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Analyzing the interrelations among investors' behavioral biases using an integrated DANP method

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C H R O N I C L E

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A B S T R A C T

This research investigates the relationships between investors' behavioral biases and compares their relative importance. For this purpose, a survey is conducted, and analytical methods are used. The sample for this study has been 512 individual investors of the Tehran Stock Exchange who completed an online questionnaire. The respondents replied about their behavior in different situations to analyze the prevalence of asymmetric discounting, mental accounting, shifting risk preference, loss aversion, regret aversion, overconfidence, proxy decision making, ambiguity aversion bias, anchoring, and herd behavior as significant fields of behavioral biases in their investment decisions. The data is analyzed using two different analytical techniques. A model based on structural equations is designed and tested to analyze the relations between these fields. Another integrated method, the DEMATEL-based analytic network process, is also used to prioritize and rank these behavioral biases. Finally, the results are compared and confirmed by each other. Analyzing the results proves the existence of 19 positive and statistically significant relations between these fields. Thus, an increase or decrease in the intensity of a particular field of behavioral biases in one's decisions significantly affects the intensity of other fields. The present study finds that shifting risk preference, anchoring, loss aversion, and regret aversion are the most important fields of behavioral biases based on their prevalence among investors and their correlations with other biases.

1. Introduction

Investors of financial markets feel various emotions when they make investment decisions because of the fluctuations of these markets and the significant amount of risk associated with this type of investment. These emotions affect their decisions, leading to less rational investments (Dalgıç et al., 2021). Wrong choices lead to poor investments and losing money in the market. Moreover, if most investors choose poor investments, profitable investment opportunities fail to raise funds, lowering societies' economic growth. Ateş et al. (2016) concluded that in addition to increasing the financial literacy level of investors, spreading awareness of behavioral biases is necessary to ensure that investors make rational decisions. One of the most known traditional finance theories is the Efficient Market Hypothesis (EMH). Fama (1970) argued that many rational investors are competing to predict the market in an efficient market, and they use freely available information. Thus, these rational investors analyze every new information rationally, prices reflect all available information, and no one can earn extra money in a robust and efficient market. Whenever new information is released, rational investors update their beliefs correctly and make acceptable choices based on the new information (Barberis & Thaler, 2002). However, investors do not always behave rationally. Their decisions are often affected by emotions and behavioral biases. Kahneman & Tversky (1979) defined some of these behavioral biases in their "Prospect Theory" theory and explained how investors make financial decisions under risk pressure. They found that investors are risk-averse when facing profits and risk-seekers when facing losses. Thus, irrational investors may prefer to keep stocks decreased in value and sell stocks whose prices have risen. This behavior is called "shifting risk preference" or "disposition effect."

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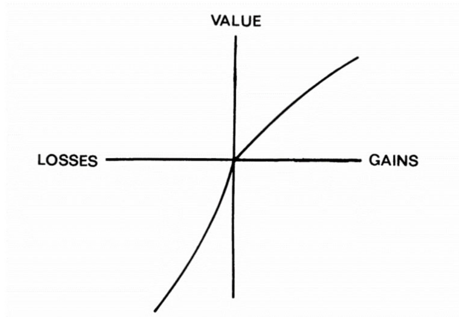

Fig. 1. Hypothetical Value Function

They also found that investors think avoiding losses is more important than gaining profits because, as shown in Fig. 1, when investors gain or lose an equal amount of money, the mental punishment for the lost money is more than the mental reward for the earned money. Moreover, irrational investors may keep stocks decreasing in value to avoid realizing losses. Losing profitable opportunities, losing money, and any wrong investment decision make investors feel regretful. However, investors should not make irrational decisions to avoid future regrets. For example, because the regret caused by a loss due to an abnormal decision is more than that caused by a loss due to a regular decision, investors may prefer to avoid abnormal decisions, leading to herd behavior (Pompian, 2006). This bias is called "regret aversion." Investors tend to segment and analyze their investments separately (Thaler, 1999). They may segmentize their investments based on the source of the invested money and show different risk tolerance for each source. For example, they may show higher risk tolerance for the money they have gained in the market (Bodie et al., 2014). This behavior is called "mental accounting." Sometimes, investors consider points like purchase price or last year's prices as a reference point and use them when making an investment decision. They may adjust any new information with this first belief to make a financial decision, leading to wrong conclusions. This phenomenon is named "anchoring" (Pompian, 2006). Overconfidence assures investors about their predictions and causes them to neglect the possibility of fault in their decisions. Overconfident investors trade frequently, take high risks, and sometimes suffer from significant losses because of ignoring risks. To analyze the effects of ambiguity on the decision-making of people, Ellsberg (1961) designed two scenarios and asked respondents about their preferred options between these two scenarios.

