Presenting a Model for Reducing the Probability of Fraud and Financial Crimes

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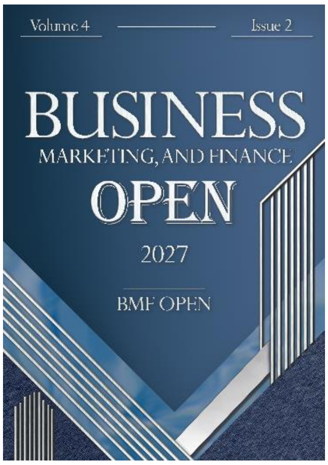

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Abstract: Today, with the increasing complexity of fraud and financial crimes, the use of traditional approaches for detection and prevention is no longer sufficient, and there is a need for an integrated and coherent model capable of reducing different levels of fraud and restoring public trust in the economy and financial institutions. Therefore, the present study was conducted with the aim of presenting a model for reducing the probability of fraud and financial crimes. The required data were collected through semi-structured interviews with 15 expert forensic accountants using the snowball sampling method. In this study, an Interpretive Structural Modeling (ISM) approach was employed to design a proposed model. Based on the interpretive structural analysis, the exploratory research model consisted of 19 factors. The results indicated that forensic accounting, through three categories of tools including legal tools, accounting tools, and other tools, contributes to reducing the occurrence of fraud and financial crimes. The accounting tools of forensic accounting included components such as data analysis, accounting standards, auditing standards, financial ratio analysis, Benford analysis, and cloud-based tools. The legal tools of forensic accounting included components such as criminal and penal laws, criminology, legal monitoring of individuals' accounts, interviewing and interrogation, forensic analysis, and legal documentation. Other forensic accounting tools included components such as information technology, employee monitoring tools, and fraud psychology.

Keywords: Forensic accounting tools, fraud, forensic accounting, financial crimes.

1. Introduction

Financial fraud and financial crimes have become among the most significant challenges facing modern economies and financial systems. The expansion of economic activities, globalization of financial markets, rapid technological development, and the increasing complexity of organizational structures have provided broader opportunities for fraudulent activities and financial misconduct. Financial crimes not only undermine the stability and transparency of economic systems, but also weaken public trust in financial institutions, reduce investment security, and impose substantial economic and social costs on governments and organizations [1]. In recent decades, numerous corporate scandals and financial collapses around the world have demonstrated that traditional auditing and accounting mechanisms alone are insufficient for the timely detection and prevention of sophisticated financial fraud. Consequently, the emergence and development of forensic accounting has attracted considerable attention as an interdisciplinary and specialized approach for combating fraud and financial crimes [2].

Forensic accounting is generally defined as the application of accounting, auditing, investigative, and legal skills for the identification, analysis, interpretation, and presentation of financial evidence suitable for judicial and legal processes [3]. This field integrates accounting expertise with legal and criminological knowledge in order to investigate financial irregularities and support litigation processes. Unlike traditional accounting approaches that primarily focus on recording and reporting financial information, forensic accounting emphasizes uncovering hidden patterns of fraud, identifying suspicious transactions, and analyzing financial evidence associated with criminal activities [1]. The increasing complexity of fraud schemes has further highlighted the necessity of employing forensic accounting tools and techniques capable of detecting concealed manipulations and preventing the escalation of financial crimes [4].

Financial fraud encompasses a broad range of deceptive and intentional activities conducted for unlawful financial gain. Such activities include manipulation of financial statements, embezzlement, corruption, money laundering, cyber fraud, asset misappropriation, and tax evasion. These crimes often occur through sophisticated organizational and technological mechanisms, making their detection increasingly difficult for conventional internal controls and auditing systems [5]. The evolution of digital technologies and electronic financial systems has further transformed the nature of financial fraud, enabling perpetrators to exploit information systems, digital transactions, and online financial platforms. Accordingly, organizations and governments are increasingly seeking advanced analytical and investigative methods to mitigate fraud risks and improve financial transparency [6].

One of the fundamental reasons for the growing importance of forensic accounting is the inadequacy of traditional auditing procedures in identifying intentional manipulations and organized financial crimes. Traditional auditing primarily aims to express an opinion on the fairness of financial statements and is not specifically designed to uncover fraud schemes. In contrast, forensic accounting adopts an investigative orientation and applies specialized analytical methods to detect anomalies, inconsistencies, and suspicious patterns in financial information [7]. This distinction has led many scholars and practitioners to recognize forensic accounting as an essential mechanism for strengthening financial integrity and organizational accountability [3].

Recent studies have emphasized the strategic role of forensic accounting in reducing fraud risks and improving organizational governance. Adejumo and Ogburie argued that forensic accounting techniques significantly enhance the ability of organizations to identify financial irregularities and improve fraud prevention frameworks [4]. Similarly, Ojo et al. demonstrated that the implementation of forensic accounting techniques in public entities contributes substantially to fraud detection and enhances transparency in financial reporting [7]. Yusuf and Harefa also highlighted that the integration of forensic accounting with compliance auditing can reduce the occurrence of financial fraud within local governmental systems [8]. These findings collectively indicate that forensic accounting is not merely a reactive mechanism for post-fraud investigation but also a proactive instrument for fraud prevention and risk reduction.

