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Original Research Article

Identifying the Suspected Cases of Money Laundering in Banking Using Multiple Attribute Decision Making (MADM)

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Money laundering is among the most common financial crimes that negatively affect countries' economies and hurt their social and political relations. With the increasing growth of e-banking and the increase in electronic financial transactions, the identification of money laundering methods and behaviors has become more complex; because money launderers, by accessing the Internet and using new technologies, find new ways to legalize their illegal income. Although many efforts have been made to identify suspected cases of money laundering and fight against this financial crime, little success has been achieved in this regard, especially in developing countries. Hence, this study tries to identify the risk factors involved in money laundering in banking transactions. To this end, multiple attribute decision-making methods, such as the Shannon entropy method, hierarchical analysis, and two-level fuzzy hierarchical analysis, have been used to assess and score the risk of various transactions in money laundering. The results indicated that the highest risk of money laundering was in the POS transactions.

Keywords: Money Laundering; Trading Organized Crime; Multiple Attribute Decision Making; Hierarchical Analysis; Fuzzy Hierarchical Analysis
JEL Classification: E5

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1 Introduction

Money laundering is one of the most reported illegal activities in the world (Raweh et al., 2017). It is illegal to make large amounts of money derived from criminal activities, such as drug trafficking or terrorist funding into legitimate money (Hopkins and Shelton, 2019; Kana, 2017). Money laundering has unpleasant consequences in economic, social, and international fields, and in addition to the destructive economic effects that cause economic instability, it carries many risks and social costs in the country and will lead to corruption in the banking system (Janjua& Khan, 2020; Beqiri & Beqiri, 2018; Armey & Melese, 2018). Efforts are being made worldwide to control banking systems and prevent them from being used as open channels for illegal money (Raweh et al., 2017). However, electronic banking and the use of electronic money have become more attractive channels for money launderers (Kruisbergen et al., 2019; Helmy et al., 2016). Money transfers can be done instantly and without geographical restrictions. Electronic transactions allow money launderers to remain anonymous and continue to operate more freely without worrying about legal requirements and financial audits (Helmy et al., 2016). Therefore, identifying suspicious financial transactions is a necessary precondition and a key aspect of the fight against money laundering (Raza et al., 2017).

Given the complexity of the key elements that make up money laundering risks, identifying money laundering risk factors has become complicated for researchers worldwide (Raza et al., 2017).

Previous studies have been done using traditional statistical methods and law-based methods to detect money laundering activities. But law-based transaction analysis is insufficient to detect complex transaction patterns (Kana, 2017). Besides, using traditional methods to detect money laundering is time-consuming, costly, and sometimes impossible. Therefore, automatic money laundering detection methods are necessary (Chun et al., 2017; Han et al., 2011). In this regard, many financial institutions have implemented anti-money laundering systems to fight against this crime. Four types of anti-money laundering systems are being implemented in different countries, namely: Rule-based anti-money laundering system in which countries define criteria for identifying suspicious transactions based on existing laws in their own country as well as international rules; multi-factor anti-money laundering system in which several factors are involved in money laundering detection

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and have their functions; transaction flow analysis system in which bank transactions are analyzed using data mining method and money laundering is detected; and link anti-money laundering system which simultaneously analyzes transactions and customer profiles using macro data method and discovers money laundering according to the rules of the system (Ahmadian, 2019). However, these systems are not suitable for Iran with the same structure due to the set of financial and banking rules and regulations and the country's cultural situation. In addition, in the Iranian economy, due to the unknown consequences and harmful effects of money laundering, no significant action has been taken (Ansari Pirsaraei & Shah Bahrami, 2014), and there is no integrated data in this field. Therefore, these questions raise: what factors affect money laundering in Iran? What is the risk of various types of banking transactions in the money laundering process according to the type of organized crime?

In recent decades, researchers have focused on using multi-criteria decision models for complex decisions, and the framework of these models and matches the complex nature of financial decision issues (Zopounidis & Doumpos, 2002). In this study, the multi-criteria decision-making methods, including the Shannon entropy method, hierarchical analysis process, and two-level fuzzy hierarchical analysis process, are used to identify and prioritize the risk factors of money laundering in banking transactions.

