning are a group of simple probability-based classifiers that work with simple independent random variables given different states and based on Bayes' theorem. Simply put, Bayes' method is a method for classifying phenomena based on the probability of occurrence or non-occurrence of a phenomenon.

Based on inherent features (especially probability sharing), the simple Bayes classifier will provide good results with initial training.

In this study, we also used expert opinions to help select the features that affect fraudulent reporting, and in this case, the best factors that affect fraudulent reporting were selected. The values of the weights calculated by the combined rough-hierarchical method in the proposed method are as follows in Table 13:

Table (12): Conceptual model of the factors affecting fraudulent reporting by managers

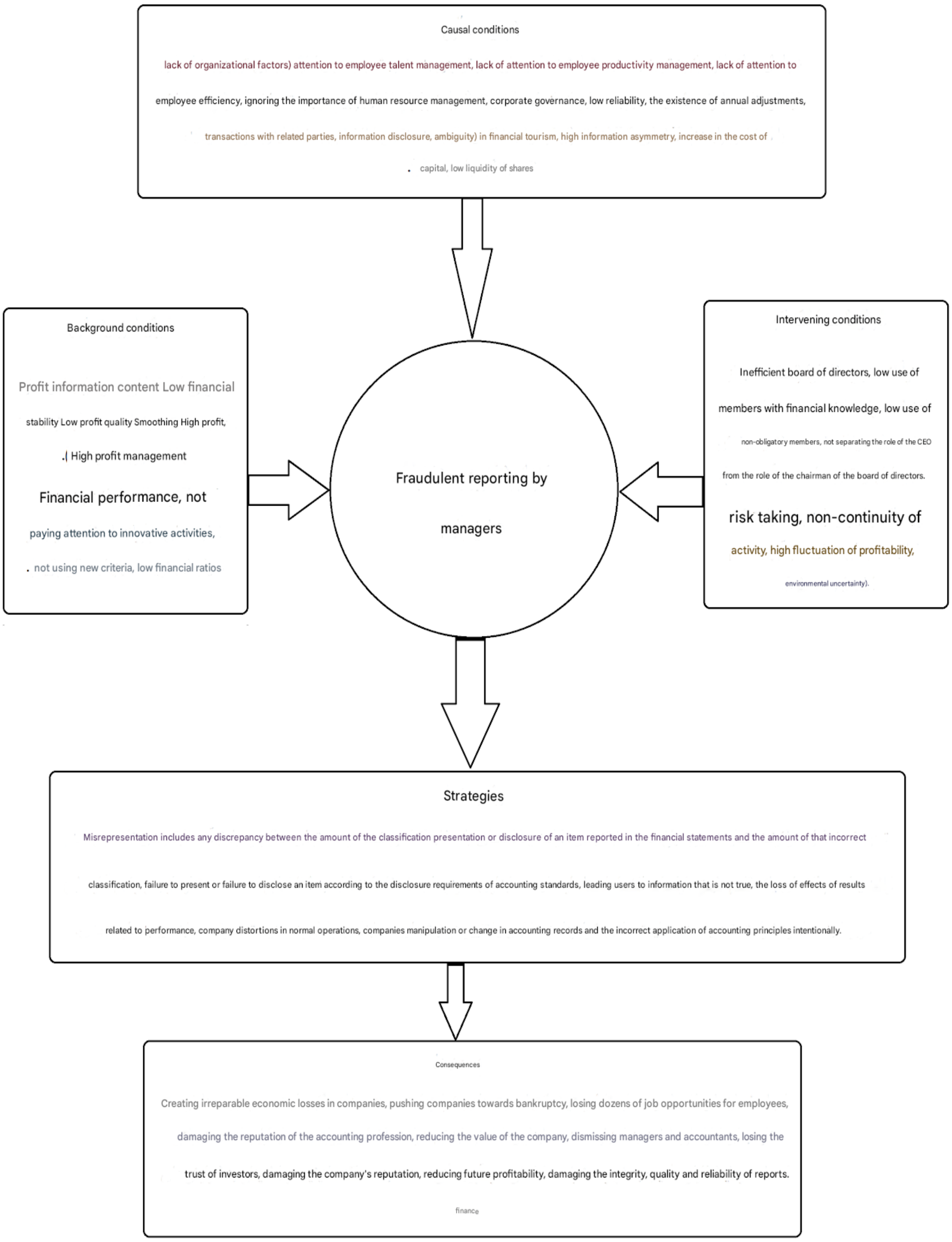


Table (13): Calculating the predictive power of managers' fraudulent reporting using the Bayesian network learning algorithm

Weight	Variable description
0.237	Lack of attention to employee talent management
0.460	Lack of attention to employee productivity management
0.521	Disregard for employee performance
0.487	Ignoring the importance of human resource management
0.620	Low reliability
0.607	Existence of annual adjustments
0.632	Transactions with related parties
0.635	Ambiguity in financial reporting
0.518	High information asymmetry
0.183	Increased capital cost
0.630	Low stock liquidity
0.605	Low financial stability
0.626	Low earnings quality
0.603	High earnings smoothing
0.199	High earnings management
0.657	Lack of attention to innovative activities
0.697	Not using new standards
0.685	Low financial ratios
0.572	Low use of financially literate members
