



ORIGINAL RESEARCH ARTICLE

## Designing a Data Analysis-Based Learning Model for Training in Accounting Fraud Detection in Digital Environments

Reza Nemati Mofarrah<sup>1</sup>, Farzin Rezaei<sup>2\*</sup>, Hosein Kazemi<sup>3</sup>, Kumars Biglar<sup>4</sup>

<sup>1</sup> PhD Candidate, Department of Accounting, Qa .c., Islamic Azad University, Qazvin, Iran. [reza.nematimofarrah@iau.ac.ir](mailto:reza.nematimofarrah@iau.ac.ir)

<sup>2</sup> Professor, Department of Accounting, Qa .c., Islamic Azad University, Qazvin, Iran. (Corresponding author)

[farzin.rezaei@iau.ac.ir](mailto:farzin.rezaei@iau.ac.ir), 0009-0005-7987-7650.

<sup>3</sup> Assistant Professor, Department of Accounting, Qa .c., Islamic Azad University, Qazvin, Iran. [hosein.kazemi@iau.ac.ir](mailto:hosein.kazemi@iau.ac.ir)

<sup>4</sup> Assistant Professor, Department of Accounting, Qa .c., Islamic Azad University, Qazvin, Iran. [kumars.biglar@iau.ac.ir](mailto:kumars.biglar@iau.ac.ir)

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### ABSTRACT

This research aims to design a data analysis-based learning model for training in accounting fraud detection in digital environments. The research was conducted in an exploratory and survey manner. The qualitative part was conducted using the Delphi method and the quantitative part using the interpretive structural model and structural equations method. In the qualitative part, the population studied was managers and experts in financial management and information technology management, 12 people were selected using the available judgment sampling method. Using the library technique, the components affecting the model were identified. First, the identified components were screened and evaluated using the Delphi technique. Then, modeling was carried out using the Delphi method and the interpretive structural method. The software used were EXCEL and MICMAC. Using the Cochran formula, 384 people were selected. Based on a researcher-made questionnaire based on qualitative analysis, data analysis was performed using coding and path analysis. Data analysis was performed using coding and path analysis. Based on sampling, the structural equation modeling technique in SMARTPLS software was used to fit the proposed model. The ten main criteria, including big data analytics, fraud machine learning, audit artificial intelligence, smart transaction tracking, encryption and transparency, financial process automation, hidden behavioral data mining, digital anomaly detection, financial blockchain platform, and continuous real-time monitoring, are classified into seven levels. This hierarchical classification shows that some criteria play a fundamental and fundamental role in the success of fraud detection systems, while others affect the operational, analytical, and monitoring layers more. ©authors

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## 1. Introduction

In recent decades, the rapid development of digital technologies has fundamentally transformed financial, accounting, and reporting structures (Abduli Abatari et al., 2024). Organizations are faced with a huge volume of financial, operational, and behavioral data that is generated and processed in the context of complex information systems, digital platforms, cloud technologies (Aisyah, 2025), blockchain, artificial intelligence, and big data (Han, 2023). In such an environment, the nature of accounting fraud has also changed, from traditional and detectable forms to complex, hidden, dynamic, and data-driven patterns. These changes have not only transformed fraud detection tools, but also fundamentally transformed the type of knowledge, skills, and learning styles required of accountants, auditors, and financial managers (Futurity Proceedings Group, 2025).

Despite these developments, accounting and auditing education in many educational systems and even professional training programs still relies on traditional, content-oriented approaches based on the transfer of theoretical knowledge (Leocádio et al., 2024). In these approaches, learning to detect fraud is mainly based on rules, standards, limited examples and individual judgments, and less attention is paid to the analysis of real data, behavioral patterns, complex relationships between variables and the use of advanced analytical tools (Kamrani et al., 2023). This gap between the complexity of digital financial environments and the level of analytical readiness of learners is considered one of the fundamental challenges of training in detecting fraud in the digital age (Gkegkas et al, 2025). On the other hand, digital environments have not only provided the platform for new frauds to occur, but have also significantly increased the possibility of detecting, predicting and preventing fraud through data analysis (Mökander et al., 2023).

Tools such as data mining, machine learning, network analysis, anomaly detection, behavioral pattern analysis and business intelligence play a key role in detecting accounting fraud today. However, the effective use of these tools requires analytical skills, data-driven thinking and the ability to interpret the results of the analysis (Ayinla et al. 2024); skills that cannot be achieved solely through theoretical training or limited case studies and require the design of new and purposeful learning models (Bhattacharya, 2024). Meanwhile, the concept of "data-driven learning" as one of the new educational approaches has attracted the attention of researchers in the fields of education, management, and accounting (Desai et al., 2024). This approach considers learning to be an active, analytical process based on interaction with real data in which learners gain a deeper understanding of complex issues by analyzing data, discovering patterns, interpreting results, and making evidence-based decisions (Chen et al, 2025). Despite the high potential of this approach, its application in accounting fraud detection training, especially in digital environments, is still faced with ambiguity, fragmentation, and lack of a coherent framework (Winarto et al., 2025).

A review of the research literature shows that existing studies in the field of accounting fraud detection have mainly focused on the development of models and technical tools and have paid less attention to the educational and learning dimensions (Zare Bahmaniri et al., 2023). In contrast, research in the field of accounting education has often been limited to traditional teaching methods, case-based learning, or general software training, and has paid less attention to designing learning models based on complex and real data analysis (Mohasani et al., 1400). This dichotomy has resulted in a significant gap between the potential power of digital fraud detection tools and the actual power of trained human resources, despite technological advances (Chen et al., 2025).

From the perspective of educational systems, the lack of a specific and indigenous model for training in fraud detection based on data analysis has led to curricula and training courses being designed in isolation (Almalki et al., 2025), incoherent and lacking continuity (Rezaei et al., 2024). In many cases, data analysis training is presented independently of accounting content, and a meaningful connection is not established between analytical skills and their application in fraud detection. This not only reduces the effectiveness of training, but also

causes confusion for learners in applying what they have learned in real situations (Alsulami, 2023). In addition, training in fraud detection in digital environments faces other challenges such as the diversity of learners' knowledge levels, the rapid pace of technological change, the complexity of data, ethical and security considerations, and the need for critical and interdisciplinary thinking. In such circumstances, the lack of a comprehensive learning model that can cover knowledge, skills, attitudes and technology in an integrated manner has become one of the main obstacles to empowering human resources in the field of fraud detection. From an organizational perspective, the inability of finance and audit staff to effectively analyze data and detect fraudulent patterns poses serious risks to financial health, organizational credibility and stakeholder trust. In many cases, the occurrence of widespread fraud is due to weaknesses in education and learning systems that have failed to prepare individuals to face the complexities of the digital environment. Therefore, designing an appropriate learning model is not only an educational necessity, but also a strategic requirement for organizations (Shevchu, 2025).