The rest of the paper is organized as follows: first, the research literature is reviewed, then the research model and method are discussed, and finally, the conclusion and recommendations for future studies are explained.

2 Literature Review

Money laundering is a process in which dirty, illegal and illegitimate money is placed in a cycle of exchanges so that after leaving the cycle, it looks legal and clean. In other words, the source of the proceeds obtained through illegal means are kept so secret by using exchange tricks and successive transfers that it seems perfectly legal (Cheng & Wang, 2020; Hopkins & Shelton, 2019; Barone & Schneider, 2018; Demetis, 2018). If this process succeeds, criminals can earn money from their crimes through a legal source (Hopkins & Shelton, 2019; Helmy et al., 2016). Money laundering includes three stages of placement (the process of transferring money to financial institutions or

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converting cash into a kind of document), layering (doing a series of financial transactions and distancing profits from illegal sources) and integration (transfer of previously laundered money to the economy, which is mainly done through the banking system, and therefore such revenues seem to be normal business income) (Hopkins and Shelton, 2019; Helmy et al., 2016; Barone & Schneider, 2018; Demetis, 2018).

Different methods, including financial transactions, opening multiple bank accounts with family members' name, buying or partnering with commercial, construction, or transportation companies, opening companies outside the country, buying real estate, buying luxury goods, etc., are used in money laundering (Demetis, 2018). Electronic banking and increased electronic financial transactions have complicated identifying money laundering methods (Helmy et al., 2016). Therefore, identifying suspicious financial transactions is a necessary precondition and a key aspect of the fight against money laundering (Raza et al., 2017). In recent years, extensive studies have been conducted in this field. For example, Jullum et al. (2020) used machine learning methods to investigate suspicious accounts of money laundering and prioritize transactions. Examining three groups of transactions, including reported money laundering transactions, alerts/unreported cases, and normal transactions, indicated that the usual approach of not using unreported alerts (for example, transactions reviewed but not reported) in model training could lead to optimal results. Singh and Best (2019) also examined the risk of money laundering in their research using data visualization and showed that link analysis could be effective in identifying suspected money laundering transactions.

In another study, Zhou et al. (2018) examined suspected accounts of money laundering using online network analysis to integrate account stability, transaction sequence, and interdependence between accounts and presented a method that could identify suspicious accounts with 94.2% accuracy. Raza et al. (2017) examined the risk of money laundering in financial institutions using two-stage fuzzy hierarchical analysis. They divided the money laundering risk of financial institutions into Internet risk and control risk as two levels of the hierarchical model and showed that the money laundering process is controllable because financial institutions have strong internal control systems. Colladon & Remondi (2017) also showed that the use of indicators and a network-based approach is very important in identifying

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suspicious financial operations and potential criminals. In another study, Helmy et al. (2016) provided a regulatory framework that examines suspicious accounts of money laundering by examining the customer's degree of suspicion and the transaction risk level. Their results indicated that monitoring with this method has been successful in several practical cases. Suresh et al. (2016) examined the relationship between accounts and cash flows and indicated that the graph theory approach could be successful in identifying the suspected account of money laundering. They also showed that graph and a priori theory approaches could accurately identify the accounts involved in the layering stage of money laundering. Hong et al. (2015) also proposed a model for allocating resources based on the Markov decision-making process that improves business transactions' efficiency and security to reduce the costs of mass multimedia processing and communications and optimized management of anti-money laundering resources such as financial institution rewards for anti-money laundering. Dreżewski et al. (2015) also used data mining and social network analysis to investigate and identify suspicious transactions and detect infringing groups. They showed that role-finding algorithms are always faster than cross-linking analysis and that network analysis is a practical and effective technique for detecting money laundering.

According to research that has been conducted in money laundering, previous studies have focused on finding the root of this problem, and the systems discussed in previous research have focused more on individuals, transaction histories, and anomaly detection to identify suspicious behaviors. However, money laundering is a group activity, and the evidence of money laundering is only visible when these groups' collective behavior is considered (Savage et al., 2016). Therefore, this study uses multiple attribute decision-making methods to identify the risk factors of money laundering in banking transactions and determine their level of risk and importance.