0.418	Low use of non-commissioned members
0.439	Not separating the role of the CEO from the role of the chairman of the board of directors
0.401	Discontinuity of activity
0.619	High capital structure
0.272	High volatility of earningsability
0.301	Environmental uncertainty

After implementing the rough theory steps and calculating the criteria, the weight of the criteria is calculated as follows.

$W=\{W_1,W_2,W_3,\ldots,W_n)$

$W=\{[0.237,0.460,0.521,0.487],[0.620,0.607,0.632],[0.635,0.518,0.183,0.630],[0.605,0.626,0.603,0.199],[0.657,0.697,0.685],[0.572,0.418,0.439],[0.401,0.619,0.272,0.301\}$

Based on the findings, it can be seen that according to this table, the variable of not using modern criteria (with weight: 0.697) has the highest predictive power and the variable of increasing capital cost (with weight: 0.183) has the lowest predictive power of fraudulent reporting by managers. Next, based on calculating the arithmetic mean of the weights; the predictive power of the Bayesian network algorithm is calculated as follows.

$$\mu = \frac{\sum Xi}{N} = \frac{(0.237 + 0.460 + 0.521 + \ldots + 0.272)}{25} = \frac{12.323}{25} = 0.492$$

Based on this, it can be stated that the Bayesian network algorithm has been able to predict fraudulent financial reporting by managers by about 49%.

On the other hand, if the intention is to check the accuracy of the calculations; the components affecting the occurrence of fraudulent reporting by managers can be represented as W1, W2, ... W27 and the probability of fraudulent reporting by managers can be represented as g. Therefore; the goal is to calculate the probability of fraudulent reporting by managers (g) provided that the influencing factors (W1, W2, ... , W27) exist.