At a macro level, digital transformation in finance and accounting systems requires a rethinking of the philosophy of education and learning (Nonaka & Takeuchi, 1995). Learning to detect fraud can no longer be based solely on memorizing rules and standards, but must be based on cultivating analytical thinking, the ability to work with big data, understanding complex relationships, and evidence-based decision-making. This requires a shift from content-based education to data-driven learning, and from a passive role of the learner to an active and exploratory role. Despite the importance of this issue, in the domestic and even international research literature, a comprehensive model that specifically addresses the design of data analysis-based learning for accounting fraud detection training in digital environments is rarely seen (Cressey, 1953). Existing studies either focus on the technical aspect of data analysis or refer to digital accounting training in general and have paid less attention to the systematic interaction between data, learning, and fraud detection. This research gap highlights the necessity of conducting the present study (Khademi, 2024).

The present study aims to design a data analysis-based learning model for teaching accounting fraud detection in digital environments, and aims to provide a coherent and practical framework by identifying key components, mechanisms, and relationships (Oladejo et al., 2020). This model can be used as a guide for educational planners, instructors, organizations, and professional institutions and help improve the quality of learning, increase the effectiveness of training, and enhance the ability to detect and prevent fraud. Paying attention to data analysis-based learning in fraud detection training is not only a response to the current needs of digital environments, but also a strategic investment for the future of the accounting profession. Cultivating a generation of accountants and auditors who can analyze data, recognize patterns, and make evidence-based decisions will be a fundamental step towards promoting transparency, accountability, and financial health in organizations and society. Therefore, addressing this issue scientifically and systematically is an undeniable necessity in contemporary research in the fields of accounting and education.

## **2. Literature Review**

The theoretical framework of the present study is based on the integration of modern learning theories, data-driven approaches and theoretical foundations of accounting fraud detection in the context of digital environments (Mijani et al., 2025). The starting point of this framework is the fundamental assumption that fraud detection in the digital age is no longer simply a technical skill or individual professional judgment, but rather the result of a data-driven analytical learning process, critical thinking and active interaction with complex information. Therefore, fraud detection training requires a theoretical framework that can establish a meaningful link between learning, data analysis and accounting decision-making (Bagharian Kasgari et al., 2024). At the first level, constructivist learning theories form the main basis of the theoretical framework (Parasuraman et al., 2000). According to this view,

learning will be deep and sustainable when learners actively participate in the process of knowledge construction and create meaning through exposure to real problems (Wolfe & Hermanson, 2004). In accounting fraud detection training, analyzing real or simulated financial data provides an authentic learning experience and helps learners understand fraud concepts not in an abstract way, but in the form of observable and analyzable patterns. This approach elevates learning from the level of memorizing rules to a deep understanding of fraud relationships and mechanisms. Next, experiential learning theory is considered as one of the important pillars of the theoretical framework (Bharadwaj et al., 2013).

This theory emphasizes a cycle consisting of objective experience, reflective observation, abstract conceptualization, and active testing. In digital environments, analyzing financial data, implementing fraud detection models, and evaluating results provide a context for this learning cycle (Venkatesh et al., 2003). Through the experience of analyzing data, reflecting on results, extracting concepts, and reusing them, learners gradually develop the ability to detect and predict fraud (Hernández-Aros, 2024). From an educational technology perspective, data-driven learning theory forms another part of the theoretical framework.

This theory emphasizes the systematic use of data as the main source of learning and considers learning to be an analytical and evidence-based process. In the present framework, financial and behavioral data act as learning drivers, and their analysis leads to the formation of new insights into fraud patterns. This approach elevates the role of data from an auxiliary tool to the core of the learning process. At the cognitive level, cognitive load theory is also important in explaining the theoretical framework. Digital environments and complex data can increase the cognitive load of learners and reduce learning effectiveness. Therefore, the design of the learning model should be done in a way that manages the cognitive load by appropriately structuring the data, using visual tools, and logically sequencing analytical activities. This theoretical consideration helps to improve the quality of learning and prevent confusion among learners. From an accounting professional perspective, the theoretical framework of the research is also based on the competency-based theory. Detecting accounting fraud in digital environments requires a set of competencies including accounting knowledge, analytical skills, the ability to work with data, critical thinking, and professional judgment. Data-based learning provides a suitable platform for the simultaneous development of these competencies and promotes education from mere knowledge transfer to professional empowerment (Compagnin, 2025).

The theory of evidence-based decision-making complements the theoretical framework of the research. The ultimate goal of fraud detection training is to empower learners to make informed, accurate, and evidence-based decisions. Data analysis allows learners to identify hidden fraud patterns, assess risks, and make their professional decisions based on sound evidence. This approach highlights the role of education in improving the quality of accounting decision-making and reducing fraud risk. Accordingly, the theoretical framework of the present study, by integrating constructivist learning theories, experiential learning, data-driven learning, cognitive load theory, competency-based approach, and evidence-based decision-making, provides a conceptual foundation for designing a data-analytics-based learning model in accounting fraud detection training. This framework creates a coherent basis for explaining the relationships between educational, technological, and professional components and systematically guides the design and evaluation of the proposed research model.

### **3. Method**

The research was conducted as an exploratory and survey study. In the qualitative part, the Delphi method was used, and in the quantitative part, the interpretive structural model and structural equations method was used. In the qualitative part, as well as the interpretive structural model method, the population under study was managers and experts in finance and information technology, and faculty members of universities in the field of financial

management and information technology, of whom 12 people were selected using the available judgment sampling method. Using the library technique, the components affecting the model were identified. First, the identified components were screened and evaluated using the Delphi technique. Then, modeling was carried out using the Delphi method and the interpretive structural method. The software used was EXCEL and MICMAC. The quantitative population was an unlimited number of accountants and information technology employees. 384 people were selected as a sample using the Cochran formula. Based on a researcher-made questionnaire based on qualitative analysis, data analysis was performed using coding and path analysis. Data analysis was performed using coding and path analysis. Based on the sampling, the structural equation modeling technique in SMARTPLS software was used to fit the proposed model.

The Partial Least Squares (PLS) technique is a prominent approach within structural equation modeling, particularly suited for exploratory, prediction-oriented, and theory-development research. The primary significance of PLS-SEM lies in its focus on maximizing the explained variance of endogenous constructs, rather than emphasizing overall model fit. As a result, PLS adopts a variance-based, data-driven perspective that is highly effective for analyzing complex research models.