Technological advancement has significantly transformed forensic accounting practices in recent years. The emergence of big data analytics, cloud computing, artificial intelligence, blockchain systems, and digital forensic tools has enabled forensic accountants to analyze vast volumes of financial information more accurately and efficiently. Akinbowale et al. emphasized that the integration of forensic accounting and big data technology frameworks strengthens internal fraud mitigation in the banking industry by improving the capability to identify hidden financial anomalies and suspicious transactions [9]. Likewise, Al Balushi demonstrated that technological tools play a critical role in enhancing fraud detection mechanisms within firms by facilitating automated monitoring and real-time analysis of financial activities [6]. These developments suggest that technology-driven forensic accounting has become increasingly essential for addressing modern forms of financial crime.

The role of forensic accounting in the public sector has also received increasing scholarly attention. Public institutions are often exposed to significant fraud risks due to bureaucratic complexity, lack of transparency, weak monitoring systems, and opportunities for corruption. Nasiri et al. proposed a forensic accounting-based model for fraud prevention in the public sector and found that the implementation of forensic accounting tools can substantially improve transparency, accountability, and fraud control mechanisms [10]. Similarly, Khajeh Hassani et al. presented a model of forensic accounting techniques aimed at predicting and reducing reporting risk and fraud risk in the Iranian public sector, emphasizing the importance of combining analytical accounting tools with legal and technological mechanisms [11]. These studies reveal that forensic accounting has considerable potential for improving governance and reducing financial misconduct within public organizations.

Another important dimension of forensic accounting concerns its relationship with behavioral and psychological factors associated with fraud. Fraudulent activities are not solely technical or financial phenomena; rather, they are deeply influenced by organizational culture, ethical climate, personality traits, and behavioral motivations. Pourali and Azareh examined the effect of dark personality traits on audit whistleblowing and found that organizational citizenship behavior mediates the relationship between personality characteristics and ethical reporting behavior [12]. This finding highlights the importance of considering psychological and behavioral dimensions alongside technical accounting tools in fraud prevention strategies. Fraud psychology, employee monitoring systems, and ethical organizational practices can therefore contribute significantly to reducing opportunities and motivations for financial misconduct.

In addition to psychological dimensions, legal and criminological approaches are central to forensic accounting practices. Financial crimes often involve complex legal procedures, judicial investigations, and evidentiary requirements. Therefore, forensic accountants must possess sufficient understanding of criminal laws, legal evidence, interviewing techniques, and investigative procedures. According to Hossain, forensic accounting combines accounting expertise with legal analysis to support litigation and facilitate the prosecution of financial crimes [3]. The integration of criminology and forensic investigation methods further strengthens the ability of forensic accounting systems to identify the root causes of fraud and design effective preventive mechanisms [1].

The maturity and institutionalization of forensic accounting systems represent another critical issue in contemporary research. Abbas Tafreshi and Soleimani Amiri proposed a forensic accounting maturity model in Iran and emphasized that the effectiveness of forensic accounting depends on the development of professional standards, legal infrastructures, educational systems, and technological capabilities [13]. The lack of standardized forensic accounting frameworks in many developing countries has limited the practical effectiveness of fraud detection systems and reduced organizational readiness for combating financial crimes. Therefore, the development of integrated forensic accounting models is essential for enhancing institutional capacity and improving anti-fraud strategies.

Research trends in forensic accounting have increasingly focused on interdisciplinary integration and emerging technological frontiers. Ellili et al. identified several new directions in forensic accounting research, including digital forensics, artificial intelligence applications, blockchain auditing, cyber fraud investigation, and predictive fraud analytics [5]. These emerging trends indicate that forensic accounting is evolving from a traditional investigative discipline into a comprehensive strategic framework that integrates accounting, law, criminology, information technology, and behavioral sciences. Such integration is particularly important in addressing complex financial crimes that involve interconnected organizational, technological, and human factors.

Despite the growing body of research on forensic accounting, several gaps remain in the literature. Many existing studies have focused on specific techniques or organizational contexts without developing comprehensive and integrated models that explain the relationships among various forensic accounting tools and their role in reducing fraud and financial crimes. Moreover, limited research has applied interpretive structural modeling approaches to identify the hierarchical relationships among accounting, legal, technological, and behavioral factors influencing fraud reduction. In particular, there is a need for context-specific models capable of reflecting the unique institutional and organizational conditions of developing economies, including Iran [14].

The present study seeks to address these gaps by developing a comprehensive model for reducing the probability of fraud and financial crimes through forensic accounting tools. By integrating accounting instruments, legal mechanisms, technological capabilities, and behavioral dimensions within an interpretive structural framework, this research attempts to provide a systematic understanding of the interrelationships among the key components affecting fraud prevention and detection. Furthermore, the study contributes to the advancement of forensic accounting literature by identifying the hierarchical structure of influential factors and clarifying their driving and dependence relationships [15].

