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RESEARCH ARTICLE **Open Access**

Prioritizing and Explaining Cause and Effect Relationships of the Most Important Behavioral Biases of Retail Investors in the Exchange Market: A Fuzzy Cognitive Mapping Approach

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Abstract
The first and most important goal of investors in the stock market is to grow their investment portfolio. Meanwhile, behavioral factors emerge as one of the most important factors that prevent optimal decision-making. Many studies have identified and introduced these factors. However, prioritizing these factors and identifying causal relationships between these factors has been neglected.Therefore, this study was conducted to prioritize and explain causal relationships between the most important behavioral biases of retail investors in the Tehran Stock Exchange. Given the qualitative and quantitative nature of the data used in this study, a Fuzzy Cognitive Mapping Approach was used. Therefore, 30 behavioral biases were discussed and examined by 15 experts, and the causal relationships between them were explained and prioritized. Accordingly, the distribution effect biases, the Salience data Bias, and the Loss Aversion Bias were introduced as the most important, and the forgiveness biases, Evolutionary Bias, and Money Illusion Bias were introduced as the least important behavioral biases. Also, behavioral biases were grouped into four categories, which in order of importance are: perceptual, experiential/informational, personality, and emotional.

Keywords: Behavioral sciences, behavioral biases, retail investors, Iranian Stock Exchange, Fuzzy Cognitive Mapping

Introduction

Capital circulation plays a very important role in the economy of every country; therefore, it is necessary for policymakers to pay special attention to this market in implementing macroeconomic planning and not to neglect its effects on other economic issues (Hemmatifar & Abbasifar, 2015). One of the new areas that has received attention in the financial behavior space is the analysis of investor behavior. When the goal is to study the capital market professionally, the most important step is to identify the elements and factors that make up this market, and investors are naturally the most important factor in this market. Therefore, understanding the behaviors of this group in the stock market plays an important role in analyzing market performance and will affect

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the entire capital market (Rostam, Sedaghat & Habibi, 2013).

In such a way identifying and analyzing behavioral factors that affect investor decision-making is of great importance not only for retail investors, but also for stock market policymakers. Properly understanding the behavior of retail investors and identifying normal and abnormal behaviors and the reasons for their occurrence (behavioral biases) in the stock market can prepare decision-makers, policymakers, and managers in planning to deal with these behavioral situations.

After the emergence of discussions about the normal person, a new discussion quickly spread, which included the integration of psychological and psychoanalytic theories with theories related to economic theories, which was called "behavioral finance". Behavioral finance tries to understand how psychological processes affect people's decision-making in their economic decisions and seeks to justify and explain the reasons for their occurrence. Many factors cause people to behave irrationally in practice and affect people's decision-making. This group of factors has created the basis for the emergence of behavioral sciences in the world of finance. Behavioral biases and their effects on investor performance are examined at the micro level of behavioral finance. Neoclassical finance believes that investors' beliefs will not be affected by behavioral biases, but real evidence in the world of finance points to the existence of systematic biases that arise as a result of transformed beliefs (Jamshidi and Ghalibaf-Asl, 2010). Despite human bias and perceptual errors, normal humans are not capable of making ideal decisions. Ultimately, it can be concluded that the assumptions of unlimited rationality and complete will and consolation in economic decision-making should be revised (Saeedi & Farahanian, 2015). This field of knowledge attempts to examine how investors collect, justify, interpret, and interpret this information. Behavioral finance specifically emphasizes cognitive and emotional biases and believes that humans will not behave rationally due to cognitive errors and emotional biases (Daders, Ashlagi, & Radfer, 2018).

To be aware of the effects of behavioral biases and overcome them, investors must first be able to identify them. Many studies have been conducted in different contexts to identify behavioral biases, and so far, more than fifty biases have been identified. However, an issue that has not been addressed so far is examining the effects of these biases and prioritizing them. Given that it is almost impossible to pay attention to all biases simultaneously during planning and in practice, due to limitations in capital and time, identifying the most important behavioral biases is one of the main concerns of both retail investors and stock market politicians. On the other hand, the relationship between behavioral biases and their effects on each other is an issue that should be addressed in the continuation of the behavioral discussion and has been neglected so far.

Regarding the discussion of behavioral finance and behavioral factors affecting individuals' decision-making in the capital market, many studies have been conducted by different researchers, each of which has examined behavior from different aspects. However, in this study, for the first time, an attempt has been made to challenge all types of behavioral biases, prioritize them, and examine the causal relationships between behavioral biases by utilizing the fuzzy cognitive mapping approach, and finally, the behavioral pattern of retail investors has been explained by considering the most important biases. By comprehensively investigating and identifying the types of behavioral biases affecting retail investors' decision-making, their consequences, and their prioritization, this study seeks to create an integrated and comprehensive perspective on this issue in order to take a step towards informing investors about the effects of these behavioral biases on their decisions and lead to the development of the Tehran Stock Exchange.