Finally, the importance of PLS-SEM is underscored by its strong predictive capabilities and its relevance for managerial and policy-oriented decision making. By emphasizing measures such as the coefficient of determination ( $R^2$ ), effect size ( $f^2$ ), and predictive relevance ( $Q^2$ ), PLS-SEM ensures that research findings are not only theoretically meaningful but also practically useful. Consequently, Partial Least Squares has become a widely accepted and influential methodological approach in contemporary research across management, accounting, and behavioral sciences.

#### 4. Findings

The Delphi section of this study was conducted based on the views of 12 experts familiar with business concepts. Finally, 5 people had between 10 and 15 years of work experience and 7 people had more than 15 years of work experience, which is specified in Table 2 by their frequency.

*Table 2. Demographic characteristics of experts*

| Demographic characteristics |                 | Frequency | Percentage |
|-----------------------------|-----------------|-----------|------------|
| Gender                      | Male            | 8         | 66%        |
|                             | Female          | 4         | 34%        |
| Work Experience             | 10 to 15 years  | 5         | 42%        |
|                             | Over 15 years   | 7         | 58%        |
| Education                   | Master's degree | 6         | 50%        |
|                             | PhD             | 6         | 50%        |
| Total                       |                 | 12        | 100%       |

In this study, a total of 10 main components were identified through a literature review. Next, the Delphi technique was used to ensure the authenticity of the identified dimensions and components, to determine the validity of these components, and to answer the research questions. The Delphi method was carried out as follows.

*Table 3. Delphi analysis of identified components*

|                                  | Questions | Average | Median | Mode | Standard deviation | Range of changes | First quartile | Second quartile | Third quartile | Status   |
|----------------------------------|-----------|---------|--------|------|--------------------|------------------|----------------|-----------------|----------------|----------|
| Big Data Analytics               | C01       | 3.302   | 3      | 3    | 0.599              | 2                | 3              | 3               | 4              | Approved |
| Machine Learning Fraud           | C02       | 3.186   | 3      | 3    | 0.732              | 2                | 3              | 3               | 4              | Approved |
| Artificial Intelligence Auditing | C03       | 3.627   | 4      | 4    | 0.655              | 2                | 3              | 4               | 4              | Approved |
| Smart Transaction Tracking       | C04       | 3.465   | 4      | 4    | 0.630              | 2                | 3              | 4               | 4              | Approved |
| Cryptography and Transparency    | C05       | 3.255   | 3      | 3    | 0.658              | 3                | 3              | 3               | 4              | Approved |

|   | Questions | Average | Median | Mode | Standard deviation | Range of changes | First quartile | Second quartile | Third quarter | Status   |
|---|-----------|---------|--------|------|--------------------|------------------|----------------|-----------------|---------------|----------|
| Financial Process Automation  | C06       | 3.248   | 3      | 3    | 0.650              | 2                | 3              | 3               | 4             | Approved |
| Latent Behavioral Data Mining   | C07       | 3.744   | 4      | 4    | 0.538              | 2                | 4              | 4               | 4             | Approved |
| Digital Anomaly Detection   | C08       | 4       | 4      | 4    | 0                  | 0                | 4              | 4               | 4             | Approved |
| Financial Blockchain Platform   | C09       | 3.754   | 4      | 4    | 0.520              | 2                | 4              | 4               | 4             | Approved |
| Continuous Real-Time Monitoring   | C10       | 3.697   | 4      | 4    | 0.513              | 2                | 3              | 4               | 4             | Approved |
| Accounting Fraud Detection with the Approach of New Developments in the Field of Digital Technology | C11       | 3.767   | 4      | 4    | 0.427              | 1                | 4              | 4               | 4             | Approved |
| <b>Number of respondents</b>  |           |         |        |      |                    | 12               |                |                 |               |          |
| <b>Kendall statistic</b>  |           |         |        |      |                    | 0.877            |                |                 |               |          |
| <b>Chi-score statistic</b>  |           |         |        |      |                    | 110.18           |                |                 |               |          |
| <b>Degrees of freedom</b>   |           |         |        |      |                    | 10               |                |                 |               |          |
| <b>Significance level</b>   |           |         |        |      |                    | 0.000            |                |                 |               |          |

Based on the results obtained in the Delphi technique, all means were obtained above 5. Therefore, no component was eliminated and all were approved. The Kendall statistic was also obtained as 0.877 and is approved, so Delphi is approved in the first round. In addition, the interpretive structural modeling (ISM) method in the MICMAC software version was used for data analysis. Interpretive structural model design (ISM) is a method for examining the effect of each variable on other variables; this design is a comprehensive approach to measuring the relationship and this design is used to develop the model framework to make the overall objectives of the research possible.

The first step in interpretive structural modeling is to calculate the internal relationships of the indicators. The experts' perspective is used to reflect the internal relationships between the indicators. The matrix obtained in this step shows which variables a variable affects and which variables it is affected by. Conventionally, symbols such as Table 4 are used to identify the pattern of element relationships.

**Table 4.** Modes and symbols used to express the relationship of identified indicators

| O               | X                          | A                    | V                    |
|-----------------|----------------------------|----------------------|----------------------|
| No relationship | Bidirectional relationship | Variable j affects i | Variable i affects j |

The structural self-interaction matrix is formed from the dimensions and indicators of the study and their comparison using four modes of conceptual relationships. The information obtained is summarized based on the interpretive structural modeling method and the final structural self-interaction matrix is formed. According to the signs in Table 4, the structural self-interaction matrix will be as Table 5.

**Table 5.** Structural self-interaction matrix SSIM

| C11 | C10 | C09 | C08 | C07 | C06 | C05 | C04 | C03 | C02 | C01 | SSIM |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| V   | V   | A   | V   | V   | V   | A   | V   | V   | V   |     | C01  |
| V   | V   | A   | V   | X   | V   | A   | V   | X   |     |     | C02  |
| V   | V   | A   | V   | X   | V   | A   | V   |     |     |     | C03  |
| V   | V   | A   | V   | A   | V   | A   |     |     |     |     | C04  |
| V   | V   | X   | V   | V   | V   |     |     |     |     |     | C05  |
| V   | A   | A   | A   | A   |     |     |     |     |     |     | C06  |
| V   | V   | A   | V   |     |     |     |     |     |     |     | C07  |
| V   | X   | A   |     |     |     |     |     |     |     |     | C08  |
| V   | V   |     |     |     |     |     |     |     |     |     | C09  |
| V   |     |     |     |     |     |     |     |     |     |     | C10  |
|     |     |     |     |     |     |     |     |     |     |     | C11  |

The received matrix is obtained by transforming the structural self-interaction matrix into a two-valued matrix of zero and one. In the received matrix, the main diagonal elements are set to one. Therefore, the received matrix of the ISM technique is presented in Table 6.