Given the increasing complexity of financial crimes, the growing limitations of traditional auditing systems, and the strategic importance of forensic accounting in enhancing financial transparency and organizational accountability, the present study aimed to develop a model for reducing the probability of fraud and financial crimes using forensic accounting tools.

2. Methodology

The present study adopted a mixed-methods methodology and was organized within a sequential exploratory design in order to benefit from the synergy of qualitative and quantitative approaches. In the first phase, semi-structured qualitative interviews with experts in the field of forensic accounting were used to conduct an in-depth examination of the dimensions of the phenomenon and to identify its fundamental components. This exploratory step made it possible to extract the key variables and explain the initial framework of the model. In the second phase, Interpretive Structural Modeling (ISM) was used to analyze reciprocal relationships and map the hierarchical sequence among the variables, which places the study, in terms of its purpose, within the category of developmental-exploratory research.

The statistical population of the study consisted of qualified experts, including official judicial experts specializing in forensic accounting, with at least five years of professional experience and membership in a university faculty. The sample selection process began using a non-random chain-referral sampling strategy and continued until theoretical saturation was reached; accordingly, data adequacy was confirmed after conducting 15 interviews. For the implementation of the quantitative phase and ISM modeling, judgmental–purposive sampling was applied to the same panel of experts.

To ensure the reliability and validity of the instrument, the data extracted from the qualitative phase were quantitatively validated using the content validity ratio (CVR). Finally, by integrating the outputs obtained from interpretive analyses and structural modeling, the research questions and hypotheses were systematically tested, and the final model was developed to respond to the main research problem.

3. Findings and Results

In the first stage, qualitative data were collected through in-depth interviews and specialized questionnaires with the aim of comprehensively identifying the components and dimensions of the phenomenon under study. This descriptive and exploratory section enabled the researcher to carefully analyze the diverse and complex aspects of the problem and to provide an appropriate foundation for model development. In the next step, based on the qualitative findings obtained, Interpretive Structural Modeling (ISM) was selected and implemented as the research method. ISM is a systematic and interpretive method that uses expert opinions to identify the structure and relationships among different factors and organizes them hierarchically. In this study, ISM was used to design the research model in an applied manner, taking into account the reciprocal effects of the factors, thereby enabling the systematic analysis and improvement of constructs and components. Sampling in this study was conducted purposively and through snowball sampling in order to benefit from the knowledge and experience of official judicial experts and faculty members of relevant universities. Sampling continued until theoretical saturation was achieved and no new information was extracted from the interviews. Finally, the quantitative data of the study were collected through researcher-made questionnaires and analyzed using structural equation modeling (SEM) to statistically confirm and validate the relationships among the variables of the model. Content validity was assessed using the CVR index, in which experts rated the importance of each component on a three-option scale: “essential,” “useful but not essential,” and “not essential.” Given the number of experts, a CVR coefficient above 0.49 was determined as the criterion for confirming validity, and the components that obtained this index were recognized as valid. This stage ensured the scientific and practical validity of the model and indicated the accuracy of selecting the influential factors.

Table 1. CVR Value of Each Factor

No.	Components	CVR Value	Result	Dimensions
1	Data analysis	1	Confirmed	Forensic accounting tools
2	Earnings quality	0.46	Rejected	
3	Beneish model	0.46	Rejected	
4	Accounting standards	1	Confirmed	
5	Auditing standards	1	Confirmed	
6	Financial ratio analysis	1	Confirmed	
7	Benford analysis	1	Confirmed	
8	Cloud-based tools	1	Confirmed	
9	Criminal and penal laws	1	Confirmed	Legal tools of forensic accounting
10	Criminology	1	Confirmed	
11	Legal monitoring of individuals’ accounts	1	Confirmed	
12	Interviewing and interrogation	1	Confirmed	
13	Forensic analysis	1	Confirmed	
14	Legal evidence	1	Confirmed	
15	Professional certification	0.46	Rejected	
16	Information technology	1	Confirmed	Other forensic accounting tools
17	Cyber tools	0.33	Rejected	
18	Employee monitoring tools	1	Confirmed	
19	Financial network analysis	0.46	Rejected	
20	Fraud psychology	1	Confirmed	
21	Fraud prevention	1	Confirmed	Reduction of fraud occurrence
22	Fraud detection	1	Confirmed	
23	Prevention of financial crimes	1	Confirmed	Reduction of financial crime occurrence
24	Detection of financial crimes	1	Confirmed	

Through the examination and collection of the gathered components, 19 components were confirmed within five dimensions.

Step One: Identification of Components

The process of determining the components was explained in the previous section. Therefore, 18 components were selected, as shown in Table 1.

Step Two: Formation of the Structural Self-Interaction Matrix

After determining the components, another questionnaire with a matrix format was designed, and the experts examined these components pairwise and determined the relationships among them using the following symbols:

V: If component i influences component j

A: If component j influences component i

X: Mutual influence between components i and j

O: If there is no relationship between components i and j

The resulting information was summarized based on the Interpretive Structural Modeling (ISM) method, and the structural self-interaction matrix of the research indicators and their comparisons was formed using the four types of conceptual relationships. The logic of Interpretive Structural Modeling (ISM) operates based on the mode in frequencies. The results obtained from the questionnaires regarding the examined components are presented in Table 2.