Theoretical Foundations and Research Background

By examining the background of domestic and foreign research, it is quite evident that many studies have been conducted in the field of examining the behavior of investors in the securities market with the aim of identifying effective behavioral biases. In Table 1, the most important research conducted in this field is presented:

Table 1.

Background of studies on behavioral biases in financial markets (Rasegoo, Abbasi, Mohammadi, and Ranaei, 2025)

Research for identifying biases	Research for examining one or more biases
Saadi, Gholipour and Gholipour (2010); Fahimi Doab (2010); Samadi, Sohrabi and Khazaei (2012); Falahati (2012); Vakili Fard, Forough Nejad and Khoshnoud (2013); Hosseini Chegni, Haqgo and Rahmani Nejad (2014); Jalilvand, Rostami and Rahmani (2015); Ebrahimi, Babajani and Hanafizadeh (2017); Ghiyor Baghbani and Behboudi (2017); Tajmir Riahi and Dejdar (2017); Dadras, Toloei and Radfar (2018); Pashoutni Zadeh, Raanaei, Abbasi and Mousavi (2019); Ghalibaf Asl and Jamshidi (2019); Khosravani, Talebnia and Saraf (2020), Bashiri Manesh and Shahnazi (2021); Jamali and Bakhtiari (2021).	Nikomaram and Saeedi (2009); Yousefi and Shahrabadi (2009); Fallah Shams Leyalistani, Ghalibaf and Nobakht (2010); Saeedi and Farahanian (2011); Ahmadi and Shi'i (2014); Jahangiri, Marfoo and Hosseini (2014); Fedaye-Nejad, Mayeli and Imam Doost (2015); Pakdel, Izadini and Dasangir (2016); Doostdar, Mohammadnejad and Javadian (2017); Haji Hashemi and Abdoli (2018); Nazaripour and Zakizadeh (2022); Zainivand; Janani, Hemmatfar and Setayesh (2023); Gerkaz, Ma'toufi, Hassani and Didekhani (2023).
Brabazon (2000); Fuller (2000); Roeder and Smiths (2009); Oprin and Tanasescu (2014); Statesman (2014); Kenneth Baker and Nofsinger (2017); Bailey and Kumar (2011); Metava, Kebirhasem and Metava (2018); Roger, Roger and Scott (2018); Abreu (2019); Farahna and Janatul (2023).	Blaine and Crocker (1995); Forgas (1995); Babcock and Lowenstein (1997); Koval and Moskowitz (1999); Brabazon (2000); Jensow and Meyer (2001); Jones and Sugden (2001); Harbaugh (2002); Campbell and Veltbanahu (2004); Oswald and Grosjean (2004); Der and Zhou (2006); Chapin and Coleman (2009); Greenblatt and Kloharjo (2009); Davis, Lueders, and Lu (2009); Kimball and Shamoy (2010); Ducky and Zielonka (2013); Desido and Somasundaram (2017); Joshi (2017); Zhang and Sussman (2018); Huebner, Fletch, and Ilch (2020); Akai and Herschleifer (2021); Kumari Radu (2024)

Many studies have examined and introduced a number of behavioral biases, and some studies have also examined and measured the impact of a number of introduced biases on investor decision-making in a specific context. Types of behavior have also been discussed and examined in a number of studies.

However, the purpose of this study is to prioritize biases and the causal relationships between them. By understanding the cause-and-effect relationships between behavioral biases, it is possible to propose very effective management scenarios and limit and control the effects of biases.

Considering the identification of more than fifty behavioral biases, in this study, in order to achieve the goal of analyzing causal relationships, only the most important behavioral biases have been examined. For this purpose, the biases in Table 2 have been selected:

Table 2.

The most important behavioral biases affecting the decision-making process (Rastgoo et al., 2014)

Dispossiotion Effect Bias	Forgivness Bias	Representativeness Bias	Distribuition effect Bias
Reaction Bias	Regret Aversion	Loss Aversion Bias	Herding Bias
Conservatism Bias	Availiability Bias	Illusion of Validity Bias	Stock Prices Bias
Self-Attribution Bias	Money Illusion Bias	Over Confidence Bias	Halo Effect Bias
Momentum Bias	Base-Rate Neglect Bias	Misconception of Chance Bias	Anchoring & Adjustment Bias
Salience data Bias	Insensitivity to Predictability Bias	Home Bias	Cognititive Dissonance Bias
Illusion of Control Bias	Confirmation Bias	Evolutionary Bias	Mental Account Bias
Self Esteem Bias	Optimism Bias		

Research Methodology

The present research is classified as exploratory research in terms of its purpose. Since both quantitative and qualitative approaches are used in this research, it is classified as mixed method research in terms of data type.

Considering that the goal of applied research is to apply the results (to use them) in solving specific issues and problems in society and the results of this research will be used to meet needs and solve problems; this research is classified as applied research. On the other hand, any research that aims to expand the boundaries of general human knowledge will be a kind of developmental research.