Table 6. Received matrix of identified indicators

| C11 | C10 | C09 | C08 | C07 | C06 | C05 | C04 | C03 | C02 | C01 | SSIM |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| 1   | 1   | 0   | 1   | 1   | 1   | 0   | 1   | 1   | 1   | 1   | C01  |
| 1   | 1   | 0   | 1   | 1   | 1   | 0   | 1   | 1   | 1   | 0   | C02  |
| 1   | 1   | 0   | 1   | 1   | 1   | 0   | 1   | 1   | 1   | 0   | C03  |
| 1   | 1   | 0   | 1   | 0   | 1   | 0   | 1   | 0   | 0   | 0   | C04  |
| 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   | C05  |
| 1   | 0   | 0   | 0   | 0   | 1   | 0   | 0   | 0   | 0   | 0   | C06  |
| 1   | 1   | 0   | 1   | 1   | 1   | 0   | 1   | 1   | 1   | 0   | C07  |
| 1   | 1   | 0   | 1   | 0   | 1   | 0   | 0   | 0   | 0   | 0   | C08  |
| 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1   | C09  |
| 1   | 1   | 0   | 1   | 0   | 1   | 0   | 0   | 0   | 0   | 0   | C10  |
| 1   | 0   | 0   | 0   | 1   | 1   | 0   | 0   | 1   | 1   | 0   | C11  |

**–Determining relationships and leveling dimensions and indicators**

To determine relationships and leveling criteria, the set of outputs and the set of inputs for each criterion must be extracted from the received matrix.

- Reaching set (row elements, outputs or effects): variables that can be reached through this variable.
- Prerequisite set (column elements, inputs or effects): variables through which this variable can be reached. The set of outputs includes the criterion itself and the criteria that are affected by it. The set of inputs includes the criterion itself and the criteria that affect it. Then, the set of two-way relationships of the criteria is determined.

Table 8. Set of inputs and outputs (effects) for each variable

|     | Output: Influenced                 | Input: Influencing                 | Common   |
|-----|------------------------------------|------------------------------------|----------|
| C01 | C1-C2-C3-C4--C6-C7-C8-C10-C11      | C1-C5-C9                           | C1       |
| C02 | -C2-C3-C4--C6-C7-C8-C10-C11        | C1-C2-C3-C5-C7-C9                  | C2-C3-C7 |
| C03 | -C2-C3-C4--C6-C7-C8-C10-C11        | C1-C2-C3-C5-C7-C9                  | C2-C3-C7 |
| C04 | -C4--C6 -C8-C10-C11                | C1-C2-C3-C4-C5-C7-C9               | C4       |
| C05 | C1-C2-C3-C4-C5-C6-C7-C8-C9-C10-C11 | C5-C9                              | C5-C9    |
| C06 | C6 - C11                           | C1-C2-C3-C4-C5-C6-C7-C8-C9-C10     | C6       |
| C07 | -C2-C3-C4--C6-C7-C8-C10-C11        | C1-C2-C3-C5-C7-C9                  | C2-C3-C7 |
| C08 | C6 -C8-C10-C11                     | C1-C2-C3-C4-C5-C7-C8-C9-C10        | C8-C10   |
| C09 | C1-C2-C3-C4-C5-C6-C7-C8-C9-C10-C11 | C5-C9                              | C5-C9    |
| C10 | C6 -C8-C10-C11                     | C1-C2-C3-C4-C5-C7-C8-C9-C10        | C8-C10   |
| C11 | C11                                | C1-C2-C3-C4-C5-C6-C7-C8-C9-C10-C11 | C11      |

For variable  $C_i$ , the reach set (output or effects) includes the variables that can be reached through variable  $C_i$ . The prerequisite set (input or effects) includes the variables that can be reached through variable  $C_i$ . After determining the reach set and prerequisite set, the intersection of the two sets is calculated. The first variable whose intersection of the two sets is equal to the reachable set (outputs) will be the first level. Therefore, the elements of the first level will have the most influence in the model. After determining the level, the criterion whose level is known is removed from the entire set and the set of inputs and outputs is formed again, and the level of the next variable is obtained.

Table 9. Determining the first level in the ISM hierarchy

| Level | Variable                      | SSIM |
|-------|-------------------------------|------|
| 6     | Big Data Analytics            | C01  |
| 5     | Machine Learning Fraud        | C02  |
| 5     | Audit Artificial Intelligence | C03  |

|   |   |     |
|---|---|-----|
| 4 | Smart Transaction Tracking  | C04 |
| 7 | Cryptography and Transparency   | C05 |
| 2 | Financial Process Automation  | C06 |
| 3 | Latent Behavioral Data Mining   | C07 |
| 5 | Digital Anomaly Detection   | C08 |
| 7 | Financial Blockchain Platform   | C09 |
| 3 | Continuous Real-Time Monitoring   | C10 |
| 1 | Accounting Fraud Detection with the Approach of New Developments in the Field of Digital Technology | C11 |

Therefore, profitability and sustainable growth (C5) are at the first level. After identifying the first level variable(s), these variable(s) are removed and the set of inputs and outputs is calculated without considering the first level variables. The common set is identified and the variables whose commonality is equal to the set of inputs are selected as the second level variables. The financial planning variable (C4) and market developments (C3) are at the second level. The risk position factor variables (C1) and investment conditions (C2) are at the third level. The final pattern of the levels of the identified variables is shown in the figure. In this figure, only the meaningful relationships of the elements of each level on the elements of the lower level as well as the meaningful internal relationships of the elements of each row are considered.