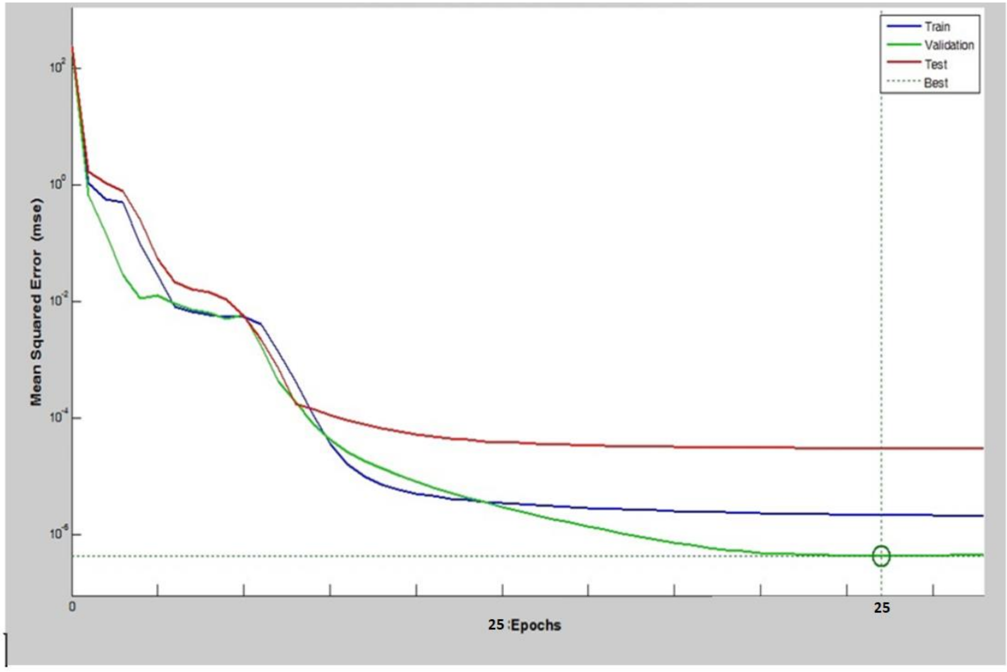
Predicting fraudulent financial reporting by managers using the svm algorithm

First, we introduce the network input data, including independent variables, to the network. The artificial intelligence algorithm model consists of two stages.

1- Training and learning

2- Testing weights and calculating the error.

Table (14): Diagram of training for predicting fraudulent financial reporting by managers using the svm algorithm



The optimal amount of training in learning is shown in the form of a graph. Their goodness of fit is also determined and the input and target data are matched. The results of training the SVM algorithm are based on the communication lines between neurons and other components, both input and output.

This graph also carries the results of training the neural network, the network weights, which are based on the communication lines between neurons and other components (both input and output). The weights between the input layer and the hidden layer are given in the relevant table. According to the weight table, we can predict fraudulent financial reporting by managers using the SVM algorithm. The graph above shows the network's prediction based on the input data and comparing them with the actual values. The red graph (left) is the prediction with the SVM algorithm and the blue graph (right) is the actual values.

In this section, we use the least squares mean error to compare the two approaches. The prediction error means the distance between the prediction and the actual value. We know that the closer our prediction is to the actual value, the better the prediction performance. After performing the calculations, the model was used as a proxy for price prediction. Finally, the obtained models were compared with each other to select the optimal model.

Based on the SVM model, we define 70% of x in the input and output layers. The network defines a series of weights using training and training and using artificial intelligence, and in the next step, it tests these weights with the remaining 30% of x; and obtains the values of fraudulent financial reporting of managers and the test is performed to determine how close the predicted value is to reality and calculates the error. The network performs training until it reaches the optimal training point, (the optimal training point is the level of training at which the network was able to estimate the best weights using training and learning). When we test the weights with the remaining 30% of the x's; the predicted values have the least difference from reality. To prevent overtraining, the network is trained gradually for a number of iterations and then tested with the test data until at least a few errors are found on the page, and from this number, the lowest minimum is considered and the optimal training of the network is selected based on them. After training, the best training is selected at different times. Here, the training operation has been performed 25 times. It should be noted that the smaller the difference between the actual weights and the predicted weights by the

SVM algorithm, the higher the predictive power of the SVM algorithm.

In the table below, you can see the actual and predicted values.

Table (15): Actual values and predicted values of components based on the SVM algorithm

Based on the findings; the lowest difference between the actual weights and the predicted weights by the SVM algorithm is related to the variable of low attention to employee productivity management (with weight: 0.004) and the highest difference between the actual weights and the predicted weights by the SVM algorithm is related to the variable of low stock liquidity (with weight: 0.501). Therefore, based on the SVM model; the variable of low attention to employee productivity management has the highest power and the variable of low stock liquidity has the lowest power to predict fraudulent reporting by managers.