3 Methodology

This study aims to estimate the risk of various types of banking transactions by considering the types of crimes and the origin of money laundering. In this study, using multiple attribute decision making (MADM) methods, including the Shannon entropy, hierarchical analysis process and two-level fuzzy hierarchical analysis, factors involved in the money laundering process, including their level of risk and importance in money laundering, were

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investigated. Multiple attribute decision making method is used in complex decisions and is well suited to the complex nature of financial decision-making issues (Zopounidis & Doumpos, 2002).

This study consists of three parts: First, different financial crimes related to money laundering were investigated and identified. In this study, the parameters were extracted using content analysis and expert opinion because of the following results. There is no integrated data in this field in Iran, and given the fact that according to banks, there is no information in this regard outside the banks, and also it was not possible for banks to share this information. Besides, according to experts, due to the lack of new analysis in this area, there is no accurate information about money laundering parameters.

At this phase, 34 types of bank transactions were extracted by reviewing the characteristics of 42 suspected money laundering accounts. Then, by conceptual study and obtaining the experts' opinions in this field, money laundering-related financial crimes were limited to factors, including 11 criteria (arms trafficking, drug trafficking, human trafficking, valuables trafficking, tax evasion, terrorism, assassination contracts, industrial and technological espionage, financial market manipulation, corruption and fraud, manipulation of technical privatization process) and 10 transactions (point of sale (POS), transfer, deposit, purchase, drafts, miscellaneous, remittances, payment advertisement, debtor advertisement and point of sale settlement). Then, the Shannon entropy method was used to determine the importance and weight of each crime (Shannon, 1948), and five crimes with the highest weight were selected for the hierarchical analysis process, which includes: fraud, drug trafficking, tax evasion, human trafficking, and terrorism.

In the second phase, the hierarchical analysis method was used to score different types of banking transactions and estimate their risk in money laundering as well. The hierarchical analysis is a theory of measurement through pairwise comparisons and relies on the judgment of experts and experts in the field to prioritize options and structures a decision problem in a different hierarchy including goals, criteria, and decision options and as one Multi-criteria decision-making techniques are known (Zare Bahnemiri and Malekian Kalebasti, 2016; Imani Brandagh et al., 2016). It simplifies making complex decisions based on diverse and unstructured information by using qualitative, quantitative, and combined criteria (Lubentsov et al., 2019).

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At this phase, 20 questionnaires were completed by money laundering experts who answered the questionnaires through the cooperation network.

When experts make pairwise comparisons, they may not assign crisp numerical values due to uncertain and insufficient information. Therefore, in the third phase, the fuzzy set theory and AHP are combined in fuzzy-AHP to use interval values instead of crisp values. Then, the results were compared with the previous method. The most common method of fuzzy hierarchical analysis is Chang's (1996) method. This method is widely used because of its computational simplicity (Wang et al., 2008). However, due to the limitations of this method, the results were zero and one. Therefore, these results were not suitable for analysis in multiple attribute decision-making and weighting, so Buckley's (1985) improved fuzzy hierarchical analysis method was used. In this method, a 9-point scale was used to select the best option for pairwise comparisons of each level. Finally, the three MADM methods were compared, and the options and criteria were ranked according to their importance.

4 Data Analysis

4.1 Weighing of Criteria by Shannon Entropy Method

The weight of each indicator should be determined to rate and cluster customers. Therefore, the Shannon Entropy was used to calculate the weight of variables R, F, M, and R_V. The Shannon Entropy is a weighting method that can be done through the following steps (Karagiannis & Karagiannis, 2020; Ranjbar Kermani & Alizadeh, 2012):

Step 1: Normalizing the indicators using Equation 1:

$$P_{ij} = \frac{X_{i,j}}{\sum_{j=1}^{m} XX_{i,j}} \quad (1)$$

Step 2: Calculating the entropy measurement of each index, in which k=1/ln (m) (Equation 2):

$$E_j = -k \sum_{j=1}^{n} P_{ij}\, Ln\,(P_{ij}) \quad (2)$$

Step 3: Defining the divergence through Equation 3, in which D_j is the deviation degree of data and provides insight into the usefulness of the relevant criteria for decision making.

