Proposing a Model of Forensic Accounting Tools to Reduce Financial Crimes

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Abstract

This study aims to propose a model for detecting the likelihood of fraud and financial crimes using forensic accounting tools. The required data were collected through semi-structured interviews with 15 expert forensic accountants using the snowball sampling method. An Interpretive Structural Modeling (ISM) approach was employed to develop a proposed model. According to the ISM analysis, the exploratory model includes 19 factors. The results revealed that forensic accounting tools include the following components: data analysis, accounting standards, auditing standards, financial ratio analysis, Benford's analysis, and cloud-based tools. Legal forensic accounting tools comprised components such as criminal and penal law, criminology, legal monitoring of individuals' accounts, interviewing and interrogation, forensic analysis, and legal documentation. Other forensic accounting tools encompassed information technology, employee monitoring tools, and fraud psychology. Ultimately, accounting tools, legal tools, and other forensic accounting instruments contribute to reducing the incidence of fraud and financial crimes. This model provides a systematic framework for combating financial fraud by creating overlap among accounting, legal, and technological domains. The findings emphasize that integrating analytical tools (e.g., Benford's analysis) with advanced technologies (such as cloud systems) and legal mechanisms significantly enhances the accuracy and speed of fraud detection. Additionally, considering psychological and monitoring factors alongside legal requirements facilitates the design of more effective preventive policies. This model can serve as a foundation for developing forensic accounting standards and strengthening regulatory frameworks within organizations.

Keywords: *Forensic Accounting Tools, Fraud, Forensic Accounting, Financial Crimes.*

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1. Introduction

In the increasingly complex financial and administrative landscapes of modern organizations, financial crimes such as fraud, embezzlement, and corruption have emerged as serious threats to organizational integrity and economic stability. These illicit activities not only damage corporate reputations but also erode public trust, distort market fairness, and lead to substantial financial losses globally. According to research, conventional internal control and auditing systems have often proved inadequate in timely detecting or preventing such crimes due to their static and rule-based nature [1, 2]. In this context, forensic accounting has emerged as a robust, investigative discipline capable of addressing these deficiencies through its systematic application of accounting, auditing, and investigative skills.

The growing prevalence of financial fraud has placed pressure on organizations, especially in developing economies, to adopt more sophisticated mechanisms for fraud detection and prevention. As forensic accounting evolves, it increasingly incorporates modern technologies, including big data analytics, cloud-based systems, and artificial intelligence, to enhance the efficiency and effectiveness of fraud detection processes [2, 3]. Studies have highlighted that integrating forensic accounting with emerging technologies can bridge significant gaps in traditional accounting systems and offer real-time, actionable insights into potentially fraudulent activities [3, 4]. These integrations also support organizations in transitioning from reactive to proactive approaches in managing financial crimes.

Forensic accounting, as a specialized branch of accounting, applies scientific methods to uncover, analyze, and present financial evidence that is suitable for legal proceedings. It is widely applied in investigating white-collar crimes, money laundering, asset misappropriation, and financial statement manipulation [5, 6]. This field has garnered increasing attention from academics and practitioners, especially as fraudulent financial activities become more sophisticated and multi-dimensional. Research in this area has demonstrated that forensic accounting methods significantly enhance the capability to detect complex fraud patterns that would otherwise be overlooked by conventional auditing techniques [7, 8].

Iran, like many developing nations, faces persistent challenges in combating financial corruption within both the public and private sectors. In recent years, considerable efforts have been made to institutionalize forensic accounting practices as a strategic tool in reducing financial crime across different sectors, including banking, municipalities, and sports organizations [9-11]. However, due to contextual differences, such as regulatory inconsistencies, limited professional expertise, and technological limitations, the application of forensic accounting in Iran demands a tailored approach. Several scholars have emphasized the importance of developing indigenous forensic accounting models that are responsive to local organizational, cultural, and legal environments [12, 13].

To address these limitations and improve forensic accounting implementation, some researchers have proposed structural modeling approaches, particularly Interpretive Structural Modeling (ISM), which enables systematic identification and prioritization of key factors influencing forensic accounting effectiveness [13]. ISM helps construct hierarchical models that clarify the interrelationships among variables and provide decision-makers with actionable frameworks for implementation. This methodological advantage is particularly useful in environments where multiple legal, institutional, and technological variables interact in complex ways to affect the detection and prevention of financial crime [14, 15].