The research method in this study is Fuzzy Cognitive Mapping. The fuzzy cognitive mapping method is a cognitive tool that can model complex qualitative and quantitative relationships. A Fuzzy Cognitive Map (FCM) is a cognitive map in which the relationships between elements (such as concepts, events, and project resources) can be used to calculate the "power of influence" of these elements (Jafari Eskandari and Farhang, 2015). These fuzzy cognitive maps were first introduced by Bart Kusko. Robert Axelrod introduced cognitive maps as a formal method for representing social scientific knowledge and modeling decision-making in social and political systems, after which calculations will be performed on this map (Axelord, 1976). Fuzzy cognitive mapping is a qualitative method or, better said, a semi-quantitative and dynamic method for structuring specialized knowledge that aims to depict an individual's understanding of a specific topic in the form of a graph(Azar and Mostafaei, 2012). Fuzzy cognitive maps are fuzzy graph structures for representing causal reasoning. Their ambiguity makes possible degrees of ambiguity of causality between causal concepts (Shokohyar, Tolai & Fatemi, 2017). Fuzzy cognitive mapping has attracted much interest and research due to its ability to represent structured knowledge and complex models in various fields. These maps can be formed based on both expert knowledge and historical data (Poczeta et al., 2018).

FCMs are a combination of fuzzy logic and cognitive mapping. Fuzzy cognitive maps are essentially fuzzy graph structures used to represent causal reasoning in the form of graphs consisting of weighted nodes and edges. A cognitive map can be defined as a type of recurrent neural network that has the main aspects of fuzzy logic. A cognitive map allows the imitation of a system or a phenomenon using key concepts and the causal relationships between them. Cognitive maps are suitable and useful for modeling and decision-making of complex systems. They have been used in various application areas, for example, for pattern recognition, in risk analysis and crisis management, as a decision support tool for political decision-making, and...

After the design and acceptance of the results of cognitive mapping, another version of this method was proposed to analyze complex and multifaceted causal relationships under the name of fuzzy cognitive mapping, which represents the strength of causal relationships with a number in the range of 1 and -1 (Mostafaei, Azar & Moqbel Ba'arz, 2018). A cognitive map expresses the direction of relationships, indicating causal relationships between concepts. The quality of relationships is also expressed by the weight assigned to each relationship. In the literature on fuzzy cognitive maps, a map is not only represented schematically, but also represented mathematically and in a matrix form, which is known as the "adjacency" or "adjacency" matrix (Mehregan, Zandiyeh et al., 2017).

Data Analysis

The first step in applying the fuzzy cognitive mapping approach is to identify nodes (Jafari & Farhang, 2015). Therefore, in the present study, it is necessary to identify all behavioral factors affecting retail investors' decision-making. As mentioned earlier, more than fifty behavioral biases have been identified so far, and in this study, the most important behavioral biases have been examined as mapping nodes (Table 2).

In order to obtain information in this study, semi-structured interviews were conducted with 15 experts, including experts, researchers, and stock exchange industry experts who have relevant experience and knowledge, and their perceptions were examined, understood, and recorded by the researcher. The main criteria and characteristics for selecting experts were at least a master's degree in management (theoretical mastery), at least 5 years of experience in the Tehran Stock Exchange, and in some experts, experience in related research activities and the desire and ability to participate in research.

Table 3.

Demographic characteristics of experts

Total	Gender		Education		Experience in Tehran Stock Exchange	
	Female	Male	Master	PhD	Between 5 and 10 years	More than 10 years
15	6	9	4	11	3	12
%100	%40	%60	%27	%73	%20	%80

The sampling method used in this study was non-random and purposive sampling. The validity of the interviews and questions used was confirmed by obtaining opinions from professors and experts.

Given that all experts had experience and education related to the research topic, the information-gathering process did not face any serious obstacles. However, for the experts to gain more mastery and to ensure that they obtained valid information based on a complete understanding of the topic, a summary of the present study was first provided to the experts along with a complete explanation of the purpose and mission of this study, and finally explanations of 30 biases along with their precise definitions were provided to the experts. In the interview with each expert, the researcher entered the information-gathering process in the form of semi-structured interviews, taking into account the experience and mastery of the expert, until finally the necessary information was obtained to enter the cognitive mapping phase.

The first step in fuzzy cognitive mapping is to form the initial success matrix. The initial success matrix is a [n×m] matrix where n is the selected biases and m is the number of people (experts) to obtain data. Each element in this matrix (Oij) represents the importance that expresses the importance of element i based on the opinion of expert j. In this step, experts were asked to express their views on the importance of each bias in the range of 0 to 100.

In the next step, the fuzzy matrix of FIIM expert opinions needs to be formed. In this step, the numerical vectors Vi are converted into fuzzy sets. The numerical vectors are converted into fuzzy sets with values between [0,1] using the mechanisms presented below.