Next, based on calculating the arithmetic mean of the weights; the predictive power of the SVM algorithm is calculated as follows.

$$\mu = \frac{\sum Xi}{N} = \frac{(0.062 + 0.004 + 0.006 + \ldots + 0.064)}{27} = \frac{3.837}{25} = 0.153$$

Based on this, it can be said that the SVM algorithm has been able to predict fraudulent financial reporting by managers by about 15%.

Fast Machine Learning Algorithm Based on RBF Kernel

Fast machine learning based on RBF kernel is one of the new and developed learning techniques in recent years. The fast machine learning algorithm based on RBF kernel is more evolved than the fast machine learning model and has shown itself to be more reliable on average in many applications. The fast machine learning model was initially proposed for single-layer hidden feedforward neural networks, then it was extended to generalized single-layer hidden feedforward neural networks. Python programming language output for RBF kernel (organizational factors)

```
import numpy as np
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
# Load dataset
iris = datasets.load_iris()
X = iris.data
y = iris.target
# Split data into training and test sets
X_train,X_test,y_train,y_test=train_test_split(X,y,
test_size=0.3, random_state=4)
# Create and train the SVM model with RBF kernel
model = SVC(kernel='rbf', gamma='scale'(
model.fit(X_train, y_train(
# Make predictions
y_pred = model.predict(X_test(
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred(
print(f"Accuracy: {accuracy * 15:.2f{%")
Accuracy: 15.00%
```

Based on the output of the Python programming language for the RBF kernel, organizational factors can predict 15% of fraudulent reporting by managers.

• Python programming language output for the RBF kernel (Corporate Governance Factors)

```
import numpy as np
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
# Load dataset
iris = datasets.load_iris()
X = iris.data
y = iris.target
# Split data into training and test sets
X_train,X_test,y_train,y_test=train_test_split(X,y,
test_size=0.3, random_state=3)
# Create and train the SVM model with RBF kernel
model = SVC(kernel='rbf', gamma='scale'(
model.fit(X_train, y_train(
# Make predictions
y_pred = model.predict(X_test(
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred(
print(f"Accuracy: {accuracy * 26:.2f{%")
Accuracy: 26.00%
```

Based on the output of the Python programming language for the RBF kernel, corporate governance factors can predict 26% of fraudulent reporting by managers.

• Python programming language output for the RBF kernel (Disclosure-based factors)

```
import numpy as np
```

from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
 # Load dataset
iris = datasets.load_iris()
X = iris.data
y = iris.target
 # Split data into training and test sets
X_train,X_test,y_train,y_test=train_test_split(X,y, test_size=0.3, random_state=4)
 # Create and train the SVM model with RBF kernel
model = SVC(kernel='rbf', gamma='scale'(
model.fit(X_train, y_train(
 # Make predictions
y_pred = model.predict(X_test(
 # Evaluate the model
accuracy = accuracy_score(y_test, y_pred(
*print(f"Accuracy: {accuracy * 26:.2f{%")*
Accuracy: 39.00%

Based on the Python programming language output for the RBF kernel, information disclosure-based factors can predict 39% of fraudulent reporting by managers.

• Python programming language output for the RBF kernel (information content-based factors of earnings)

import numpy as np
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
 # Load dataset
iris = datasets.load_iris()
X = iris.data
y = iris.target
 # Split data into training and test sets
X_train,X_test,y_train,y_test=train_test_split(X,y, test_size=0.3, random_state=4)
 # Create and train the SVM model with RBF kernel
model = SVC(kernel='rbf', gamma='scale'(
model.fit(X_train, y_train(
 # Make predictions
y_pred = model.predict(X_test(
 # Evaluate the model
accuracy = accuracy_score(y_test, y_pred(
*print(f"Accuracy: {accuracy * 26:.2f{%")*
Accuracy: 18.00%

Based on the output of the Python programming language for the RBF kernel, factors based on the information content of earnings can predict 18% of fraudulent reporting by managers.