Table 2. Results Obtained from the Questionnaires

No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	0	41	40	45	41	39	19	28	10	26	20	8	7	10	6	42	44	45	45
2	14	0	16	36	15	42	6	8	6	10	10	10	9	12	8	44	39	42	45
3	39	34	0	32	42	41	12	22	23	23	23	16	7	6	4	39	40	45	45
4	12	42	8	0	10	45	5	20	11	20	14	6	11	10	6	42	43	44	45
5	33	40	41	37	0	31	15	26	12	8	7	8	4	10	2	39	42	45	45
6	9	26	6	17	10	0	9	5	4	3	4	10	4	4	3	42	43	44	45
7	22	10	25	26	22	20	0	42	39	25	26	28	14	10	12	39	41	43	45
8	4	2	26	6	16	23	26	0	24	29	28	15	4	4	2	45	45	45	45
9	5	10	11	6	14	20	34	43	0	15	12	10	3	3	3	39	39	42	41
10	2	9	22	5	15	20	40	41	39	0	39	41	2	3	2	42	43	44	45
11	4	10	20	10	12	28	41	42	40	40	0	40	3	3	2	40	41	42	42
12	2	16	3	9	5	12	42	40	42	41	42	0	2	2	3	39	40	41	45
13	3	28	26	27	6	22	10	12	6	19	8	28	0	39	36	38	39	42	45
14	4	27	29	28	10	26	11	22	14	28	19	22	18	0	32	39	38	40	42
15	4	25	22	26	11	23	18	26	20	27	18	25	28	27	0	39	40	41	43
16	5	5	12	6	5	14	15	14	12	14	16	18	4	11	4	0	42	45	42
17	2	3	2	3	2	3	11	16	10	11	9	18	5	3	2	45	0	45	45
18	2	10	12	6	3	4	14	18	16	18	12	14	4	4	7	26	20	0	45
19	3	14	8	8	7	2	18	22	26	23	25	18	7	5	1	28	28	44	0

Step Three: Formation of the Initial Reachability Matrix

The initial reachability matrix is obtained by converting the structural self-interaction matrix into a binary matrix consisting of zeros and ones. To replace the four symbols in Table 2 with zeros and ones and extract the initial reachability matrix, the following rules are used:

If the entry (i, j) in the structural self-interaction matrix is V, then in the initial reachability matrix, the entry (i, j) will be 1 and the entry (j, i) will be 0.

If the entry (i, j) in the structural self-interaction matrix is A, then in the initial reachability matrix, the entry (i, j) will be 0 and the entry (j, i) will be 1.

If the entry (i, j) in the structural self-interaction matrix is X, then in the initial reachability matrix, both the entry (i, j) and the entry (j, i) will be 1.

If the entry (i, j) in the structural self-interaction matrix is O, then in the initial reachability matrix, both the entry (i, j) and the entry (j, i) will be 0.

Table 3. Initial Reachability Matrix

Components	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	1	1
2	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	1	1	1
3	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	1	1
4	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	1	1	1
5	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	1	1
6	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	1	1
7	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	1	1	1	1
8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	1	1
9	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	1	1	1	1
10	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	1	1	1	1
11	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	1	1	1	1
12	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	1	1	1	1
13	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
14	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1

Step Four: Formation of the Final Reachability Matrix

After the initial reachability matrix was obtained, the secondary relationships among the components were examined. A secondary relationship means that if component i leads to component j and component j also leads to component k, then component i will also lead to component k. If this condition is not present in the initial reachability matrix, the matrix must be modified and the omitted relationships must be inserted. This process is technically referred to as making the initial reachability matrix compatible. In this step, all secondary relationships among the components were examined; however, no secondary relationship was identified. Therefore, the initial reachability matrix is the same as the final reachability matrix. In this matrix, the driving power and dependence level of each component are also shown. The driving power of an indicator is obtained from the sum of the number of components affected by it and the component itself, while the dependence level of each component is obtained from the sum of the components that influence it and the component itself. Table 4 shows the final reachability matrix.

Table 4. Final Reachability Matrix

Components	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Driving Power
1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	1	1	10
2	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	1	1	1	7
3	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	1	1	10
4	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0	1	1	1	1	7

5	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	1	1	10
6	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	1	1	5
7	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	1	1	1	1	7
8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	1	1	5
9	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	1	1	1	1	7
10	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	1	1	1	1	10
11	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	1	1	1	1	10
12	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	1	1	1	1	10
13	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	7
14	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	6
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	5
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	4
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	4
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
Dependence Level	3	5	3	5	3	6	5	6	5	3	3	3	1	2	3	17	17	19	19	-

Step Five: Determining Relationships and Leveling the Components

In this step, using the reachability matrix, after determining the input and output sets, the intersection of these sets is obtained for each factor.

The output set of a factor includes the factor itself and the factors it influences, which can be identified by the "1" values in the corresponding row.