In this case, the largest value in Vi should be found and Xi=1 assigned to it:

$$\text{MAX (Oiq)} \Rightarrow \text{Xi (Oiq)} = 1$$

$$\text{MIN (Oip)} \Rightarrow \text{Xi (Oip)} = 0$$

The other elements of the vector Vi in the interval [0,1] are calculated proportionally, according to the following formula:

$$\text{Xi (Oij)} = \text{Oij} - \text{Min (Oip)} / \text{Max (Oiq)} - \text{Min (Oip)}$$

In this formula, Xi (Oij) is the membership degree of element Oij in the vector Vi and Oij is the importance of each indicator in the FZIM matrix.

Given that the values lie directly in the interval [0,1], determining the membership degree of the indicators may not reflect the results corresponding to the real world and may not be logical. In this case, a value is considered as the upper threshold and a value as the lower threshold by the analyst for data analysis. Therefore, if Vi is a numerical vector of m elements related to the concept i and Oij with j=1,2,…,m are the components of Vi, the upper and lower threshold values (αu and αl, respectively) are as follows:

$$\forall\ \text{Oij (Oij} \geq \alpha u) \Rightarrow \text{Xi (Oij)} = 1$$

$$\forall\ \text{Oij (Oij} \leq \alpha l) \Rightarrow \text{Xi (Oij)} = 0$$

In the next step, the SIRM relationship strength matrix is formed. The relationship strength matrix is an (n×n) matrix in which both rows and columns represent concepts (variables), i.e. behavioral biases, and represents one of three possible states of the relationship between variables. Each element Sij represents the correlation between concepts i and j and can take a value in the range [0,1]. According to the above, three types of correlation can be expected.

When Sij>0, it indicates a positive (direct) relationship between concepts i and j. In this case, an increase in the value of concept i causes an increase in concept j. When Sij<0, it indicates a negative (inverse) relationship between concepts i and j. In this case, an increase in the value of concept i causes a decrease in concept j. The third state is when Sij=0. This state is when the existence of a relationship between two elements i and j is negated and the expert believes that there is no relationship between the two factors.

In examining each Sij, three parameters should be considered. The first parameter determines the direction of the cause and shows whether concept i causes concept j or vice versa. The second parameter indicates the polarity, that is, the relationship between concepts i and j is direct or inverse, and the third parameter indicates the strength of the influence of concept i on j.

The type and intensity of relationships were examined separately by semi-structured interviews with each expert and completed in the form of triangular fuzzy numbers in separate matrices.

To merge the matrices (maps), the arithmetic mean of fuzzy numbers was used.

$$A = \left(l^{(i)}, m^i, u^i\right) \qquad i = 1, 2, \ldots, n$$

Number of experts = n

$$A_{ave} = \frac{\sum_{i=1}^{n}(l^i, m^i, u^i)}{n}$$

The resulting matrix is a concatenation matrix of fuzzy triangular numbers that must be converted to definite numbers between zero and one:

$$X = \frac{l + 2m + u}{4}$$

Mathematical calculations may be misleading in some cases, so experts should be consulted to analyze the data and convert the SIRM matrix to the FMI matrix. The final matrix contains elements of the SIRM matrix that indicate causal relationships between the indicators.

Therefore, the relationship strength matrix was re-examined by the researcher and the relationships obtained were confirmed, and the SIRM matrix was considered as the FMI matrix and the input matrix in the Mental Modeler and FCMapper software without any changes.

The following outputs were extracted from these software:

Table 4.

Information from the FCM

Total	Transmitter	Receiver	Ordinary	No Connection	Density
30	2	1	27	0	0.124137931

The table above shows that out of the 30 factors under study, one factor is only an affected factor, two factors are only identified as influential factors, and the remaining 27 factors are factors that have both influence and influence. Density means the number of connections between different factors in the final mapping map compared to the number of all possible connections. The higher this value, the more potential management policies there are. One of the most important outputs of the cognitive mapping approach is the determination of the id or dependency (influence) and od or influence (influence) of each factor. The influence of each factor indicates the degree of influence of the factor on other factors, which will be obtained from the sum of the absolute magnitude of the influence of this factor on all factors.