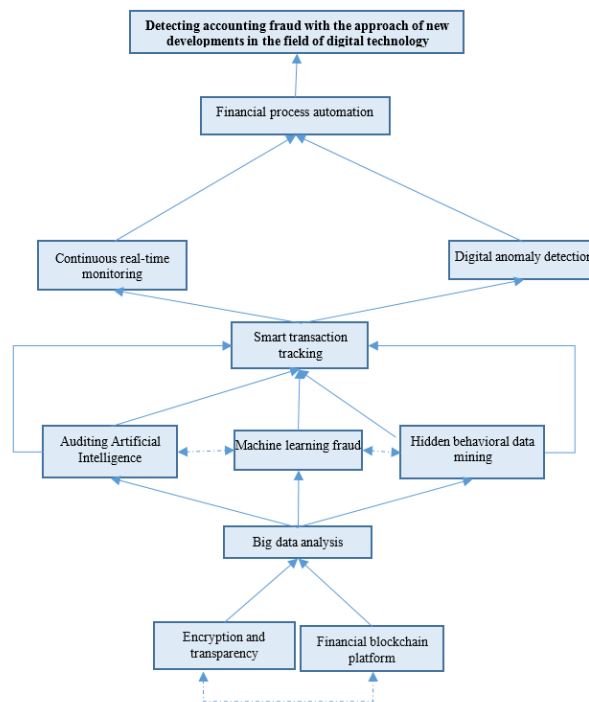


Figure 1. Data analytics-based learning model for training in accounting fraud detection in digital environments

30 categories were also categorized based on these concepts. These 27 categories are: transactional data aggregation, simultaneous information processing, abnormal pattern detection, fraud classification algorithms, accountant behavioral modeling, violation prediction, human error detection, financial document analysis with AI, adaptive system learning, suspicious transaction tracking, source-destination matching, hidden transfer detection, financial information protection, data manipulation reduction, encrypted change logging, human intervention elimination, intelligent instruction execution, document matching facilitation, recurrent fraud pattern detection, employee behavior analysis, data hidden data mining, illogical point detection, outlier detection, unusual fluctuation assessment, transaction recording without intermediaries, elimination of bookkeeping manipulation, distributed data validation, live financial flow monitoring, rapid violation alert, and intelligent automated reporting. The qualitative questionnaire was determined

based on these categories. In Table 10, the demographic characteristics of Arvand Petrochemical Company employees in terms of age and education level are specified.

**Table 10.** Descriptive information related to the gender of the subjects

| Demographic Characteristics | Category          | Percentage | Frequency |
|-----------------------------|-------------------|------------|-----------|
| Age                         | Under 30          | 8          | 30        |
|                             | 31 to 40          | 45         | 173       |
|                             | 41 to 50          | 26         | 100       |
|                             | 51 and above      | 21         | 81        |
| Education Level             | Bachelor's degree | 60         | 230       |
|                             | Master's degree   | 35         | 134       |
|                             | PhD and above     | 5          | 20        |
| <b>Total</b>                |                   | 100        | 384       |

The descriptive statistics of the identified criteria are given in Table 11.

**Table 11.** Mean and standard deviation of model components

| Variables | Average | Skewness | Range of variation | Kurtosis | Variance | Minimum | Maximum |
|-----------|---------|----------|--------------------|----------|----------|---------|---------|
| C01       | 3.6     | 0.808    | 3                  | 0.002    | 0.375    | 2       | 5       |
| C02       | 3.775   | 1.461    | 3.33               | -0.584   | 0.446    | 1.67    | 5       |
| C03       | 4.0842  | -0.058   | 2.33               | -0.263   | 0.231    | 2.67    | 5       |
| C04       | 3.825   | -0.216   | 2                  | 0.566    | 0.225    | 3       | 5       |
| C05       | 3.6729  | -0.496   | 2.25               | 0.314    | 0.339    | 2.75    | 5       |
| C06       | 4.2229  | -0.625   | 2                  | -0.47    | 0.358    | 3       | 5       |
| C07       | 4.0938  | 0.018    | 2.25               | -0.032   | 0.192    | 2.75    | 5       |
| C08       | 3.8734  | -0.883   | 2.5                | 0.163    | 0.465    | 2.5     | 5       |
| C09       | 3.7405  | -0.301   | 3                  | -0.171   | 0.473    | 2       | 5       |
| C10       | 4.3938  | -0.241   | 2                  | -0.621   | 0.302    | 3       | 5       |
| C11       | 4.1     | -0.938   | 2                  | 0.134    | 0.319    | 3       | 5       |

In Table 5, it can be seen that the mean of the variables, standard deviation, and minimum and maximum data related to the components of the data analysis-based learning model for training in accounting fraud detection in digital environments are seen separately. Considering that each statement has five options, the number 3 is considered as the mean of each statement. As can be seen, the mean of all components is greater than 3, so it is seen at a desirable level in the statistical population. Also, considering that the value of skewness and kurtosis for the aforementioned variables is in the range (2+ and -2), it can be concluded that the data distribution is probably normal. In Table 12, the convergent validity of the criteria is specified based on Cronbach's alpha, composite reliability, and extracted variance indices.

**Table 12.** Three measures of Cronbach's alpha, composite reliability, and convergent validity of the data analysis-based learning model index for training in accounting fraud detection in digital environments

| Variable | Cronbach's Alpha | AVE   | CR    |
|----------|------------------|-------|-------|
| C01      | 0.856            | 0.611 | 0.896 |
| C02      | 0.736            | 0.535 | 0.827 |
| C03      | 0.794            | 0.582 | 0.736 |
| C04      | 0.781            | 0.620 | 0.804 |
| C05      | 0.764            | 0.609 | 0.763 |
| C06      | 0.790            | 0.566 | 0.864 |
| C07      | 0.737            | 0.601 | 0.783 |
| C08      | 0.811            | 0.604 | 0.764 |
| C09      | 0.825            | 0.633 | 0.758 |
| C10      | 0.803            | 0.614 | 0.794 |
| C11      | 0.784            | 0.628 | 0.733 |

Given that the appropriate value for Cronbach's alpha is 0.7, for composite reliability is 0.7, and for AVE is 0.5, and according to the findings in Table 11, all criteria have adopted appropriate values for latent variables, it can be confirmed that the reliability and convergent validity of the identified criteria are appropriate. To examine the divergent validity, the Fornell-Larker index was used, which is specified in Table 13. Table 13 shows the correlation of the latent constructs of the research model to examine the divergent validity of the research model.