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$D_j=1-e$ *(3)*

Step 4: Obtaining the normalized weights of the index in which W_j is each indicator's weight. (Equation 4):

$$W_j = \frac{dj}{\sum_{j=1}^{n} dj} \quad (4)$$

Table 1 indicates the weight for each indicator using Shannon's Entropy Weighting Method.

Table 1

Weighing of Criteria Using Shannon Entropy

	Valuables Trafficking	Terrorism	Human Trafficking	Terrorist Contracts	Tax Evasion	Industrial and Technological Espionage	Manipulation of the Privatization Process	Corruption and Fraud	Arms Trafficking	Drug Trafficking	Financial Market Manipulation
Ej	0.9601	0.9295	0.934	0.9583	0.9296	0.9727	0.9718	0.9187	0.9679	0.9296	0.9723
Dj	0.0399	0.0705	0.066	0.0417	0.0704	0.0272	0.0282	0.0813	0.0321	0.0704	0.0277
Wj	0.079	0.1269	0.1188	0.0751	0.1266	0.0492	0.0507	0.1464	0.0578	0.1267	0.0499

Source: Research Findings

According to the weights obtained by Shannon's entropy, the four offenses of corruption and fraud, drug trafficking, tax evasion, human trafficking, and terrorism have gained more weight and have a higher priority. Therefore, these factors were selected as the main criteria. In addition, among transactions are related to deposit, transfer, terminal purchase, and remittance transactions, which will be used in the hierarchical analysis process, Point of Sale, transfer, deposit, and drafts had higher weights and were selected for further analysis.

4.2 Hierarchical Analysis

After obtaining each indicator's weight, the hierarchical analysis was used to accurately evaluate the weights and analyze the indicators. In this technique, first, the hierarchical structure of the problem was created. The main objective is presented at the first (highest) level of the structure. In the second level, five

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criteria were defined, and in the third level (lowest), four options were evaluated. Figure 1 indicates the hierarchy. Then, by pairwise comparison between the studied criteria and indicators, each indicator's relative weight was determined, and the matrices of pairwise comparisons were created. Then, 20 experts in this field were asked to express their opinions about each option and score them according to the set criteria by using the questionnaire. The experts' scores' geometric mean was then calculated and divided by the sum of its peer columns to obtain the normalized value of the scores. After calculating the sum of the rows, the geometric means were normalized, and then the line mean of the normalized matrix was obtained. Finally, the mean of the normalized geometric matrix of each option relative to the criterion was multiplied by the mean of the normalized geometric matrix of the criteria, and the sum of the rows was obtained. The values obtained will determine the priority of the options. The final results are indicated in Table 2.