The input set of a factor includes the factor itself and the factors from which it is influenced, which can be identified by the "1" values in the corresponding column.

After determining the input and output sets, their intersection is determined for each factor. Factors whose output set and intersection set are completely identical are placed at the highest level of the hierarchy of the interpretive structural model. To identify the components forming the next level of the system, the components at the highest level are removed from the mathematical calculations of the corresponding table, and the process of determining the components of the next level is performed in the same way as the process used to determine the components of the highest level. This operation is repeated until the components forming all levels of the system are identified.

Table 5. Leveling of Components Based on the Final Reachability Matrix (1)

Component	Output Set	Input Set	Intersection Set	Level
1	19, 18, 17, 16, 6, 5, 4, 3, 2, 1	5, 3, 1	5, 3, 1	
2	19, 18, 17, 16, 6, 4, 2	5, 4, 3, 2, 1	4, 2	
3	19, 18, 17, 16, 6, 5, 4, 3, 2, 1	5, 3, 1	5, 3, 1	
4	19, 18, 17, 16, 6, 4, 2	5, 4, 3, 2, 1	4, 2	
5	19, 18, 17, 16, 6, 5, 4, 3, 2, 1	5, 3, 1	5, 3, 1	
6	19, 18, 17, 16, 6	6, 5, 4, 3, 2, 1	6	
7	19, 18, 17, 16, 9, 8, 7	12, 11, 10, 9, 7	9, 7	
8	19, 18, 17, 16, 8	12, 11, 10, 9, 8, 7	8	
9	19, 18, 17, 16, 9, 8, 7	12, 11, 10, 9, 7	9, 7	
10	19, 18, 17, 16, 12, 11, 10, 9, 8, 7	12, 11, 10	12, 11, 10	
11	19, 18, 17, 16, 12, 11, 10, 9, 8, 7	12, 11, 10	12, 11, 10	
12	19, 18, 17, 16, 12, 11, 10, 9, 8, 7	12, 11, 10	12, 11, 10	
13	19, 18, 17, 16, 15, 14, 13	13	13	
14	19, 18, 17, 16, 15, 14	14, 13	14	

15	19, 18, 17, 16, 15	15, 14, 13	15	
16	19, 18, 17, 16	17, 16, 15, 14, 13, 12, 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1	17, 16	
17	19, 18, 17, 16	17, 16, 15, 14, 13, 12, 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1	17, 16	
18	19, 18	19, 18, 17, 16, 15, 14, 13, 12, 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1	19, 18	1
19	19, 18	19, 18, 17, 16, 15, 14, 13, 12, 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1	19, 18	1

As shown in the table above, the output set and intersection set of components 18 and 19 are completely identical; therefore, they are placed at the first level and are removed from the above table for the continuation of the leveling process. The remaining stages of leveling are summarized in the following table.

Table 6. Leveling (Second Iteration)

Iteration	Component	Output Set	Input Set	Intersection Set	Level
Second	16	17, 16	17, 16, 15, 14, 13, 12, 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1	17, 16	2
	17	17, 16	17, 16, 15, 14, 13, 12, 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1	17, 16	2
Third	6	6	6, 5, 4, 3, 2, 1	6	3
	8	8	12, 11, 10, 9, 8, 7	8	3
	15	15	15, 14, 13	15	3
	2	4, 2	5, 4, 3, 2, 1	4, 2	4
	4	4, 2	5, 4, 3, 2, 1	4, 2	4
	7	9, 7	12, 11, 10, 9, 7	9, 7	4
	9	9, 7	12, 11, 10, 9, 7	9, 7	4
	14	14	14, 13	14	4
Fourth	1	5, 3, 1	5, 3, 1	5, 3, 1	5
	3	5, 3, 1	5, 3, 1	5, 3, 1	5
	5	5, 3, 1	5, 3, 1	5, 3, 1	5
	10	12, 11, 10	12, 11, 10	12, 11, 10	5
	11	12, 11, 10	12, 11, 10	12, 11, 10	5
	12	12, 11, 10	12, 11, 10	12, 11, 10	5
	13	13	13	13	5

Step Six: Drawing the Final Model

At this stage, based on the levels of the components and the final reachability matrix, an initial model is drawn, and by eliminating transitive relationships in the initial model, the final model is obtained. By categorizing the components into the main dimensions, the initial ISM model is obtained based on the model for detecting the probability of financial crime occurrence using forensic accounting tools (Figure 1).