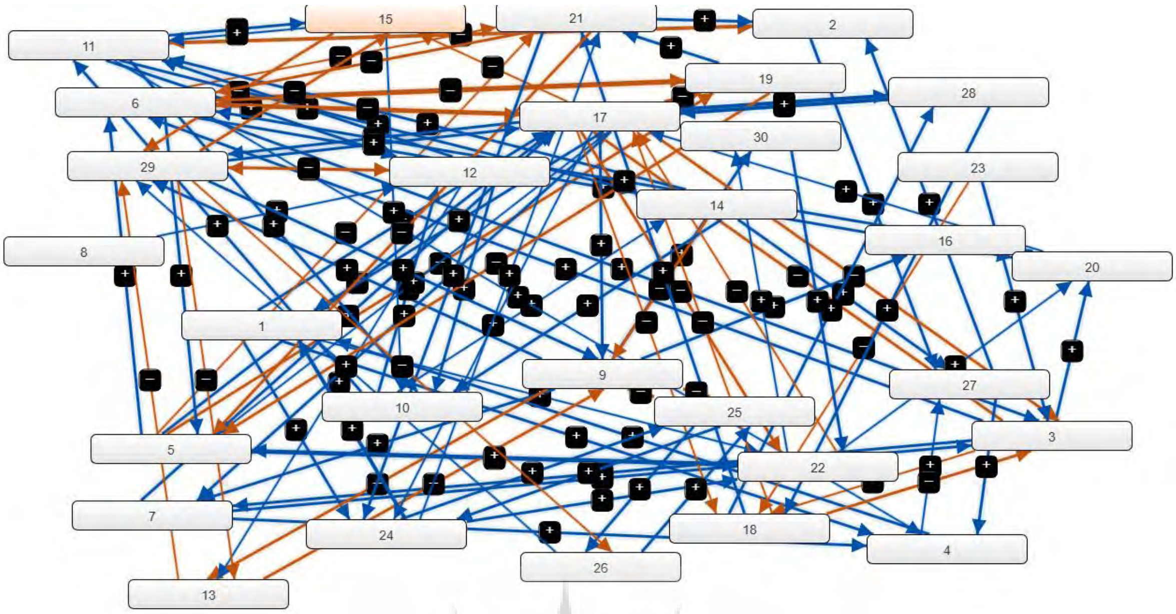
Table 5.

Ranking of fuzzy cognitive map variables based on centrality index

Rank	Factor	Indegree	Outdegree	Centrality
1	Distribuition effect	7.25	5.25	12.5
2	Salience data Bias	4	4.25	8.25
3	Loss Aversion Bias	3.5	3.5	7
4	Over Confidence Bias	3.25	2.75	6
5	Reaction	2.5	3.25	5.75
6	Regret Aversion	2.75	2.75	5.5
7	Momentum	2.5	2.75	5.25
8	Representativeness	2.25	2.5	4.75
9	Herding	2.25	2.25	4.5
10	Base-Rate Neglect	2.25	1.75	4
11	Conservatism	2	1.75	3.75
12	Self-Attribution	1.75	2	3.75
13	Illusion of Validity	1.75	2	3.75
14	Insensitivity to Predictability	2	1.5	3.5
15	Availiability	1.25	2.25	3.5
16	Mental Account	1.75	1.75	3.5
17	Dispossiotion Effect	1.75	1.5	3.25
18	Stock Prices	1.75	1.5	3.25
19	Self Esteem	2.25	1	3.25
20	Halo Effect	1	2	3
21	Anchoring & Adjustment	1	1.75	2.75
22	Optimism	1.25	1.5	2.75
23	Confirmation	1	1.25	2.25
24	Illusion of Control	1	1	2
25	Cognititive Dissonance	0.75	1.25	2
26	Misconception of Chance	0.75	0.75	1.5
27	Home	0.5	0.75	1.25
28	Money Illusion	1	0	1
29	Evolutionary	0	0.75	0.75
30	Forgivness	0.25	0	0.25

After determining the final matrix, the matrix data is displayed graphically using the Mental Modeler software. In this map, firstly, the direction of each cursor (edge) indicates the existence of a relationship and influence between two factors. Then, the color of each edge indicates whether the relationship between the two factors is direct or inverse. In this way, blue indicates a direct relationship orange indicates an inverse relationship between the two factors, and finally, increasing the diameter of the edges indicates an increase in the strength of the relationships. The figure below shows a graphical representation of the causal relationships between the biases affecting decision-making.

Figure 1.
FCM graphical map of decision biases



By comparing the degree of centrality of concepts related to each category, the four main categories can be ranked.

Table 6.
Ranking of the four main categories of behavioral biases

No	Rank	Category	Biases	Centrality	Mean of centrality
1			Representativeness	4.75	
2			Cognititive Dissonance	2	
3			Reaction	5.75	
4	1	Perceptual	Halo Effect	3	4.64
5			Momentum	5.25	
6			Salience data	8.25	
7			Mental Account	3.5	
8			Distribuition effect	12.5	
9			Stock Prices	3.25	
10			Conservatism	3.75	
11	2	Experiential/ Informational	Anchoring & Adjustment	2.75	4.39
12			Base-Rate Neglect	4	
13			Availiability	3.5	
14			Money Illusion	1	
15			Forgivness	0.25	
16			Loss Aversion	7	
17			Illusion of Validity	3.75	
18			Over Confidence	6	
19	3	Personality	Self-Attribution	3.75	3.28
20			Illusion of Control	2	
21			Self Esteem	3.25	
22			Optimism	2.75	
23			Evolutionary	0.75	
24	4	Emotionl/ Affective	Herding	4.5	3.11
25			Insensitivity to Predictability	3.5	

No	Rank	Category	Biases	Centrality	Mean of centrality
26			Misconception of Chance	1.5	
27			Confirmation	2.25	
28			Dispossiotion Effect	3.25	
29			Regret Aversion	5.5	
30			Home	1.25	

In the next step, the information obtained from the fuzzy cognitive mapping was measured using a questionnaire. For this purpose, a researcher-made questionnaire was used. Considering the 4 categories and 30 identified concepts, a questionnaire with 30 items was designed, which was approved by professors and experts in terms of content and concept. However, each questionnaire must be examined in terms of validity and reliability before distribution and to ensure its efficiency. For this purpose, the content validity ratio and content validity index of the questionnaire were examined.