• Python programming language output for the RBF kernel (Financial performance-based factors)

import numpy as np
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
 # Load dataset
iris = datasets.load_iris()
X = iris.data
y = iris.target
 # Split data into training and test sets
X_train,X_test,y_train,y_test=train_test_split(X,y, test_size=0.3, random_state=3)
 # Create and train the SVM model with RBF kernel
model = SVC(kernel='rbf', gamma='scale'(
model.fit(X_train, y_train(
 # Make predictions
y_pred = model.predict(X_test(
 # Evaluate the model
accuracy = accuracy_score(y_test, y_pred(
*print(f"Accuracy: {accuracy * 44:.2f{%")*
Accuracy: 44.00%

Based on the Python programming language output for the RBF kernel, financial performance-based factors can predict 44% of fraudulent reporting by managers.

• Python programming language output for the RBF kernel (Inefficient Board-Based Factors)

import numpy as np
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
 # Load dataset
iris = datasets.load_iris()
X = iris.data
y = iris.target
 # Split data into training and test sets
X_train,X_test,y_train,y_test=train_test_split(X,y, test_size=0.3, random_state=3)
 # Create and train the SVM model with RBF kernel
model = SVC(kernel='rbf', gamma='scale'(
model.fit(X_train, y_train(
 # Make predictions
y_pred = model.predict(X_test(
 # Evaluate the model
accuracy = accuracy_score(y_test, y_pred(

```
print(f"Accuracy: {accuracy * 39:.2f{%")
Accuracy: 39.00%
```

Based on the Python programming language output for the RBF kernel, factors based on ineffective boards can predict 39% of fraudulent reporting by managers.

• Python programming language output for the RBF kernel (Risk-based factors)

```
import numpy as np
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
# Load dataset
iris = datasets.load_iris()
X = iris.data
y = iris.target
# Split data into training and test sets
X_train,X_test,y_train,y_test=train_test_split(X,y,
test_size=0.3, random_state=4)
# Create and train the SVM model with RBF kernel
model = SVC(kernel='rbf', gamma='scale'(
model.fit(X_train, y_train(
# Make predictions
y_pred = model.predict(X_test(
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred(
print(f"Accuracy: {accuracy * 39:.2f{%")
Accuracy: 57.00%
```

Based on the output of the Python programming language for the RBF kernel, risk-based factors can predict 57% of fraudulent reporting by managers.

Analysis of findings and presentation of suggestions arising from testing research hypotheses

Financial reports extracted from financial statements provide useful and relevant information to external users and other stakeholders in order to evaluate the current and future performance of the company. These reports should be in a form that, in the first step, complies with the necessary standards and has an appropriate structure, and in the next step, provides comprehensive and complete information to other user groups. Obviously, the more complete and transparent these reports are, the more they will provide the basis for making correct and informed decisions, and in this way, they can reduce the information asymmetry between external users and different levels of management.

Since financial statements reflect management performance, managers are always trying to better show the general condition of the company; to make their performance record more brilliant and to provide reasons for their further retention. Therefore, they may seek to achieve this goal through some illegal actions. One of these actions is manipulation of the company's activities and their effects on transparency in financial reporting. This impairs financial reporting and changes its quality. The result is ambiguity in financial reporting, which provides opportunities for fraud in financial reporting. Since fraudulent reporting is an intentional and deliberate activity, managers can identify points that can affect financial reporting and seek illegal solutions to improve the company's financial situation. It should be noted that fraud in financial reporting has grown significantly in recent years. Fraud includes deviations and manipulations in financial statements carried out by parties to a financial matter. Fraudulent financial reporting also deals with matters such as distortion or fraud in financial statements. The increase in the number and variety of fraud in the financial reporting system is a threat to the quality of this system. Today, many frauds are committed by managers, which are caused by financial and non-financial incentives in organizations. Fraud in financial statements has received a lot of attention from investors and accountants themselves. On the one hand, it reduces the risk of investors with respect to frauds that occur in financial statements, and on the other hand, it calls into question the credibility of accountants. Fraudulent financial reporting leads to the provision of incorrect information to the market and affects the efficiency of the market in allocating resources, which will result in the loss of investor confidence in the market. In fraudulent financial reporting, executive managers often violate controls that are functionally effective under normal circumstances. Preventing such situations requires the implementation of proper shareholder governance through close supervision of executive management and regular auditing of companies.