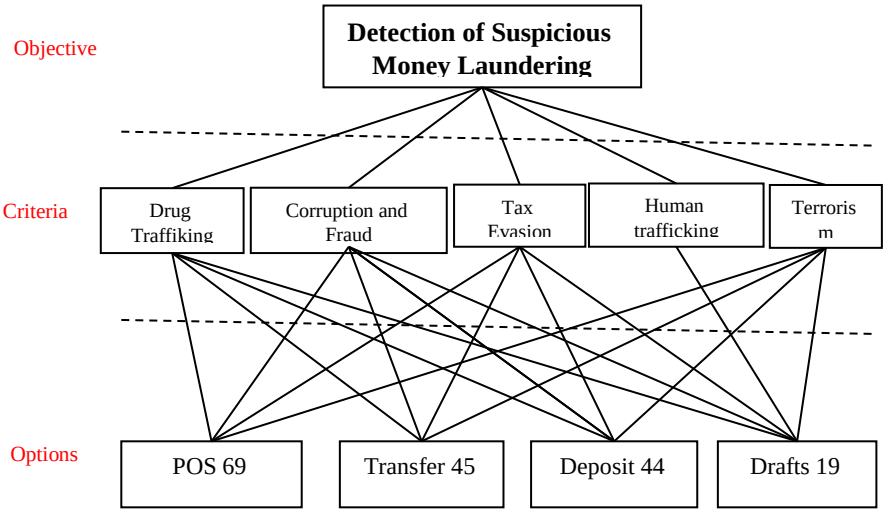

Figure 1. Hierarchy of Decision-Making

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Table 2

Combined Matrix of Options and Criteria by Hierarchical Analysis

	Terrorism	Human Trafficking	Tax Evasion	Corruption and Fraud	Drug Trafficking	Score of Options
Weight of Criteria	0.07	0.30	0.06	0.12	0.35	-
Drafts	0.11	0.08	0.14	0.21	0.10	**0.11**
Deposit	0.39	0.49	0.14	0.12	0.29	**0.32**
Transfer	0.14	0.18	0.033	0.21	0.15	**0.19**
POS	0.36	0.25	0.38	0.46	0.46	**0.38**

Source: Research Findings

4.3 Chang's (1996) Fuzzy Hierarchical Analysis Method

Due to the answers' uncertainty, the fuzzy set theory and AHP were combined in fuzzy-AHP to use interval values instead of crisp values and to calculate the results more accurately. At this phase, the change (1996) method, which is one of the most popular methods in the domain of Fuzzy-AHP, was used. Then, the results were compared with the previous method. In this method, after forming a hierarchical model (Figure 1), the following steps are performed:

First, a pairwise comparison was made for every fuzzy weight, and the corresponding degree of possibility of being greater than other fuzzy weights was determined. Then, the inconsistency rate of pairwise comparisons was evaluated. The inconsistency index in fuzzy matrices can be calculated in two ways. In this study, Gogus and Boucher (1997) method was used to calculate the inconsistency index. In this method, first, the fuzzy pair comparison matrix is divided into two definite matrices, and then the inconsistency of each definite matrix A^m and A^g is calculated by the hourly method. The only difference here is the use of a random index suggested by Gogus and Boucher (1997). Finally, two inconsistency rates were obtained, which were displayed with CR^m and CR^g. If both methods show an inconsistency index above 0.1, the experts should be asked to revise the matrices and compare them again. To calculate the inconsistency index, the number of criteria was considered 5 (n = 5), the random index was considered to be 1.072 for its middle matrix and 0.3597 for the upper and lower limits of the matrix (Table 3).

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Table 3

Inconsistency Rates of Criteria

Criteria	1	2	3	4	5	6	7	8	9	10
CRm	0.03	0.06	0.05	0.03	0.08	0.06	0.03	0.05	0.09	0.08
CRg	0.08	0.08	0.02	0.10	0.06	0.06	0.01	0.07	0.06	0.08

Source: Research Findings

When several respondents have made pairwise comparisons, the geometric mean method (GMM) is used to integrate them and derive information from pairwise comparison matrices (Tomashevskii, 2014). It is done so that the first values of all comparisons are taken together with the geometric mean, the second values are taken together, and the third values are taken together with the geometric mean.

Then, the weight of each criterion (S_i) is calculated through Equation 5:

$$S_i = \sum_{j=1}^{m} M_{gi}^{i} \times \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{i}\right]^{-1} \quad (5)$$

Then, based on Equation 6, the magnitude (degree of preference) of each S_i over S_k is obtained:

$$V(S_i > S_k) = \begin{cases} 1 & m_i \geq m_k \\ 0 & l_k \geq u_i \\ \frac{l_k - u_i}{(m_i - u_i) - (m_k - l_k)} & otherwise \end{cases} \quad (6)$$

In the last step, using Equation 7, each criterion's normal weight is calculated, which is obtained by dividing each raw weight by the total raw weights. It should be noted that the degree of possibility for a convex fuzzy number to be greater than convex fuzzy numbers is given through Equation 7:

$$V(S \geq S_1, S_2, \dots, S_K) = (V((S \geq S_1), (S \geq S_2), \dots (S, S_K)) = min(V((S \geq S_1), (S \geq S_2), \dots (S, S_K)) = minV(S \geq S_1)$$
$$I = 1, 2, 3, \dots, k \quad (7)$$

The final results of the fuzzy hierarchical analysis of Chang's method are indicated in table 4.