**Table 13.** Correlation coefficient of the latent constructs of the research model (to confirm the divergent validity)

|     | C01   | C02   | C03   | C04   | C05   | C06   | C07   | C08   | C09   | C10   | C11   |
|-----|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| C01 | 0.855 |       |       |       |       |       |       |       |       |       |       |
| C02 | 0.634 | 0.846 |       |       |       |       |       |       |       |       |       |
| C03 | 0.434 | 0.578 | 0.857 |       |       |       |       |       |       |       |       |
| C04 | 0.592 | 0.410 | 0.376 | 0.866 |       |       |       |       |       |       |       |
| C05 | 0.543 | 0.533 | 0.556 | 0.554 | 0.869 |       |       |       |       |       |       |
| C06 | 0.549 | 0.537 | 0.804 | 0.536 | 0.663 | 0.870 |       |       |       |       |       |
| C07 | 0.604 | 0.345 | 0.587 | 0.436 | 0.536 | 0.463 | 0.860 |       |       |       |       |
| C08 | 0.597 | 0.335 | 0.354 | 0.553 | 0.456 | 0.600 | 0.627 | 0.855 |       |       |       |
| C09 | 0.584 | 0.656 | 0.584 | 0.634 | 0.670 | 0.627 | 0.735 | 0.567 | 0.856 |       |       |
| C10 | 0.667 | 0.456 | 0.656 | 0.330 | 0.753 | 0.537 | 0.635 | 0.537 | 0.696 | 0.847 |       |
| C11 | 0.330 | 0.595 | 0.610 | 0.738 | 0.332 | 0.526 | 0.638 | 0.629 | 0.636 | 0.465 | 0.910 |

As can be seen in Table 13, the value of the AVE square root of the structures specified in the table is greater than their correlation with other structures, so it can be concluded that the correlation of the structures with their indicators is greater than the correlation of that structure with other structures. Therefore, the divergent validity of the latent structures of the research model is confirmed.

**Table 14.** Results of the HTMT method to examine the divergent validity

|     | C01   | C02   | C03   | C04   | C05   | C06   | C07   | C08   | C09   | C10   | C11 |
|-----|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-----|
| C01 |       |       |       |       |       |       |       |       |       |       |     |
| C02 | 0.373 |       |       |       |       |       |       |       |       |       |     |
| C03 | 0.363 | 0.467 |       |       |       |       |       |       |       |       |     |
| C04 | 0.537 | 0.649 | 0.635 |       |       |       |       |       |       |       |     |
| C05 | 0.619 | 0.453 | 0.756 | 0.500 |       |       |       |       |       |       |     |
| C06 | 0.554 | 0.363 | 0.591 | 0.500 | 0.536 |       |       |       |       |       |     |
| C07 | 0.793 | 0.646 | 0.338 | 0.557 | 0.599 | 0.648 |       |       |       |       |     |
| C08 | 0.735 | 0.592 | 0.621 | 0.543 | 0.582 | 0.637 | 0.627 |       |       |       |     |
| C09 | 0.440 | 0.638 | 0.483 | 0.527 | 0.345 | 0.555 | 0.637 | 0.373 |       |       |     |
| C10 | 0.526 | 0.750 | 0.238 | 0.666 | 0.584 | 0.548 | 0.730 | 0.540 | 0.786 |       |     |
| C11 | 0.700 | 0.505 | 0.559 | 0.610 | 0.594 | 0.509 | 0.710 | 0.638 | 0.483 | 0.557 |     |

**The coefficient of determination R2**

R2 is a criterion used to connect the measurement part and the structural part of structural equation modeling and indicates the amount of change in each of the dependent variables of the model that is explained by the independent variables. The crucial point here is that R2 is calculated only for endogenous (dependent) structures of the model and for exogenous structures, the value of this criterion is zero. The higher the R2 value related to the endogenous structures of a model, the better the fit of the model. Chin (1998) determines three values of 0.19, 0.33 and 0.67 as weak, moderate and strong fit of the model. Also, Hensler (2009) and Herr et al. (2011) have defined three values of 0.25, 0.50 and 0.75 as the criterion values for weak, moderate and strong fit of the structural part of the model by the coefficient of determination criterion.

$$R^2 = \frac{0.350 + 0.386 + 0.335 + 0.336 + 0.433 + 0.499 + 0.419 + 0.251 + 0.309}{9} = 0.368$$

Based on the results of Figure 2, the coefficient of determination (R<sup>2</sup>) of the endogenous structures of the research model is desirable. The value of the coefficient of determination of the performance of the dependent components shows that 37% of the changes in the model variables are explained by the sum of the effects of the independent and dependent variables, which is strongly acceptable.

**Effect size criterion F<sup>2</sup>**

The effect size is another index of the structural fit of the model and is applicable to exogenous independent variables. The effect size index was introduced by Jacob Cohen (1988) and was also discussed in the discussion of calculating the Cohen index. The F<sup>2</sup> index for an independent variable shows the amount of change in the estimate of the dependent variable when the effect of that variable is removed. According to Cohen, the values of this index are 0.02 (weak), 0.15 (moderate), and 0.35 (strong), respectively. The coefficient of determination is used to calculate the effect size.

$$F^2 = \frac{R_{included}^2 - R_{excluded}^2}{1 - R_{included}^2}$$

Path coefficient with the presence of the predictor variable =  $R_{included}^2$

Path coefficient in the absence of the predictor variable =  $R_{excluded}^2$

Based on the above relationship, it is sufficient to calculate the coefficient of determination once by considering the effect of the independent variable in question and then calculate it by removing this effect. Then, the calculated value is interpreted based on the values proposed by Cohen.

**Criterion Q<sup>2</sup>**

The predictive power of the model or redundancy sharing is another criterion for examining the structural model. The predictive ability of the model can be measured using the nonparametric Stone-Geisser test (1974), while Q<sup>2</sup> evaluates the success rate of this prediction. Herr et al. (2019) have stated different values regarding the intensity of the predictive power of the model for endogenous structures and have determined three values of 0, 0.25 and 0.50 as weak, medium and strong predictive power, respectively. The blindfolding technique is used to calculate the Q<sup>2</sup> value in PLS software.

*Table 15. Effect size criterion (Cohen index)*

| Variables      | C01   | C02   | C03   | C04   | C05   | C06   | C07   | C08   | C09   | C10   | C11   |
|----------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Q <sup>2</sup> | 0.394 | 0.444 | 0.406 | 0.637 | 0.339 | 0.382 | 0.110 | 0.383 | 0.773 | 0.549 | 0.490 |
| F <sup>2</sup> | 0.483 | 0.305 | 0.552 | 0.493 | 0.403 | 0.480 | 0.634 | 0.483 | 0.425 | 0.372 | 0.320 |

As shown in Table 15, the value obtained from the Q<sup>2</sup> criterion, which indicates the predictive power of the model for endogenous constructs, indicates that the predictive power of the research constructs is estimated to be strong.

According to the output of the PLS software and the significance levels for confirmatory factor analysis of the indicators and components of the data-based learning model for training in accounting fraud detection in digital environments in Table 13, all factors had appropriate factor loadings and their relationship with the latent variable was confirmed (the significance level for all questions is less than 0.05). Also, the structural model fit using t-coefficients is such that these coefficients must be greater than 1.96 in order to confirm their significance at a 95% confidence level. According to Table 13, all t-coefficients are greater than 1.96,

which confirms the significance of all questions and relationships between variables at a 95% confidence level.