Next, the research hypotheses were tested, and in this process, based on the test of the first main hypothesis, we found that the lack of attention to talent management and employee productivity causes fraudulent financial reporting. Therefore, by creating a healthy work environment, sharing employee experiences, smart planning, delegating non-essential tasks, and paying attention to innovative activities, areas for improving talent management and employee productivity should be provided so that fraudulent reporting can be controlled through this channel.

Based on the test of the second main hypothesis, we found that increasing transactions with related parties leads to fraudulent reporting. Therefore, in order to reduce the adverse effects of these transactions, it is necessary to provide opportunities for improving the disclosure of more details of such transactions, so that in this way, one of the dimensions of corporate governance is strengthened and fraudulent reporting is prevented.

Based on the test of the third main hypothesis, we found that the greater the ambiguity in financial reporting, the greater the possibility of fraudulent financial reporting. Therefore, by improving information transparency and disclosing more non-financial information, it is necessary to provide opportunities to gain the trust of investors and other external users and through this channel, try to reduce fraudulent reporting.

Based on the test of the fourth main hypothesis, it was concluded that low financial stability can be a prerequisite for fraudulent reporting. Therefore, it can be suggested to managers to reduce earnings management by not manipulating revenues and expenses and also reducing accounting conservatism, initially and then strengthen transparency and quality of earnings in order to reduce fraudulent reporting.

Based on the test of the fifth main hypothesis, it was concluded that paying attention to innovative activities can cause a decline in fraudulent reporting. From this perspective, it is possible to improve innovation by planning to achieve long-term goals, providing a necessary solution for greater use of the company's capacities, etc., and in the next step reduce fraudulent reporting.

Based on the findings, it can be stated that while it is not credible for any company or organization to commit fraud, unfortunately it is possible and does happen. Typically, fraud is a crime that occurs based on opportunities, which means that implementing preventive measures in this area can help reduce fraud before it begins. There are several steps in this process that can be used to reduce the risk of fraud, regardless of the size of the organization. It should be noted that one way to reduce fraud is to have established mechanisms for formal fraud reporting.

Also, the results of the sixth main hypothesis of the study stated that excessive CEO stability and low use of financially literate members lead to fraudulent reporting. Accordingly, it can be stated that defining a transparent fraud disclosure policy for the organization and employees is a priority; it should be ensured that this fraud prevention policy is part of the employee recruitment conditions and part of the employee handbook.

In this process, employees can be encouraged to present any points or concerns regarding fraud when they encounter them and their ability to do so via email, telephone or suggestion box can be ensured. Employees can also be helped to be aware of the fact that they are also part of the fraud protection team in the organization. They can also ensure the internal control of the security of their data, assets and any proprietary information and update them on a regular schedule.

One of the most important controls that can be implemented to reduce fraud is the segregation of transactions. In this way, if the intention is to involve several people in a process, fraud will be more difficult. Because fraud is usually committed by only one person alone, so if more people are involved in the process, the possibility of preventing fraud is greater.

On the other hand, it is recommended that no one employee be used alone to manage the cash processing cycle. In this way; organizations can reduce the opportunity for fraud by dedicating more than one employee to handle cash processing and accounting from start to finish. Because multiple personnel processing systems are beneficial not only in reducing fraud but also in ensuring the security of cash received and the proper reconciliation of financial contributions.

It is also recommended that when processing cash and checks or reconciling cash, checks, and payments, ensure that the organization's financial functions are segregated. Because it is much easier to conceal fraudulent activities if the person committing fraud is the only person with access to the entire accounting system.