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Table 4

Combined Matrix of Options and Criteria by Chang's Method

	Terrorism	Human Trafficking	Tax Evasion	Corruption and Fraud	Drug Trafficking	Score of Options
Weight of Criteria	0	0	1	0	0	-
Drafts	0	0	0	0	0	0
Deposit	1	1	0	0	0	0
Transfer	0	0	0	0	0	0
POS	0	0	1	1	1	1

Source: Research Findings

There are some drawbacks to Chang's developmental analysis of fuzzy hierarchical analysis, including the fact that the weight of the criteria could be zero or negative, which was inherent in Chang's method and did not indicate that the method was wrong. Therefore, to overlap Chang's method's weaknesses, Buckley's fuzzy (improved fuzzy) hierarchical analysis method was used.

4.4 Buckley's Improved Fuzzy Hierarchical Analysis Method for Scoring the Transactions

The fuzzy hierarchical analysis method proposed by Buckley (1985) is a generalized form of the classical hierarchical analysis method. Fuzzy numbers are chosen to manage and work with data that is inherently uncertain. In this method, after the common steps of other fuzzy hierarchical analysis methods, the geometric mean of the rows is calculated based on Equation 8:

$$\tilde{r}_i = \left(\prod_{j=1}^{n} \tilde{P}_{ij}\right) \qquad i = 1, 2, 3, \dots, n \qquad (8)$$

In the next step, the geometric mean calculated in the previous step is aggregated. Then each geometric mean is multiplied by the inverse of this sum, and the fuzzy weights of each criterion are obtained through Equation 9:

$$W_i = r_i \otimes (r_2 \oplus r_2 \oplus \dots \oplus r_m)^{-1} \qquad (9)$$

where W_i is the geometric mean of the fuzzy comparison of the i^{th} criterion, which is indicated by a triangular fuzzy number $W_i = (LW_i, MW_i, UW_i)$.

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Then, the fuzzy weights were de-fuzzified through Shannon 10:

$$W_{crisp} = \frac{1+2m+u}{4} \qquad (10)$$

Finally, the obtained weights were normalized by the linear normalization method. The results of this method are given in Table 5. In this method, which has fewer and simpler calculations than the Chang method, the results are similar to the hierarchical analysis method results, and the highest risk in all types of money laundering transactions belongs to the POS transaction.

Table 5

Combined Matrix of Options and Criteria by Buckley Hierarchical Analysis

	Terrorism	Human Trafficking	Tax Evasion	Corruption and Fraud	Drug Trafficking	Score of Options
Weight of Criteria	0.13	0.16	0.18	0.21	0.32	-
Drafts	0.17	0.17	0.29	0.23	0.13	0.18
Deposit	0.26	0.41	0.15	0.15	0.23	0.26
Transfer	0.20	0.19	0.27	0.27	0.24	0.23
POS	0.36	0.23	0.29	0.36	0.40	0.32

Source: Research Findings

By comparing the two methods' results, the weight and importance of the "POS" were greater than in other cases. Table 6 indicates the priority of the transaction in money laundering in each of the offenses. According to the results, in each of the terrorism, tax evasion, corruption and fraud, and drug trafficking crimes, the transaction of POS had higher priority and importance, and in human trafficking, the deposit transaction has higher priority, which should be paid more attention.

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Table 6

Priority of the Transaction in Money Laundering In Each of the Offenses

Crimes Priority	Terrorism	Human Trafficking	Tax Evasion	Corruption and Fraud	Drug Trafficking
1	POS	Deposit	POS	POS	POS
2	Deposit	POS	Drafts	Transfer	Transfer
3	Transfer	Transfer	Transfer	Drafts	Deposit
4	Drafts	Drafts	Deposit	Deposit	Drafts

Source: Research Findings

The priority of the options (type of transaction) for money laundering as well as the importance of each transaction offense, is shown in Table 7. According to the table, POS and drug trafficking have a higher priority and should be given more attention.