The first option included a 50% probability of earning 100 Dollars. The second option had an unknown probability of earning 100 Dollars. These two scenarios are the same, and the probability of earning 100 Dollars is equal for both scenarios. However, the second scenario is ambiguous. Ellsberg found that people prefer the first scenario because it is less ambiguous. In financial markets, people prefer less ambiguous investment options, which may lead to losing prosperous investment options. This behavior is called "ambiguity aversion bias." Investors may prefer doing what others say instead of making their own decisions. Although consulting with experts is fine, following what others say is harmful. This bias is called "proxy decision-making," and social media can facilitate this bias. Investors prefer profits to be gained in the short term and prefer losses to happen in the long term rather than in the short term because the discount rate they apply for their money when they are facing profit is higher than the discount rate applied for their money when they are facing loss (Appelt et al., 2011). This bias is called "asymmetric discounting." People tend to imitate what others do because they think there should be a rational reason why the majority does that action. In financial markets, this phenomenon is called "herd behavior". This bias may lead to significant trends or bubbles (Lux, 1995).

This paper is organized as follows: The literature related to our study is reviewed in the second section. The third section presents the research methodology and hypotheses, and in the fourth section, our data is analyzed. The fifth section presents the result of the present study, and the sixth section provides insights for managers. In the final section, conclusions are explained, and suggestions for future studies are provided.

2. Literature review

Goodell et al. (2023) reviewed papers on emotions and finance (1989–2020), focusing on articles referring to emotions affecting stock-market anomalies through first generating behavioral patterns. They reviewed literature connecting market anomalies to particular investor emotions, along with determining directions for more research on the emotional behavior of investors. Parveen et al. (2023) examined the effect of the COVID-19 pandemic on behavioral biases, investors' sentiments, and investment decisions in an emerging stock exchange. The study has evaluated investors' behaviors and the stock market overreaction during COVID-19 by applying a survey. The findings recommend that behavioral biases, including overconfidence bias and disposition effect, negatively affected investors' decisions. Chishti et al. (2022) investigated the behavioral factors that change an individual's decision to invest in one specific stock exchange. The data has been analyzed statistically, and hidden variables have been identified with the structural equation model (SEM) and asset management operating system (AMOS) methods. Investor investment decisions are affected by five behavioral factors: herding, overconfidence, prospect and gambler fallacy and anchoring-ability bias. Most variables have a modest impact;

nevertheless, the market element has a significant impact. Only three behavioral elements, herding, prospect and heuristic, influence investment performance among the others. Ul Abdin et al. (2022) examined the factors of overconfidence bias that, in turn, affect investment performance through risk appetite. This research also considered the three cognitive biases that cause overconfidence bias, impact investment performance, and establish the indirect relationship via risk propensity. Moreover, the results denote that all the cognitive biases show a positive relation with investment performance.
Kartini & Nahda (2021) investigated the effects of psychological factors on the decision-making of Indonesian investors. Anchoring, representativeness, loss aversion, overconfidence, optimism, and herd behavior are biases investigated in this research. A snowball sampling survey is used to gather the data used in this study, and a One-Sample t-test is used to test the hypothesis.

Table 1
The summary of the literature review

Author(s)	Case	Methods	Key findings related to the present study
(Tehrani & Gharehkoolchian, 2012)	Investors of TSE[1]	Survey, Regression Analysis	Overconfidence and mental accounting do not correlate with the disposition effect. Regret aversion has a positive relationship with the disposition effect.
Tekçe & Yilmaz, (2015).	Turkish investors	Regression Analysis	Male, individual, and younger investors with a lower portfolio value and income level living in less developed regions show upper overconfidence.
(Tekçe et al., 2016)	Turkish investors	Regression analysis	Shifting risk preference is prevalent among Turkish investors and is more common among older female investors and investors with high portfolio values.
(Ateş et al., 2016)	Investors of ISE[2]	Survey, Regression Analysis	Male investors show overconfidence, the illusion of control, and the illusion of knowledge more than female investors.
(Aren et al., 2016)	Studies between 2005 and 2014	Literature review	The lack of confidence, risk aversion, and fear of losing reputation cause herd behavior. Experience, confidence, and returns in up markets mitigate the disposition effect.
(Setayesh et al., 2017)	investors of TSE	Survey, Statistical tests	A significant negative relationship exists between religious attitudes and the overconfidence of investors.
(Pakdel et al., 2018)	investors from Ardebil province	Survey, Delphi technique, CFA[3]	Lack of experience, anchoring, adjustment, market sentiment, optimism, regret aversion, shifting risk preference, and pessimism affect mental accounting.
(Alshalabı & Çankaya, 2019).	G7 and BRICS countries	Regression Analysis	Excessive optimism increases trading volume, and Excessive pessimism decreases trading volume.
(Dalgic et al., 2019)	Borsa Istanbul	Tick-by-tick data	Herd behavior of nonprofessional investors is more seen on large stocks, down markets, and in the first or last minutes of the trading day.
(Sabir et al., 2019)	Investors of PSE[4]	Survey, SEM	Past experiences and overconfidence motivate investors toward her behavior. Cognitive factors affect herd behavior, and financial literacy affects their relationship.
(Adem & Eren, 2020)	ISE (2000 to 2018)	CSSD[5] and CSAD[6] models	Herd behavior is more common in daily data rather than weekly and monthly data, in volatile markets, and when the market falls.
(Kartini & Katiya, 2021)	Indonesi-an investors	Survey, t-test	Overconfidence, anchoring, loss aversion, and optimism are based on cognitive factors. Emotional factors cause herd behavior.
(Ahmed et al., 2022)	Investors of PSE	Survey, SEM	Shifting Risk Preference has a strong relationship with risk perception. Risk perception does not have a mediation role between herding and investment decisions.
current research	Investors of TSE	Survey, SEM and DANP	Interrelations between many behavioral biases are investigated in this study, and their relative importance is analyzed.