Finally, the results of the seventh main hypothesis of the study stated that high volatility of earningsability and environmental uncertainty lead to fraudulent reporting.

Accordingly, it can be stated that opaque financial reporting affects all the interests of different groups using financial statement information in different ways. Thus, the survival of the company and the sustainability of its performance are changed and the quality of its financial reporting is degraded. There may also be some laws and regulations that have the ability to reduce fraudulent financial reporting in some way, but none of them can completely prevent the presentation of fraudulent financial reports. Given the importance of this issue, the need to develop a conceptual model to identify and discover the factors affecting fraudulent financial reporting by managers is evident. Obviously, identifying these factors can reduce audit risk by reducing fraudulent reporting, and this is reflected in improving the sustainability of performance.

Therefore, it is suggested that business unit managers improve their attention to employee talent management, pay attention to employee productivity management, reduce transactions with related parties, reduce ambiguity in financial reporting, improve financial stability, reduce earnings management, pay attention to innovative activities, use more members with financial knowledge, reduce excessive CEO stability, reduce high earningsability volatility, and reduce environmental uncertainty, all of which provide opportunities to reduce fraudulent reporting. It is also suggested that managers include internal fraud assessments in their annual organizational calendar and ensure that managers and employees are aware that the company regularly conducts fraud assessments. Managers can also include annual fraud awareness training in their organization's program. Because experience has shown that most guidance on fraud is provided by organizations that, in addition to fraud procedures, have also provided standard fraud awareness training.

Investors are advised to rank target companies for investment based on factors such as the level of attention to employee talent management, attention to employee productivity management, reduction of transactions with related parties, reduction of ambiguity in financial reporting, improvement of financial stability, reduction of earnings management, attention to innovative activities, greater use of members with financial knowledge, reduction of excessive CEO stability, reduction of high earningsability volatility, and reduction of environmental uncertainty, and to invest in units that are at a desirable level of the aforementioned factors, because as a result, in such units the probability of encountering fraudulent reporting is at a low level and the probability of successful investments will be higher. It is recommended that standard-setting authorities develop written and enforceable standards to reduce excessive CEO stability, reduce environmental uncertainty, increase the use of members with financial knowledge in the composition of the board of directors, and increase the use of non-executive members in the composition of the board of directors in order to reduce fraudulent reporting by managers; Compile.

Practical suggestions

Initially, it is suggested that training on fraud prevention and accounting for fraudulent financial reporting be provided to executive directors, managers, attorneys, board members, audit committee members, and other interested stakeholders.

It is also necessary to form a technical group for forensic accounting training consisting of experts in various fields in order to prevent fraudulent financial reporting, detect, investigate, and investigate (after fraud is detected), and forensic accounting, and to assess the educational and skill needs of independent auditors, financial managers, and financial analysts in the field of detecting and disclosing fraudulent financial reporting.

Investors and financial analysts, especially risk-averse investors, can more carefully purchase shares of companies with a high probability of fraudulent reporting, because in years when these companies have experienced a financial crisis, they may identify large losses in order to clean up the major effects of fraudulent reporting, which will cause short-term losses for shareholders. Therefore, investors are advised to examine the financial status of companies more carefully so that they can identify signs of fraudulent reporting by managers in these companies at the right time and make the right decision regarding investment in these companies.

Future Suggestions

It is suggested that field studies be conducted to the extent necessary from different groups using management reports in Iran and that the opinions of users regarding fraudulent reporting by managers and its effects on each of the stakeholder groups be carefully documented and evaluated. Because this type of information is of great help in determining the best way to deal with the issue of management reports in Iran. The degree to which the various dimensions of the importance of the present study have been clarified; the following topics can be suggested to future researchers.

- Identifying factors affecting fraudulent reporting by managers with a meta-synthesis approach.
- Identifying factors affecting fraudulent reporting by managers with an emphasis on the role of conflict between auditors, managers, and the board of directors.
- Identifying factors affecting managers' fraudulent reporting, with an emphasis on the role of their personality traits.

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