Table 7

Priority of Transactions and Crimes

Priority	Type of Transaction	Money Laundering Offenses
1	POS	Drug Trafficking
2	Transfer	Corruption and Fraud
3	Deposit	Tax Evasion
4	Drafts	Human trafficking
5	-	Terrorism

Source: Research Findings

5 Discussion and Conclusion

If left unchecked or dealt with ineffectively, the possible social and political costs of money laundering are serious. Therefore, identifying suspicious financial transactions is a necessary precondition and a key aspect of the fight against money laundering, especially with the increased volume of transactions using electronic tools such as ATMs, sales terminals, branch terminals, cell phones, and the Internet.

Although efforts for anti-money laundering activities have begun in the early stages, solutions appear to be strategically limited. For this purpose, in this study, using multi-criteria decision-making methods, including the Shannon entropy, hierarchical analysis, and two-level fuzzy hierarchical

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analysis, were used to identify and prioritize the factors involved money laundering process.

This study adds to the existing literature in this field by examining suspected cases of money laundering using multi-criteria decision-making in the banking industry and would help bankers, policymakers, and banking supervisors' better control the bank's financial process and identify and prevent any suspicious money laundering transactions. In addition, this research has been conducted in a developing country that, despite the great efforts that have been made to identify suspected cases of money laundering and fight against this crime, little success has been achieved.

The results indicated that decision-making models provide a suitable framework for assessing and prioritizing the risk of various banking transactions. Because these models inherently provide a suitable rule for the relationship between qualitative and quantitative criteria, several criteria determine each criterion's value and position in decision-making. Thus, the costs of money laundering detection are reduced, and the unit's productivity responsible for it is increased.

According to the results, drug trafficking and POS transactions are more important in Iran, and more attention should be paid to these cases. Considering that the best place to track these transactions is the connection of banking network components to each other in the comprehensive payment system, creating effective customer identification systems by banks and credit institutions is the best strategy to deal with money launderers.

In addition, to fight against money laundering and prevent this crime, the regulatory system should create the legal conditions to identify and close the infiltration of dirty money into the country's financial network. In this regard, the most important area of securing the national economy against the damage caused by the entry of dirty money into the official and legal sector of the country can be monitoring the purchase of various financial assets. By reviewing the executive mechanisms of the stock exchange, and supervision of banking activities and other financial institutions, the deposit of dirty money in banks and financial institutions of Iran or their conversion into other financial instruments and assets could be prevented. The country's tax system's efficiency in identifying the main areas of tax evasion and increasing the

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possibility of tracking the huge transactions made on immovable properties must be considered.

Moreover, the economic security and cyberspace police must develop the necessary equipment and expertise to use cyber and telecommunications tools and information to advance money laundering's preventive objectives. Besides, there should be extensive cooperation between anti-money laundering institutions to successfully implement government legal measures in this area. In this case, exchanging information and conducting joint investigations between customs, tax, and anti-trafficking officials will often lead to the identification of money launderers. In this way, exchanging information and conducting joint investigations between customs, tax, and anti-trafficking officials will often lead to the identification of money launderers.

Altogether, some of the requirements and tools for fighting against money laundering are: the adoption and implementation of anti-money laundering laws and regulations, creation of an insecure environment for criminals, membership in international monetary and financial treaties, and the removal of obstacles to international cooperation, reforming the country's tax structure, controlling and supervising foreign currencies, distancing oneself from the state economy, establishing a powerful apparatus and organization to fight against money laundering, naming anonymous bank accounts, providing statistical reports, implementing Islamic banking operations, and rebuilding and reforming the banking system.

6 Limitations and Recommendations

Despite the huge amount of data generated in banking operations, due to banks' sensitivity in providing customer account information, the use of data mining and graph mining methods in this study was not possible. Since money laundering practices are constantly changing and money launderers are using newer methods, it will be challenging and even impossible to investigate fraud and misuse patterns among the vast amount of data generated in banking operations. Therefore, using data mining techniques and implementing expert systems can help detect money laundering patterns and unusual behaviors. Therefore, it is suggested that future research use these methods to identify more detailed suspected factors of money laundering in banking transactions and the extent of their risk and importance.

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Furthermore, more criteria and indicators in addition to the type of transactions and crimes are effective in the money laundering process. Therefore, it is suggested to identify and examine other factors affecting the money laundering process.

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