The findings of this study show that anchoring, representativeness, loss aversion, overconfidence, and optimism are cognitive factors affecting investors' decision-making significantly. Moreover, Herd behavior is the emotional aspect investigated in this research that significantly affects investors' decision-making. Atif Sattar et al. (2020) examined how behavioral biases affect investment decision-making under uncertainty. They concluded that the sub-variables of Personalities, Heuristics, and Prospect Theory affect investors' decision-making. Moreover, feelings and emotions have effects on investors' decision-making. Previous studies have investigated many aspects of behavioral biases. However, most focus only on a limited number of biases and the factors individually affecting them (e.g., Bashir et al., 2013; Kumar & Goyal, 2016; Bahrami et al., 2021). The current study uses a comprehensive approach to study the interrelations between many behavioral biases to give a dynamic vision of behavioral biases. Moreover, an index is defined based on the prevalence of each bias in TSE and the correlations that bias has with other biases to compare the importance of biases. Table 1 reviews some research related to investors' behavioral biases. Sabir et al. (2019) investigated the influence of overconfidence and past investment experience on the herding behavior of Pakistan Stock Exchange investors using A partial least square method to analyze the structural equations model. Moreover, this study investigated the moderating effect of financial

[1] Tehran Stock Exchange
[2] Istanbul Stock Exchange
[3] Confirmatory Factor Analysis
[4] Pakistan Stock Exchange
[5] Cross-Sectional Dispersion of stock returns model
[6] Cross-Sectional Absolute Deviation of stock returns model

literacy. The sample used in this study has been 352 individual investors. The results show that overconfidence motivates investors toward Herd Behavior, and the cognitive factors of investors are significant predictors of the herding behavior of investors. In the study of Antony and Joseph (2017), the impact of five behavioral biases (overconfidence, representative bias, regret aversion, mental accounting, and herd behavior) has been assessed on a sample of investors from Kerala using an AHP approach. The findings show that cognitive biases and heuristics affect investors' decisions, and the effects of overconfidence are more than other biases investigated in this research. Based on the priority vector, it was found that the investors of Kerala were highly influenced by overconfidence bias and regret aversion. Herd behavior had less effect on their decision-making.

3. Methodology

The current research analyzes the interrelations between investors' behavioral biases using two techniques and compares them mutually. To analyze the interrelations between different fields of behavioral biases, we designed a Structural Equations Model (SEM). SEM is a valuable tool in studies related to business and finance (Torabi et al., 2021). Another integrated method, the DEMATEL-based analytic network process (DANP), is also used to prioritize and rank these behavioral biases. DEMATEL is combined with the ANP method to form DANP to determine each criterion's effective weights (Lu et al., 2013). The conceptual model of the study is illustrated in Fig. 2.

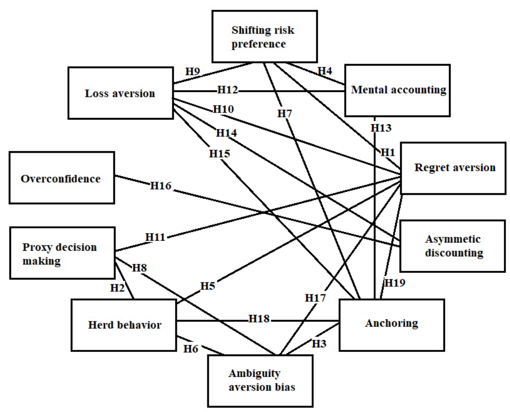

Fig. 2. Conceptual model of the research

The investigated relationships are presented in Table 2, which defines the research hypotheses.