From a theoretical standpoint, forensic accounting is grounded in a combination of economic crime theory, fraud triangle theory, and audit risk frameworks, which collectively explain the motivations, opportunities, and rationalizations behind financial misconduct [5, 16]. Modern models of fraud risk management emphasize that prevention and early detection are more cost-effective than post-crisis remediation. In line with this, empirical research has shown that forensic accounting reduces unethical practices by enhancing internal audit capabilities, increasing transparency, and supporting legal enforcement through high-quality financial evidence [1, 17].

The multidimensional nature of forensic accounting requires it to interact with several domains, including auditing, legal frameworks, criminology, psychology, and data science. For instance, components such as Benford's Law, ratio analysis, data analytics, and structured interviews are often integrated into forensic investigations to provide a holistic view of financial behaviors [4, 8]. Legal instruments such as penal codes, compliance standards, and evidentiary procedures are equally central to forensic analysis, ensuring that findings are admissible in court and contribute meaningfully to judicial decisions [3, 18].

The effectiveness of forensic accounting also relies heavily on the institutional and regulatory environment in which it operates. Studies conducted in different countries have demonstrated that without regulatory support, forensic accounting efforts can be rendered ineffective or politically constrained [19, 20]. In Iran, financial oversight mechanisms are gradually evolving to include forensic dimensions, but systemic weaknesses in accountability, political interference, and insufficient professional training remain critical barriers [9, 11].

To navigate these challenges, scholars have stressed the role of organizational transparency and ethical culture in preventing administrative and financial corruption [9, 21]. Transparent reporting systems, internal whistleblowing mechanisms, and compliance audits are among the most effective non-technological strategies that complement forensic tools. Moreover, cultural readiness and management commitment to ethical governance are necessary for sustaining forensic accounting practices over time [10, 12].

Another critical consideration in implementing forensic accounting practices is the cost-benefit tradeoff. Many organizations, especially in the public sector, hesitate to invest in advanced forensic systems due to resource constraints or a lack of awareness regarding their potential long-term benefits [17, 22]. However, multiple case studies indicate that the cost of undetected fraud far outweighs the investment in proactive forensic auditing systems [16, 18]. Thus, the strategic integration of forensic accounting within financial oversight frameworks is not only a protective measure but also a financially prudent decision.

Despite growing interest, there remains a notable gap in applied frameworks that guide the implementation of forensic accounting in localized contexts such as Iran. This research aims to fill this gap by developing a model—through ISM methodology—that identifies and prioritizes the forensic accounting tools most effective in reducing the probability of fraud and financial crimes.

2. Methodology

The present study employs a mixed-methods approach. To this end, the research initially involved collecting qualitative data. This stage guided the researcher in describing numerous aspects of the phenomenon under investigation. Through this preliminary identification, the key components for model design were obtained. Subsequently, the researcher designed the research model using Interpretive Structural Modeling (ISM). This study is exploratory in nature, as it addresses an issue that has not been examined in this particular form and depth before.

The study population consisted of certified forensic accounting and auditing experts affiliated with the Judiciary and Justice Administration who are also faculty members at universities and have academic credentials in accounting and auditing along with a minimum of five years of forensic accounting experience. The sampling continued until theoretical saturation was reached during the interviews.

Two types of sampling methods were used in this research:

1. **Snowball Sampling Based on Theoretical Saturation for Expert Interviews**: The experts in this study were certified forensic accounting and auditing professionals from the judiciary who are also university faculty members, as well as senior managers with academic qualifications and at least five years of forensic accounting experience. Sampling continued until no new findings emerged from the interviews. The researcher reached theoretical saturation after conducting 15 interviews.
2. **Purposeful Judgmental Sampling for ISM (Interpretive Structural Modeling)**: Lashkarebolouki et al. (2012) stated in their research (which utilized the ISM method) that the number of experts required ranges from 4 to 15 individuals. Nevertheless, the same 15 experts from the interview phase were used in this stage.

After the researcher identified the research method and collected the necessary data using appropriate tools, the next step was to categorize and analyze the collected data using techniques consistent with the research method. Finally, the questions that guided the research thus far were put to the test to determine their outcome and ultimately answer the central research question, which this study systematically sought to address. The research employed the Content Validity Ratio (CVR) method and Interpretive Structural Modeling (ISM).

3. Findings and Results

In this study, data analysis was conducted using the Content Validity Ratio (CVR), Interpretive Structural Modeling (ISM), and Structural Equation Modeling (SEM), which are described step-by-step below.