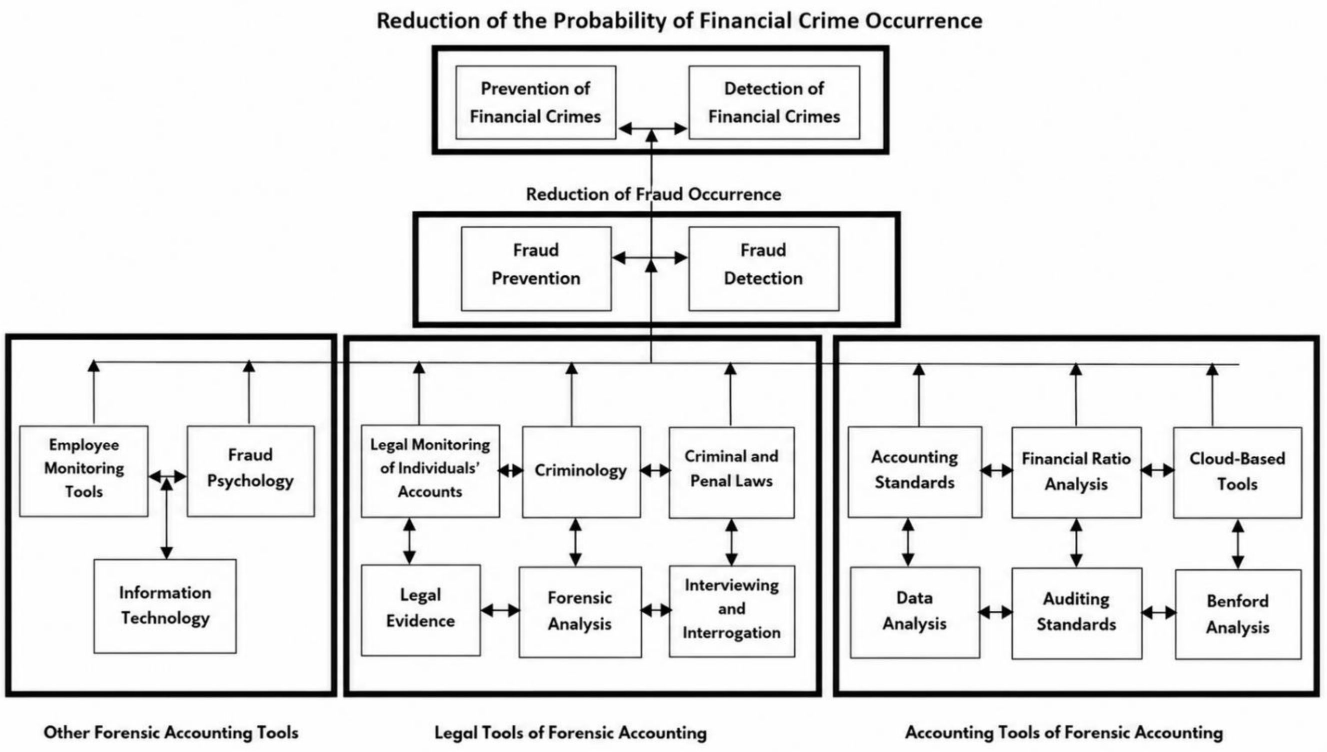

Figure 1. Final Research Model

Step Seven: Analysis of Driving Power and Dependence Level (MICMAC Diagram)

At this stage, the factors are classified into four groups. Using the data obtained from the fourth step, the factors under study can be classified according to the driving power of each factor over other factors and the dependence level of each factor on other factors into the following four categories:

Autonomous factors: Factors that have minimal dependence and driving power in relation to other factors.

Dependent factors: Factors that have high dependence on other factors.

Linkage factors: Factors that have a two-way relationship with other factors.

Independent factors: Factors that have significant influence over other factors.

To determine the coordinates of each factor in the MICMAC matrix, the driving power and dependence level of that factor must be used. These values are obtained from the final reachability matrix. Table 7 shows the driving power and dependence level of each factor.

Table 7. Driving Power and Dependence Level of Each Component

No.	Components	Dependence Level	Driving Power
1	Data analysis	3	10
2	Accounting standards	5	7
3	Auditing standards	3	10
4	Financial ratio analysis	5	7
5	Benford analysis	3	10
6	Cloud-based tools	6	5
7	Criminal and penal laws	5	7
8	Criminology	6	5
9	Legal monitoring of individuals’ accounts	5	7
10	Interviewing and interrogation	3	10
11	Forensic analysis	3	10

12	Legal evidence	3	10
13	Information technology	1	7
14	Employee monitoring tools	2	6
15	Fraud psychology	3	5
16	Fraud prevention	17	4
17	Fraud detection	17	4
18	Prevention of financial crimes	19	2
19	Detection of financial crimes	19	2

Using the coordinates of the components presented in Table 7, the MICMAC matrix is formed (Table 8).

Table 8. MICMAC Matrix

Classification	Components
Dependent area	16, 17, 18, 19
Driving/influence area	1, 3, 5, 10, 11, 12, 13
Autonomous area	2, 4, 6, 7, 8, 9, 14, 15
Linkage area	No component was identified in this area.

As observed in the MICMAC matrix, components 16, 17, 18, and 19 are located in the dependent area, meaning that they have low driving power but high dependence on other components. Components 1, 3, 5, 10, 11, 12, and 13 are located in the driving area. These components have high driving power with minimal dependence. Components 2, 4, 6, 7, 8, 9, 14, and 15 are located in the autonomous area, meaning that they have low driving power and low dependence. At this point, the process of presenting the model for detecting the probability of fraud and financial crimes using forensic accounting tools is completed.