Content validity ratio or CVR is a method of measuring the validity of a questionnaire. To calculate this ratio, the opinions of experts specializing in the content of the question test are used. First, the objectives of the test are explained to the experts, and operational definitions related to the content of the questions are stated, and then the CVR can be calculated by examining the experts' views.

Therefore, the first step is to select experts or experts. In this regard, eight experts were selected, and this committee includes people who have relevant education or extensive experience in the field of research and for whom the research results are of great importance. The characteristics of the experts are presented in Table 7:

Table 7.
Demographic characteristics of experts

Total	Gender		Education			Experience in Tehran Stock Exchange	
	Female	Male	Master	PhD Candidate	PhD	Between 5 to 10 years	More than 10 years
5	30.3	55	3	2	3	2	6
100	0.375	0.625	0.375	0.25	0.375	0.25	0.75

The Content Validity Index (CVI) is also used to measure the validity of a questionnaire. This index was proposed by Waltz and Bassel. To calculate the CVI, a committee of experts is asked to evaluate each item based on three criteria: representativeness, comprehensiveness, and transparency. The results of the CVI and CVR validity studies are presented in Table 8:

Table 8.
Content validity index of the behavioral bias assessment test among retail investors (n=8)

Question	CVR	CVI Relevancy	CVI Clarity	Comprehensiveness CVI
1	1	1	1	1
2	1	0.875	1	0.875
3	0.75	1	1	1
4	1	0.875	1	1

Question	CVR	CVI Relevancy	CVI Clarity	Comprehensiveness CVI
5	0.75	1	1	1
6	1	1	1	1
7	1	1	1	1
8	1	1	1	1
9	0.75	1	0.875	1
10	1	1	1	1
11	0.75	1	1	1
12	0.75	0.875	1	1
13	0.75	1	1	1
14	1	1	1	1
15	1	1	0.875	1
16	1	1	1	1
17	0.75	0.875	0.875	1
18	1	1	1	1
19	1	0.875	0.875	0.875
20	1	1	0.875	1
21	1	1	1	1
22	0.875	1	1	1
23	0.75	1	1	1
24	0.75	1	0.875	1
25	1	0.875	1	0.875
26	1	1	1	1
27	0.75	0.875	1	0.875
28	0.75	1	1	1
29	1	1	1	1
30	1	1	1	1

To measure and examine the reliability of the questionnaire, the Cronbach's alpha method was used. In this method, information related to 30 questionnaires is usually collected and if the reliability is confirmed, the questionnaire will be distributed in its entirety among the sample individuals. Therefore, 30 questionnaires were collected and information related to their reliability is presented. The table below shows the Cronbach's alpha coefficient for all questions in the questionnaire and the questions related to each category separately. The specified value was calculated using SPSS 26 software. For the reliability of a questionnaire to be confirmed, the alpha coefficient must be more than 0.70. Given that the coefficients of all categories and the total coefficient all have values greater than 0.7, the questionnaire has high reliability.

Table 9.
Cronbach's alpha of the questionnaire

Categories	Number of Questions	Cronbach's alpha coefficient
Perceptual	7	0.843
Experiential/Informational	7	0.92
Personal	9	0.834
Emotional/ Affective	7	0.933
Total Questionnaire	30	0.975

Given that the context of this study is the Tehran Stock Exchange, the statistical population of this study is all the activists and investors in this market throughout Iran. One of the common methods for selecting the sample size is the Cochran method. Given the unlimited statistical population, considering the maximum error of 0.05, the sample size is 384 people. For this purpose, with the cooperation of some respected managers in the useful and knowledgeable brokerage, several questionnaires were randomly distributed to several stock market activists throughout Iran. These questionnaires were sent online to the sample individuals and the first 384 questionnaires that were returned in full were used as the basis for data fitting and subsequent steps.

To implement statistical methods and calculate appropriate test statistics and logical inferences, the most important action before any action is to select the appropriate statistical method for the research. For this purpose, awareness of whether or not the data distribution is normal is of fundamental priority. For this purpose, in this study, the valid Kolmogorov-Smirnov test was used to examine the assumption of normality of the research data.