Factor Validity Assessment Using the CVR Index

At this stage, the CVR index was used to calculate the content validity ratio of each factor. A questionnaire was administered to the experts, asking them to evaluate each factor and dimension using a three-point Likert scale: "essential," "useful but not essential," and "not essential." Given that there were 15 experts, a CVR value above 0.49 was considered indicative of content validity for each factor. The results of the CVR application are presented in Table 1.

Table 1. CVR Values for Each Factor

No.	Component	CVR Value	Result	Dimension
1	Data Analysis	1	Approved	Forensic Accounting Tools
2	Earnings Quality	0.46	Rejected	
3	Beneish Model	0.46	Rejected	
4	Accounting Standards	1	Approved	
5	Auditing Standards	1	Approved	
6	Financial Ratio Analysis	1	Approved	
7	Benford's Analysis	1	Approved	

8	Cloud-Based Tools	1	Approved	
9	Criminal and Penal Laws	1	Approved	Legal Forensic Accounting Tools
10	Criminology	1	Approved	
11	Legal Monitoring of Accounts	1	Approved	
12	Interviewing and Interrogation	1	Approved	
13	Forensic Analysis	1	Approved	
14	Legal Documentation	1	Approved	
15	Professional Certification	0.46	Rejected	
16	Information Technology	1	Approved	Other Forensic Accounting Tools
17	Cyber Tools	0.33	Rejected	
18	Employee Monitoring Tools	1	Approved	
19	Financial Network Analysis	0.46	Rejected	
20	Fraud Psychology	1	Approved	
21	Fraud Prevention	1	Approved	Fraud Reduction
22	Fraud Detection	1	Approved	
23	Financial Crime Prevention	1	Approved	Financial Crime Reduction
24	Financial Crime Detection	1	Approved	

Upon reviewing and compiling the collected components, a total of 19 components across five dimensions were validated.

Step One: Identification of Components

The process of identifying components was described in the previous section. Accordingly, 18 components were selected, as presented in Table 1.

Step Two: Development of the Structural Self-Interaction Matrix (SSIM)

After determining the components, another questionnaire in a matrix format was designed. The experts evaluated the components in pairwise comparisons and identified the relationships between them using the following notations:

- **V**: If component *i* influences component *j*
- **A**: If component *j* influences component *i*
- **X**: If components *i* and *j* influence each other
- **O**: If there is no relationship between components *i* and *j*

The data obtained were compiled based on the interpretive structural modeling (ISM) method. The Structural Self-Interaction Matrix (SSIM) was constructed by comparing the study indicators using the four types of conceptual relationships. The logic of ISM operates based on the mode of frequencies. The results obtained from the questionnaires regarding the evaluated components are presented in Table 2.

Table 2. Results Obtained from the Questionnaires

Row	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											

Step Three: Formation of the Initial Reachability Matrix

The Initial Reachability Matrix is derived by converting the Structural Self-Interaction Matrix into a binary matrix (composed of 0s and 1s). To replace the four symbolic notations used in Table 2 with binary digits for the extraction of the Initial Reachability Matrix, the following rules are applied:

- If the entry (i, j) in the Structural Self-Interaction Matrix is denoted by **V**, then the corresponding entry (i, j) in the Initial Reachability Matrix will be **1**, and the entry (j, i) will be **0**.
- If the entry (i, j) is denoted by **A**, then the entry (i, j) will be **0**, and (j, i) will be **1**.
- If the entry (i, j) is denoted by **X**, then both (i, j) and (j, i) will be **1**.
- If the entry (i, j) is denoted by **O**, then both (i, j) and (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							

Step Four: Creation of the Final Reachability Matrix

Once the Initial Reachability Matrix is obtained, the transitive (secondary) relationships among the components are examined. A transitive relationship implies that if component *i* leads to component *j*, and component *j* leads to component *k*, then component *i* should also lead to component *k*. If this condition is not met in the Initial Reachability Matrix, the matrix must be revised to include the missing relationships; this process is referred to as matrix consistency adjustment.

In this step, all transitive relationships among the components were evaluated. However, no additional transitive relationships were identified. Therefore, the Initial Reachability Matrix remained unchanged and was adopted as the Final Reachability Matrix.

This matrix also indicates the driving power and dependence of each component. The driving power is calculated by summing the number of components that are influenced by a given component, including the component itself. The dependence of a component is calculated by summing the number of components that influence it, including the component itself.

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	5	
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	4	
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	4	
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	
19	0	0	0	0	0	0	0	0												

Step Five: Determining Relationships and Component Leveling

In this step, using the reachability matrix, the **input and output sets** for each component are determined, and their **intersection** is calculated.