4. Discussion and Conclusion

The present study aimed to develop a model for reducing the probability of fraud and financial crimes using forensic accounting tools. The findings demonstrated that forensic accounting can reduce fraud occurrence and financial crimes through three major categories of instruments, namely accounting tools, legal tools, and other supporting tools. The interpretive structural modeling results further revealed that these components are hierarchically interconnected and possess varying degrees of driving power and dependence. Specifically, components such as data analysis, auditing standards, Benford analysis, interviewing and interrogation, forensic analysis, legal evidence, and information technology were identified as highly influential factors with substantial driving power, whereas fraud prevention, fraud detection, prevention of financial crimes, and detection of financial crimes were located within the dependent area of the MICMAC matrix. These findings indicate that operational outcomes related to fraud reduction are highly dependent on the effective implementation of underlying accounting, legal, and technological infrastructures.

One of the most important findings of the study was the confirmation of accounting-based forensic tools, including data analysis, accounting standards, auditing standards, financial ratio analysis, Benford analysis, and cloud-based tools, as central components in reducing fraud and financial crimes. This finding is consistent with the theoretical perspective proposed by Ozili, who argued that forensic accounting extends beyond traditional accounting by integrating analytical and investigative techniques to uncover financial irregularities and fraudulent patterns [1]. The strong driving power of data analysis and auditing standards identified in the present study suggests that analytical accounting techniques are fundamental to the effectiveness of fraud detection systems.

These results are aligned with the findings of Ojo et al., who demonstrated that forensic accounting techniques significantly improve fraud detection in public entities by enabling the identification of suspicious financial activities and inconsistencies in reporting systems [7]. Similarly, Adejumo and Ogburie emphasized that data-driven forensic accounting methods enhance the ability of organizations to detect and investigate complex financial fraud schemes [4].

The significance of Benford analysis and financial ratio analysis in the proposed model also supports the growing emphasis on quantitative analytical tools in forensic investigations. Benford analysis is widely recognized as a useful statistical approach for identifying irregular numerical patterns associated with manipulation and fraud. The current findings indicate that such analytical methods function as foundational mechanisms with substantial influence on other fraud reduction processes. This result corresponds with the observations of Khajeh Hassani et al., who highlighted the importance of advanced accounting techniques in predicting and reducing reporting risk and fraud risk in the Iranian public sector [11]. In addition, Majboori Yazdi et al. reported that analytical accounting indicators and investigative auditing methods are among the most effective approaches for constructing fraud detection models in forensic accounting systems [14].

Another important finding of the study concerns the role of legal forensic accounting tools, including criminal and penal laws, criminology, legal monitoring of individuals' accounts, interviewing and interrogation, forensic analysis, and legal evidence. The results demonstrated that these components occupy central positions within the interpretive structural model and possess considerable driving power. This finding suggests that accounting mechanisms alone are insufficient for combating sophisticated financial crimes and that effective fraud reduction requires integration with legal and criminological frameworks. This interpretation is strongly supported by Hossain, who argued that forensic accounting fundamentally relies on the integration of accounting expertise with legal investigation and judicial procedures [3]. Financial crimes often involve intentional concealment, manipulation of evidence, and organized criminal behavior, making legal investigative procedures essential for uncovering fraudulent activities.

The role of interviewing, interrogation, and forensic analysis as influential factors in the present study further emphasizes the importance of investigative capabilities in forensic accounting systems. These findings are consistent with the arguments presented by Oyedokun, who noted that forensic accounting combines accounting theories with investigative methodologies to facilitate the detection and prosecution of fraud [2]. Criminology and legal evidence were also identified as significant elements within the proposed model, indicating that understanding criminal motivations and legal evidentiary requirements contributes substantially to effective fraud prevention strategies. These findings collectively suggest that forensic accounting should be conceptualized as an interdisciplinary field involving accounting, law, criminology, and investigative sciences rather than a purely financial or auditing discipline.

The findings also confirmed the importance of technological and behavioral tools, including information technology, employee monitoring tools, and fraud psychology, in reducing financial crimes. Information technology emerged as one of the most influential components in the MICMAC analysis, indicating that technological infrastructures play a critical role in enabling effective forensic accounting practices. This finding aligns with recent developments in forensic accounting research emphasizing the integration of digital technologies, artificial intelligence, and big data analytics into fraud detection systems [5]. The increasing digitization of financial systems has created new forms of cyber-enabled financial crimes, thereby requiring organizations to adopt advanced technological monitoring and analytical tools. The present results support the findings of Akinbowale et al., who concluded that integrating forensic accounting with big data technology frameworks substantially improves internal fraud mitigation within banking systems [9].

Likewise, the findings regarding cloud-based tools and information technology correspond with the results of Al Balushi, who found that technological innovations significantly enhance the effectiveness of forensic accounting in fraud detection and organizational monitoring [6]. Modern forensic accounting increasingly depends on automated transaction analysis, digital evidence extraction, continuous monitoring systems, and intelligent anomaly detection mechanisms. The strong driving role of information technology identified in the current study demonstrates that technological capabilities function as enabling infrastructures for other forensic accounting processes and therefore exert indirect influence on fraud prevention and financial crime reduction.