Table 10.
Kolmogorov–Smirnov test result

Variable	Sample size	Test statistic	Significance level	Result
Perceptual	384	0.115	0.000	It's not normal.
Experiential/ Informational	384	0.051	0.019	It's not normal.
Personal	384	0.07	0.000	It's not normal.
Emotional/ Affective	384	0.049	0.028	It's not normal.

Considering the values in the table above, where the significance level of the test for all variables is less than 0.05, it can be stated that hypothesis H0 is rejected and therefore the distribution of the variables does not follow a normal distribution. Therefore, non-parametric methods should be used to examine the relationships between the research variables and to examine the hypotheses. In this section, due to the non-parametric nature of the data distribution, the Spearman correlation test method has been used to examine the relationship between the main variables.

Table 11.
Correlation between research variables

Variable	Perceptual	Experiential/ Informational	Informational	Personal
Perceptual	1	0.569	0.386	0.36
Experiential/ Informational	0.569	1	0.33	0.33
Informational	0.386	0.33	1	0.395
Personal/ Affective	0.36	0.33	0.395	1

The results of Spearman's correlation between the main research variables are given in the table above. As is clear from the table (all numbers are between zero and one), the significance level of the correlation coefficients is less than 5%. As a result, the null hypothesis is rejected and the opposite hypothesis is confirmed, indicating that there is a significant correlation between all research variables.

Based on the data obtained from the questionnaire, the research variables can be described. On this basis, the mean, variance, skewness and kurtosis values can be calculated for each behavioral bias and the biases can be prioritized based on that.

Table 12.

Descriptive data of research variables

No	Category	Biases	Mean	Variance	Skewness	Kurtosis
1	Perceptual	Representativeness	2.8151	2.052	0.119	-1.358
2		Cognititive Dissonance	3.0313	2.243	-0.321	-1.367
3		Reaction	3.1536	2.25	-0.189	-1.384
4		Halo Effect	3.1042	2.386	-0.175	-1.514
5		Momentum	3.1432	2.207	0.099	-1.433
6		Salience data	3.2083	2.374	-0.195	-1.485
7	Experiential/ Informational	Mental Account	3.1458	2.047	-0.156	-1.298
8		Distribuition effect	3.3099	2.157	-0.239	-1.384
9		Stock Prices	2.9323	1.818	0.040	-1.286
10		Conservatism	3.0391	2.032	0.018	-1.39
11		Anchoring & Adjustment	2.888	1.865	-0.018	-1.229
12		Base-Rate Neglect	2.9453	2.229	-0.005	-1.456
13		Availiability	3.000	1.713	0.014	-1.216
14		Money Illusion	3.0365	2.004	-0.037	-1.314
15	Personality	Forgivness	2.9214	1.997	0.006	-1.335
16		Loss Aversion	3.0313	1.842	0.025	-1.23
17		Illusion of Validity	2.6740	2.099	0.051	-1.36
18		Over Confidence	3.1224	1.888	-1.106	-1.269
19		Self-Attribution	3.1172	1.968	-1.118	-1.257
20		Illusion of Control	3.1094	1.993	-0.161	-1.311
21		Self Esteem	3.0625	2.106	-0.094	-1.337
22		Optimism	3.0095	2.225	-0.052	-1.402
23	Emotional/ Affective	Evolutionary	2.9188	2.088	-0.013	-1.365
24		Herding	3.0885	2.091	-0.067	-1.342
25		Insensitivity to Predictability	2.9375	2.007	-0.067	-1.283
26		Misconception of Chance	2.9922	2.091	0.024	-1.388
27		Confirmation	2.8177	2.05	0.114	-1.357
28		Dispossiotion Effect	3.1328	2.131	-0.106	-1.356
29		Regret Aversion	3.1484	1.975	-0.158	-1.256
30		Home	2.8698	1.973	0.068	-1.312

Using the average score of each bias, the behavioral categories corresponding to each set of biases can be ranked using the mixed mean.

Table 13.

Ranking of behavioral categories based on questionnaire data

No	category	Biases	Mean	Mixed Average
1	Perceptual	Representativeness	2.8151	3.085929
2		Cognititive Dissonance	3.0313	
3		Reaction	3.1536	
4		Halo Effect	3.1042	
5		Momentum	3.1432	
6		Salience data	3.2083	

No	category	Biases	Mean	Mixed Average
7	Experiential/ Informational	Mental Account	3.1458	3.021586
8		Distribuition effect	3.3099	
9		Stock Prices	2.9323	
10		Conservatism	3.0391	
11		Anchoring & Adjustment	2.888	
12		Base-Rate Neglect	2.9453	
13		Availiability	3.000	
14	Personality	Money Illusion	3.0365	2.999611
15		Forgivness	2.9214	
16		Loss Aversion	3.0313	
17		Illusion of Validity	2.6740	
18		Over Confidence	3.1224	
19		Self-Attribution	3.1172	
20		Illusion of Control	3.1094	
21		Self Esteem	3.0625	
22		Optimism	3.0095	
23		Evolutionary	2.9188	
24	Emotional/ Affective	Herding	3.0885	2.998129
25		Insensitivity to Predictability	2.9375	
26		Misconception of Chance	2.9922	
27		Confirmation	2.8177	
28		Dispossiotion Effect	3.1328	
29		Regret Aversion	3.1484	
30		Home	2.8698	