- The **output set** of a component includes the component itself and all other components it influences, which can be identified through the "1"s in the corresponding row.
- The **input set** of a component includes the component itself and all other components that influence it, which can be identified through the "1"s in the corresponding column.

After determining the input and output sets, the intersection of these sets is identified for each component. Components whose **output set and intersection set are identical** are placed at the **highest level** of the Interpretive Structural Modeling (ISM) hierarchy. To determine the components of the next level, the top-level components are removed from the matrix, and the process is repeated as described above. This process continues until all components are assigned to hierarchical levels.

Table 5. Component Leveling Based on Final Reachability Matrix (1)

Component	Output Set	Input Set	Intersection	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, ..., 1	19, 18	1
19	19, 18	19, 18, ..., 1	19, 18	1

As indicated in the table above, the output set and intersection set of components 18 and 19 are identical; thus, they are placed at Level 1. These components are then removed from the matrix for the continuation of the leveling process. The following table summarizes the subsequent iterations.

Table 6. Leveling (Second Iteration)

Iteration	Component	Output Set	Input Set	Intersection	Level
Second	16	17, 16	17, 16, ..., 1	17, 16	2
	17	17, 16	17, 16, ..., 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
Fourth	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
Fifth	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

In this stage, based on the hierarchical levels of the components and the Final Reachability Matrix, an initial model is created. By eliminating the transitive relationships from the initial model, the final ISM model is obtained. Consequently, the initial ISM model derived from components related to detecting the likelihood of fraud and financial crimes through forensic accounting tools is refined into the final model. By categorizing components into main dimensions, the final research model is developed based on the pattern for detecting the probability of financial crime using forensic accounting tools:

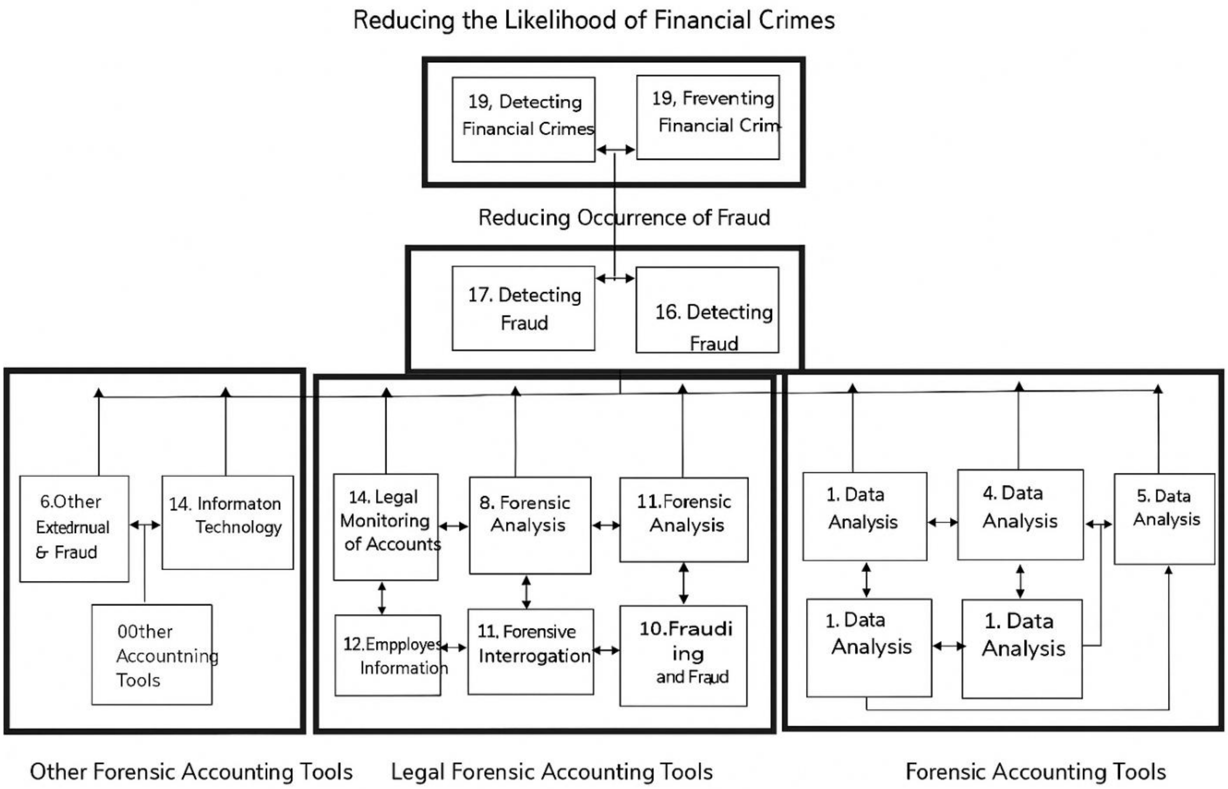

Figure 1. Final Research Model

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

In this step, the components are categorized into four groups. Based on the data obtained from Step Four, the studied components can be classified according to their **driving power** (influence over other components) and **dependence** (extent of being influenced by other components) into the following four categories:

- **Autonomous Components**: Components that have minimal dependence and minimal driving power over other components.
- **Dependent Components**: Components with high dependence on other components.
- **Linkage Components**: Components that maintain mutual relationships with other components (high influence and high dependence).
- **Independent (Driving) Components**: Components that exert considerable influence over other components but have low dependence.

To determine the coordinates of each component in the MICMAC matrix, its driving power and dependence value must be used. These values are derived from the Final Reachability Matrix. **Table 7** presents the driving power and dependence of each component.

Table 7. Driving Power and Dependence of Each Component

No.	Components	Dependence	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's Analysis	3	10
6	Cloud-Based Tools	6	5
7	Criminal and Penal Laws	5	7
8	Criminology	6	5
9	Legal Monitoring of Accounts	5	7
10	Interviewing and Interrogation	3	10
11	Forensic Analysis	3	10
12	Legal Documentation	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	Financial Crime Prevention	19	2
19	Financial Crime Detection	19	2

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

Table 8. MICMAC Matrix

High	19																			
	18																			
	17																			
	16																			
	15																			
	14																			
	13																			
	12																			
	11																			
Influence	10			12 ،11 ،10 ،5 ، 3 ،1																
	9																			
	8																			
	7	13				9 ،7 ، 4 ،2														
	6		14																	
	5			15			8 ، 6													
	4																	17 ، 16		
	3																			
	2																			19 ، 18
	1																			
Low		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19

Dependency High

As shown in the MICMAC Matrix, components 16, 17, 18, and 19 fall into the dependent zone, indicating they have low driving power but high dependence on other components.

Components 1, 3, 5, 10, 11, 12, and 13 are located in the independent (driving) zone, meaning they have high driving power and low dependence.

Components 2, 4, 6, 7, 8, 9, 14, and 15 are situated in the autonomous zone, which signifies that they possess low driving power and low dependence.

Here, the process of developing a model for detecting the likelihood of fraud and financial crimes using forensic accounting tools concludes.

4. Discussion and Conclusion

The present study aimed to develop a structural model for detecting the likelihood of fraud and financial crimes through forensic accounting tools using Interpretive Structural Modeling (ISM). The analysis identified 19 critical components, which were grouped into five dimensions: accounting tools, legal tools, complementary forensic tools, fraud reduction mechanisms, and financial crime mitigation mechanisms. The findings underscore the importance of integrating forensic, legal, and technological components to form a comprehensive system for fraud detection and financial crime prevention.

One of the most salient outcomes was the categorization of components based on their driving power and dependence through MICMAC analysis. Components such as *data analysis*, *Benford's analysis*, *forensic documentation*, *interrogation techniques*, and *forensic analytics* were shown to possess high driving power but low dependence, placing them in the category of independent (or key driving) components. This classification is consistent with the argument that data-driven and investigative techniques lie at the core of forensic accounting's efficacy in uncovering fraudulent activity [4, 8]. These findings align with the theoretical framework proposed by [5], which emphasizes the forensic accountant's toolkit as an assemblage of analytical and evidentiary instruments.

The presence of *Benford's Law analysis*, *financial ratio analysis*, and *cloud-based tools* in the upper layers of the ISM hierarchy further validates previous research advocating for the technological modernization of forensic auditing systems [2, 3]. These tools have the capability to sift through vast amounts of financial data to detect anomalies that suggest fraudulent intent. The findings support the proposition that the integration of big data frameworks and forensic methodologies significantly enhances the timeliness and reliability of fraud detection mechanisms [4, 6].