Another notable finding of the study was the confirmation of fraud psychology and employee monitoring tools as influential components within the model. This result reflects the behavioral nature of fraud and highlights the importance of understanding human motivations, ethical behavior, and organizational culture in fraud prevention efforts. Financial fraud is often associated with psychological factors such as rationalization, opportunity, pressure, and unethical decision-making. The present findings are consistent with the study conducted by Pourali and Azareh, who demonstrated that personality traits and organizational citizenship behavior influence whistleblowing and ethical conduct within auditing environments [12]. This suggests that organizations should not limit anti-fraud strategies to technical and legal mechanisms alone but should also promote ethical culture, behavioral monitoring, and psychological awareness among employees and managers.

The MICMAC analysis provided additional insights into the structural relationships among the components of the proposed model. Components associated with fraud prevention and financial crime reduction were located in the dependent area, indicating that they are strongly influenced by the effectiveness of other accounting, legal, and technological components. This finding implies that fraud reduction outcomes cannot be achieved independently; rather, they emerge as the result of coordinated interactions among multiple organizational and institutional mechanisms. Such an interpretation aligns with the forensic accounting maturity perspective proposed by Abbas Tafreshi and Soleimani Amiri, who argued that the effectiveness of forensic accounting systems depends on the simultaneous development of legal infrastructures, professional standards, technological capabilities, and institutional support systems [13].

The hierarchical structure identified through interpretive structural modeling further demonstrated that some components function as foundational drivers within the system. Data analysis, auditing standards, forensic analysis, legal evidence, and information technology exhibited strong driving power and relatively low dependence, suggesting that these factors constitute the core infrastructure of fraud prevention systems. This finding is highly consistent with the integrated forensic accounting framework proposed by Rahbari et al., who emphasized the interdependence of accounting, legal, technological, and behavioral dimensions in reducing financial crimes [15]. The current study extends previous research by empirically illustrating the hierarchical relationships among these dimensions and clarifying their relative influence within the fraud reduction system.

The findings also contribute to the broader literature on public sector fraud prevention. Public institutions often face high levels of fraud risk due to administrative complexity, inadequate oversight, and opportunities for corruption. The present study demonstrated that combining legal monitoring, accounting analysis, technological tools, and behavioral mechanisms can significantly enhance the capability of organizations to prevent and detect financial crimes. These findings are consistent with the results reported by Nasiri et al., who developed a forensic accounting-based model for fraud prevention in the public sector and emphasized the importance of integrating multiple anti-fraud dimensions within organizational governance frameworks [10]. Similarly, Yusuf and Harefa found that forensic accounting and compliance auditing contribute substantially to reducing financial fraud within governmental organizations [8].

Overall, the findings of the present study demonstrate that reducing the probability of fraud and financial crimes requires a comprehensive and integrated forensic accounting framework. Accounting tools provide the analytical foundation for detecting anomalies and suspicious financial patterns, legal tools facilitate investigation and prosecution, technological tools enable continuous monitoring and advanced data analysis, and behavioral mechanisms address the human and ethical dimensions of fraud. The interaction among these components creates a systematic structure capable of improving transparency, accountability, and financial integrity within organizations. Therefore, the present study contributes both theoretically and practically to the advancement of forensic accounting literature by proposing a hierarchical and integrated model for fraud reduction.

One limitation of the present study was the relatively limited number of experts participating in the qualitative and ISM phases of the research. Although theoretical saturation was achieved, the inclusion of a broader range of forensic accounting professionals, legal experts, and technology specialists from different organizational sectors could provide a more comprehensive perspective on fraud prevention mechanisms. Another limitation concerns the contextual focus of the study, as the model was primarily developed within the institutional environment of Iran. Consequently, cultural, legal, and organizational differences may limit the generalizability of the findings to other countries or financial systems. In addition, the study relied heavily on expert judgment and interpretive structural modeling, which may involve subjective evaluations regarding the relationships among components.

Future research should investigate the applicability of the proposed model across different organizational and national contexts in order to examine its external validity and adaptability. Comparative studies between public and private sector organizations may provide deeper insights into the contextual effectiveness of forensic accounting tools. Future researchers may also integrate advanced quantitative methods such as machine learning, artificial intelligence modeling, and predictive analytics into forensic accounting frameworks to enhance the accuracy of fraud prediction systems. Furthermore, future studies could examine the mediating or moderating role of organizational culture, ethical climate, and digital transformation in the relationship between forensic accounting practices and fraud reduction outcomes.

From a practical perspective, organizations and policymakers should prioritize the institutionalization of forensic accounting systems by strengthening accounting standards, legal infrastructures, technological capabilities, and employee training programs. Public and private organizations should invest in advanced analytical technologies, continuous monitoring systems, and digital forensic tools to improve fraud detection and prevention capacities. Educational institutions and professional associations should also expand specialized training programs in forensic accounting, criminology, and digital investigation in order to prepare qualified professionals capable of addressing emerging financial crimes. Finally, organizations should promote ethical culture, transparency, and accountability mechanisms to reduce opportunities and motivations for fraudulent behavior and enhance public trust in financial systems.

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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