The importance of goodness-of-fit indices in Structural Equation Modeling (SEM) lies in their role in determining whether the proposed theoretical model is consistent with the empirical data. Given that SEM simultaneously examines multiple causal relationships involving both latent and observed variables, statistical significance of path coefficients alone is insufficient; rather, the overall model structure must be rigorously evaluated.

The first and most fundamental role of goodness-of-fit indices is to validate the credibility of the conceptual model. If a model does not demonstrate adequate fit, even statistically significant parameter estimates cannot be considered reliable, as the hypothesized relationships fail to accurately represent the underlying data structure. In essence, acceptable model fit indicates congruence between the researcher's theoretical assumptions and the observed empirical reality.

Second, goodness-of-fit indices facilitate the comparison of competing models. In many studies, multiple theoretically plausible models may be proposed. Fit indices such as the Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA) allow researchers to evaluate and compare alternative models, identifying the one that offers greater explanatory power while maintaining parsimony. This aspect is particularly critical in doctoral research and theory-development studies.

Third, fit indices serve as diagnostic tools for identifying model misspecification. Poor model fit may indicate omitted paths, incorrect specification of latent constructs, construct overlap, or weaknesses in the measurement model. Therefore, goodness-of-fit indices not only provide evaluative judgments but also guide researchers in refining and improving model structure.

Fourth, the use and transparent reporting of goodness-of-fit indices enhance the methodological rigor and defensibility of research findings. In academic publications, presenting multiple fit indices from different categories (absolute, incremental, and parsimonious fit indices) reflects analytical precision and strengthens the credibility of the results in the eyes of reviewers and readers.

Ultimately, the primary significance of goodness-of-fit indices in SEM is that they bridge theory and data. Without evidence of acceptable model fit, researchers cannot confidently claim that their proposed theoretical framework adequately explains the phenomenon under investigation. Consequently, goodness-of-fit indices constitute a core component of model evaluation and interpretation in structural equation modeling.

## Discussion

The aim of the research was to identify a data analysis-based learning model for training in accounting fraud detection in digital environments. The results of this research, which aimed to develop an interpretive structural modeling of accounting fraud detection based on digital innovations, showed that digital transformation has not only provided new tools for detecting and preventing fraud, but also created more complex structures in the financial environment that require a systematic analysis of the relationships between effective factors.

The application of the structural interaction analysis method (MICMAC) made it possible to accurately assess the dependencies and effects of key variables and, finally, ten main criteria including big data analytics, fraud machine learning, audit artificial intelligence, smart transaction tracking, encryption and transparency, financial process automation, hidden behavioral data mining, digital anomaly detection, financial blockchain platform, and continuous real-time monitoring were classified into seven levels. This hierarchical classification shows that some metrics play a fundamental and fundamental role in the success of fraud detection systems, while others affect the operational, analytical and monitoring layers more.

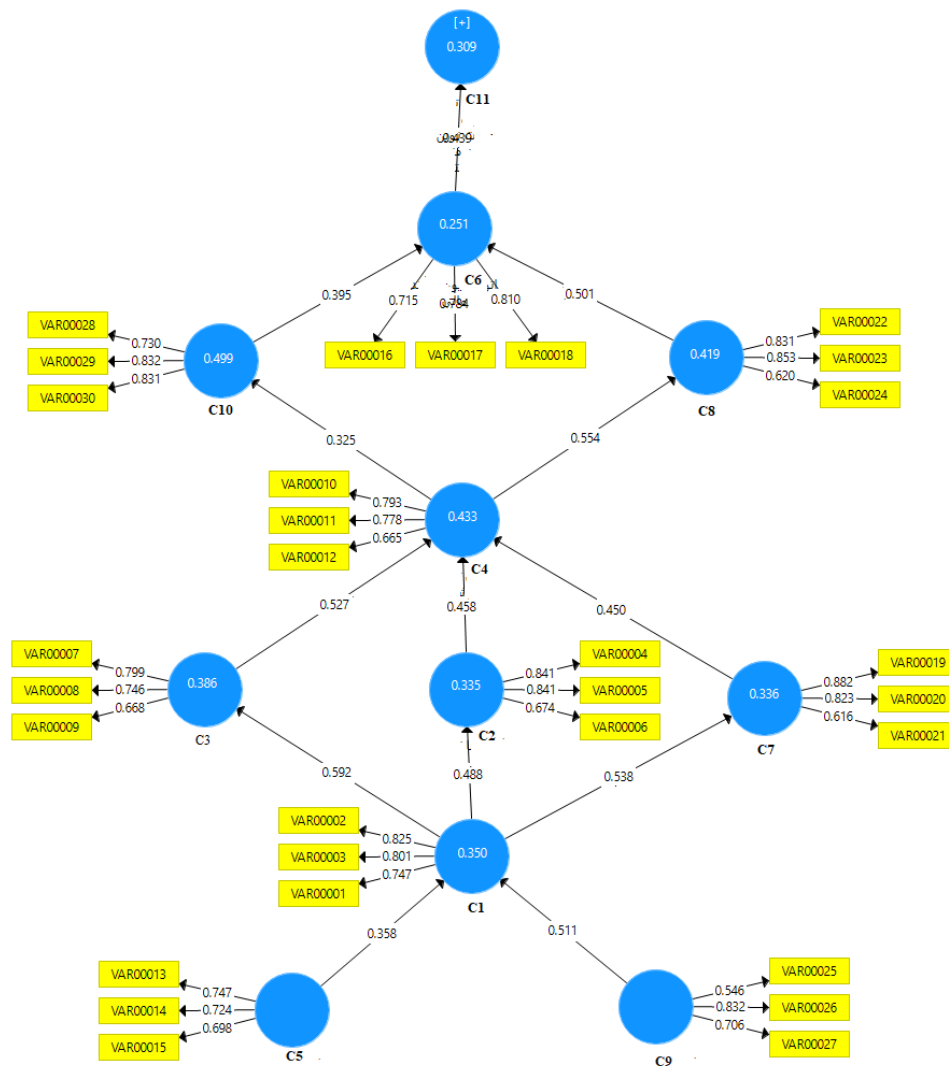


Figure 2. Model analysis in the case of significant coefficients.