Legal components such as *criminal and penal codes*, *compliance audits*, and *legal account monitoring* also emerged as foundational pillars in the model. These elements were shown to provide the necessary institutional and regulatory scaffolding for forensic accounting to operate effectively. The critical role of legal instruments in forensic audits was underscored in earlier works emphasizing the alignment between financial oversight and judicial enforceability [3, 16, 18]. The model reinforces the notion that forensic accounting is not just a financial or investigative function but also a legal mechanism empowered by structured regulatory frameworks [19].

Additionally, the findings highlight the importance of *psychological tools* (such as fraud psychology) and *employee monitoring systems* as complementary forensic components. These elements, though traditionally overlooked, were identified in this study as having meaningful driving roles within the ISM hierarchy. This echoes the findings of [9] and [10], who emphasized the behavioral dimension of fraud and the need for enhanced internal surveillance and ethical training. The emergence of *fraud prevention* and *detection components* in the final levels of the model signifies their role as ultimate outcomes of the functioning of all previous layers.

The MICMAC analysis showed that components like *fraud prevention*, *fraud detection*, *financial crime prevention*, and *financial crime detection* fall into the "dependent" quadrant—indicating that these outcomes are highly reliant on the effectiveness of upstream components such as analytical tools, legal measures, and technological infrastructure. This finding supports the causality model proposed by [14] and [15], which argued that fraud mitigation is a systemic consequence rather than an isolated function.

The study also provides empirical support to the layered and interdependent nature of forensic accounting systems. For instance, lower-tier components in the ISM model such as *information technology*, *employee surveillance tools*, and *fraud psychology* directly influence upper-tier outcomes. This hierarchical structure aligns with the structural models proposed by [12, 13], emphasizing the necessity of coordinated interactions across functional, behavioral, and technological domains in forensic frameworks.

The fact that forensic accounting components were effectively structured into five dimensions—*forensic accounting tools*, *legal tools*, *other forensic instruments*, *fraud reduction*, and *crime reduction*—highlights the systemic and interdisciplinary nature of effective forensic models. This is corroborated by findings from [18] and [20], which identified multi-sectoral collaboration as a prerequisite for effective forensic performance in the public sector. Moreover, the study echoes [1] in asserting that forensic accounting systems function optimally when embedded within transparent and compliance-oriented environments.

Furthermore, this research emphasizes the contextual relevance of localized models for countries like Iran. The selection of ISM methodology provided a framework that is both systematic and adaptable to local institutional, legal, and cultural conditions. This finding complements [11] and [9], who argued that anti-fraud systems in Iran must consider indigenous challenges such as regulatory loopholes, institutional opacity, and lack of forensic training.

The broader implications of the study also extend to governance and public trust. The model indicates that forensic accounting tools, when effectively operationalized, lead to greater organizational transparency, higher audit quality, and improved legal accountability. This reinforces the arguments of [21] and [19], who identified strong internal controls and ethical oversight as key to reducing fraud and restoring public confidence in financial institutions.

Despite the study's methodological rigor, several limitations warrant acknowledgment. First, the sample size was limited to 15 experts, which, although sufficient for ISM and theoretical saturation, may not represent the full diversity of perspectives in Iran's financial and legal ecosystem. Second, the reliance on qualitative data through expert judgment introduces subjectivity into component selection and relationship mapping. Third, the ISM model, while effective in structural analysis, does not capture the temporal or dynamic aspects of how these components evolve in practice. Finally, the model has not yet been tested for empirical validity through quantitative techniques such as structural equation modeling (SEM).

Future studies could expand the sample base to include stakeholders from additional sectors such as banking, insurance, and government oversight agencies to enhance the model's generalizability. Quantitative validation of the ISM framework using SEM or fuzzy DEMATEL could also provide additional robustness and predictive capability. Furthermore, comparative studies across different countries or regions could offer insights into how legal, cultural, and technological environments mediate the success of forensic accounting models. Lastly, future research could explore the integration of artificial intelligence and machine learning in enhancing the real-time detection and predictive functions of forensic accounting systems.

Organizations should invest in training and capacity-building programs to develop forensic accounting expertise, particularly focusing on advanced data analytics, legal compliance, and behavioral auditing. Regulatory agencies must revise existing legal frameworks to include explicit mandates for forensic auditing procedures and ensure judicial enforceability. Moreover, financial institutions and public organizations should adopt the ISM-derived model as a diagnostic tool to assess their current anti-fraud infrastructure and identify gaps in legal, technological, or organizational dimensions. Finally, it is critical to promote inter-agency collaboration, ensuring that forensic accounting efforts are integrated across audit, legal, and information systems functions to maximize effectiveness.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

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

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