Discussion and Conclusion

Investing in financial markets has always been an attractive choice for increasing capital and making profits. However, given the intuitive nature of the decision-making process by investors, this process often does not lead to profits. The best case for investing and selecting a stock portfolio is to have a mechanical strategy and stick to it. However, in most cases, people's intuition (behavioral factors) prevents adherence to principles and strategies. This study aimed to achieve a high level of recognition and understanding of the effective intuitive factors and greater mastery of the key factors affecting investor behavior in the stock market and how these factors affect the decision-making process among people active in this market across different age groups. In this regard, the present study sought to examine the most important behavioral biases, the impact and effectiveness of each bias on each other, and their prioritization, which was pursued with the fuzzy cognitive mapping approach. Based on the experts' perspective, 30 behavioral biases were examined and the causal relationships between them were identified and prioritized. These concepts (biases) were also categorized into 4 main categories. After that, the information obtained from cognitive mapping was evaluated. For this purpose, a questionnaire with 30 items was designed and, after examining its validity and reliability, was distributed to 384 investors through random sampling. Accordingly, the biases were ranked again by SPSS software based on the mixed mean. The results of cognitive mapping were fully confirmed by the results of the questionnaires, and the perceptual category was identified as the most important category, followed by the experiential/informational, personality, and emotional/affective categories as the most important behavioral categories.

References

Akhavan Anvari, M., Mehregan, M., Zandieh, M., & Kazemi, A. (2017). Modeling factors affecting natural gas consumption in the household sector using fuzzy cognitive mapping (FCM). Industrial Management, 9(3), 515-538.

Axelord, R. (1976). Structure of Decision: *The Cognitive Maps of Political Elites. Princeton Legacy Library. Princeton*. NJ.

Azar, A., & Mostafayi, Kh. (2012). Cognitive mapping as a new method in optimizing budgeting decisions, *Management Research in Iran*, 16(3), 83.

Casco, B .(2010) Fuzzy Thinking, translated by Ghasimi., Ppprmomtaz, A., Maghsoodpour, A., & Ghaffari., A., Tehran: Khajeh Nasir al-Din Tusi University.

Dadras, K., Toloie, A., & Radfar, R. (2018). Role of Behavioral Finance In Understanding Individual Investor's Behavior (A Review of Empirical Evidences from Tehran Stock Exchange). Journal of Investment Knowledge, 7 (28), 83-102. Hemmti , H., & Abbasifar, Abdorrahman. (2015). Effect of Stock Market Volatility on Banks Performance Accepted in Tehran Stock Exchange, *Journal of Economics and Business Research*, 6(10), 13-26.

Jafari Eskandari,M., Farhang, M. (2015). Designing a fuzzy cognitive map model of factors affecting cost-time-quality in oil and gas projects, case study: Refinery 15 of South Pars Gas Complex Company, Monthly Journal of Oil and Gas Exploration and Production, 125, 30-37.

Jamshidi, N., & Ghalibaf asl, H. (2019). Dynamics of the Behavior of Individual Investors in Tehran Stock Exchange. Financial Management Perspective, 9(25), 101-120.

Mostafaei Dolatabad, Kh., Azar, A., & Moqbel Ba'arz, A. (2018). Identifying and analyzing operational risks using fuzzy cognitive mapping. Asset and Financing Management, 6(4 (23)), 1-18.

Poczeta, K., Kubuś, Ł., Yastrebov, A., & Papageorgiou, E. I. (2018). Application of Fuzzy Cognitive Maps with Evolutionary Learning Algorithm to Model Decision Support Systems Based on Real-Life and Historical Data. *Recent Advances in Computational Optimization*. 153- 175.

Rastgoo, F., Abbasi, A., Mohammadi, A., & Ranaeiy, H. (2025). Identifying the Most Important Behavioral Biases of Individual Investors in Tehran Stock Exchange: A meta-Synthesis approach, Under revision.

Rostami Norouzabad, M., Sedaghat, P., & Habibi, F. (2013). Investigating the Factors Affecting Investors' Behavior in the Reality Investment Income (Case Study of Investors of Tehran Stock Exchange). Financial Management Perspective, 5 (10), 69-94.

Saeedi, A., Farahanian, M.,J. (2015). Fundamentals of Behavioral Economics and Finance .Journal of Securities Exchange, 4 (16), 175-198.

Shokohiyar, S., Tolaei, R ., and Fatemi, LS. (2017). Prioritizing the Components of the Information System for Evaluating Jihadi Management Performance in the Organization, Basij Strategic Studies, 74, 91-118.