The results of the analysis indicate that metrics such as big data analytics, cryptography and financial blockchain platforms are located at the infrastructure levels and play a fundamental role in creating a secure, integrated and reliable platform for fraud detection. These technologies enable the aggregation, storage, protection and transparency of data and are a prerequisite for the successful operation of more advanced technologies. On the other hand, metrics such as fraud machine learning, audit AI and digital anomaly detection are located at the intermediate and analytical levels; these technologies play a major role in data processing, analyzing behavioral patterns and identifying anomalies and are considered the heart of the intelligent fraud detection process.

Also, measures such as hidden behavioral data mining, intelligent transaction tracking, and real-time monitoring are classified at operational and executive levels that directly interact with the real business environment and enable continuous monitoring, real-time alerting, and precise control of financial behaviors (Bierstaker et al., 2006; Appelbaum et al., 2017).

This seven-layer hierarchy clearly shows that accounting fraud detection in the digital age is not a single-factor process, but rather a combination of infrastructure, tooling, analytics, and monitoring technologies that must be integrated into a coordinated and integrated structure.

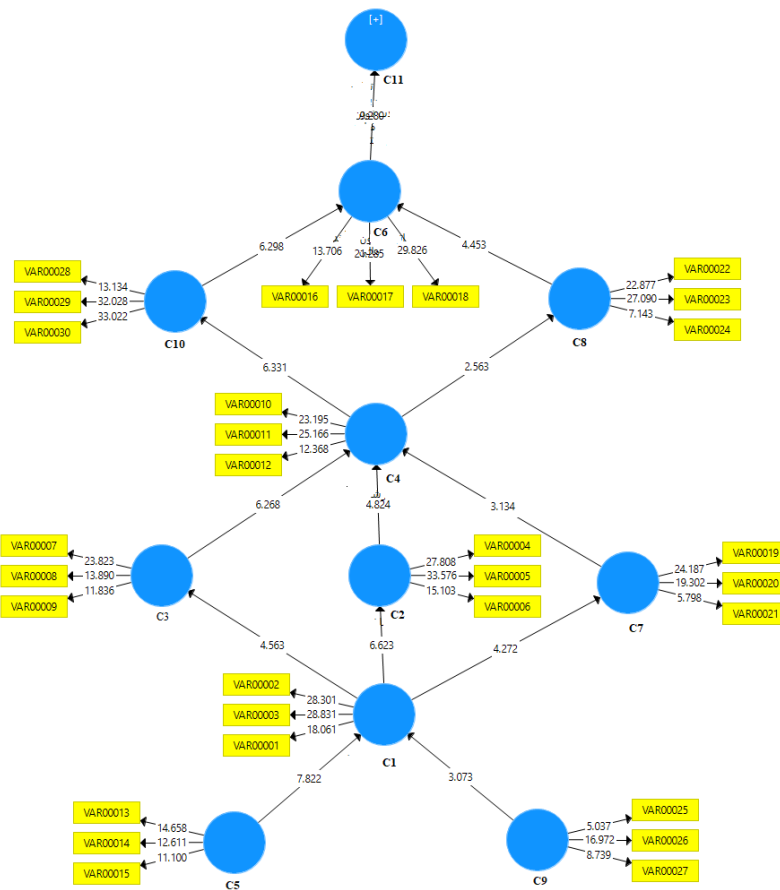


Figure 3. Model analysis in t-statistic model

One of the key results of the research is that no technology alone is capable of fully and accurately detecting fraud; rather, real effectiveness is achieved when these technologies are implemented together, in accordance with their role and level of impact, in a logical structural model. For example, machine learning is ineffective without big data, blockchain is meaningless without encryption, and real-time monitoring is incomplete without artificial intelligence and anomaly detection (Alles, 2015; Jans et al., 2014).

The findings also show that organizations should pay special attention to digital infrastructure, data quality, information architecture design, technology adoption culture, and human resource empowerment to implement new fraud detection approaches. Accordingly, the presented interpretive structural model can be a valuable guide for policymakers, regulatory agencies, financial managers, and auditors to know which technologies are more prioritized, what relationships exist between different tools, and where to start and how to evolve the deployment of intelligent fraud detection systems.

The results of this research emphasize that digital innovations are the future of the accounting fraud detection system and the presented model can be a framework for moving from traditional approaches to intelligent, predictive, and data-driven approaches. The development of this seven-level structure is an important step towards developing robust, reliable, and technology-intelligence-based systems to prevent and detect financial fraud in organizations.

## Conclusion

Structural equation modeling was used to simultaneously examine correlational relationships. Structural equation modeling is used to fit the model for a variety of reasons. Structural equation modeling is a powerful analytical method that allows researchers to model complex, multivariate relationships in a statistical model and examine the interactions between variables. This method allows researchers to create their models based on

theoretical assumptions and variable relationships and then fit them with real data to ensure the accuracy and consistency of the model with the observed data. Structural equation modeling also allows researchers to examine the effects of mediators and moderator variables between independent and dependent variables and identify hidden relationships in the model. In this way, the use of structural equation modeling allows researchers to examine complex relationships more comprehensively and completely in statistical models and improve the various factors that are involved in the effect of each other. Based on the results obtained, it is suggested:

- Given the importance of big data analysis and the need for real-time access to information, it is suggested that financial and audit organizations design and implement centralized and integrated databases. This infrastructure should have the ability to collect, store, and analyze data from various sources to provide the necessary platform for the use of artificial intelligence and machine learning tools.
- Realizing the identified dimensions is not possible with technology alone and also requires the development of human skills. It is suggested that specialized courses in data analysis, machine learning, cybersecurity, and digital auditing be held for auditors and financial managers. This training can improve employees' ability to work with modern tools and reduce dependence on external consultants.
- To improve the transparency and security of transactions, it is suggested that financial institutions invest in advanced cryptographic technologies and blockchain platforms. In addition to reducing the likelihood of fraud, this measure increases stakeholder trust and can become a competitive advantage for organizations at the national and international levels.
- Given the importance of quickly detecting anomalies, it is necessary to design and implement intelligent real-time monitoring systems in organizations. These systems can issue immediate warnings about suspicious transactions, unauthorized entries, or unusual changes in data and prevent financial crises from occurring.
- Given the global nature of financial transactions, it is recommended that domestic organizations enter into international cooperation in the field of sharing experiences, standards, and new technologies. Such cooperation can lead to synergy and mutual learning and improve the quality level of digital auditing.
- To reduce risk, it is recommended that organizations first implement new technologies on a pilot basis in limited areas and then expand them throughout the organization after reviewing the results. This approach reduces potential costs and increases the likelihood of success.

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The author declares that he has no competing financial interests or known personal relationships that would influence the report presented in this article.

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