Table 2
Research hypotheses

	Hypothesis Definition
	There is a statistically significant relationship between variables.
H_1	Shifting risk preference and Regret aversion.
H_2	Proxy decision-making and Herd behavior.
H_3	Ambiguity aversion bias and Anchoring.
H_4	Mental accounting and Shifting risk preference.
H_5	Herd behavior and Regret aversion.
H_6	Ambiguity aversion bias and herd behavior.
H_7	Shifting risk preference and anchoring.
H_8	Proxy decision-making and Ambiguity aversion bias.
H_9	Shifting risk preference and Loss aversion.
H_{10}	Loss aversion and Regret aversion.
H_{11}	Proxy decision-making and Regret aversion.
H_{12}	Mental accounting and Loss aversion.
H_{13}	Mental accounting and anchoring.
H_{14}	Asymmetric discounting and Loss aversion.
H_{15}	Loss aversion and anchoring.
H_{16}	Asymmetric discounting and overconfidence.
H_{17}	Ambiguity aversion bias and Regret aversion.
H_{18}	Anchoring and Herd behavior.
H_{19}	Anchoring and Regret aversion.

3.1 Structural equations modeling (SEM)

SEM lets us simultaneously estimate and model relationships among various dependent and independent variables. The subjects under consideration are usually unobservable and measured indirectly by several indicators. In estimating the relationships, SEM represents measurement error in observed variables. Consequently, the method precisely measures the theoretical concepts of interest (Hair Jr et al., 2021). Two methods dominate SEM in practice: Partial least squares SEM (PLS-SEM) and Covariance-based SEM (CB-SEM).

3.2 DEMATEL-based analytic network process (DANP) method

In traditional ANP, it is implicitly assumed that each cluster has the same weight, although it is clear that the influence of one cluster on other clusters may differ. Therefore, the traditional ANP assumption that the weight of the clusters is the same in creating the balanced supermatrix is not reasonable; subsequently, effective weights of DANP can solve this defect (Ritika & Kishor, 2022). In this method, the results are obtained based on the basic concept of ANP from the complete correlation matrix T_C and T_D which are calculated by DEMATEL. Therefore, the DEMATEL technique is used to build the network structure model for each criterion and improve the traditional ANP normalization process. This technique is very suitable for real-world problems compared to traditional methods and considers the dependence between criteria. DEMATEL is combined with the ANP method to form DANP to determine each criterion's effective weights (Lu et al., 2013). The steps of forming the structure of network relationships using the DEMATEL technique (steps 1-4) and determining the effective weights of DANP based on the complete relationship matrix are described as follows (Chiu et al., 2013).

3.2.1 DEMATEL steps to form a map of network relations

Step I: Calculation of the direct relationship matrix

The evaluation of the relationship between criteria (the influence of one criterion on another criterion) is done based on the opinions of research experts using a rating scale of 0 to 4, where 0 means no effect, 1 means little effect, 2 means medium effect, 3 means high impact, and 4 means very high impact. Experts are asked to determine the effect of one criterion on another. That is, if they believe criterion i affects criterion j, they should show it as d_c^{ij}. Therefore, the matrix $D = \left[d_c^{ij}\right]$ will be obtained from the direct relationship.

$$D = \begin{bmatrix} d_c^{11} & \dots & d_c^{1j} & \dots & d_c^{1n} \\ \vdots & & \vdots & & \vdots \\ d_c^{i1} & \dots & d_c^{ij} & \dots & d_c^{in} \\ \vdots & & \vdots & & \vdots \\ d_c^{n1} & \dots & d_c^{nj} & \dots & d_c^{nn} \end{bmatrix}$$

Step II: Normalizing the direct relationship matrix

The direct correlation matrix D is normalized using Eq. 1**,** and the matrix N is obtained.

$$N = VD;\ V = min\{1/\max_i \sum_{j=1}^{n} d_{ij}\ , 1/\max_j \sum_{i=1}^{n} d_{ij}\}\ , i,j \in \{1,2,\dots,n\} \tag{1}$$

Step III: Calculation of the complete relationship matrix

When the D matrix is normalized, and the N matrix is obtained, the complete relationship matrix will be computed through Eq. 2, where I represents the unit matrix.

$$T = N + N^2 + \cdots + N^h = N(I-N)^{-1}, when\ h \to \infty \tag{2}$$

The complete relationship matrix can be identified by the criteria denoted by T_C:

$$\boldsymbol{T}_c = \begin{array}{cc} & \begin{array}{ccccc} \boldsymbol{D}_1 & & \boldsymbol{D}_j & & \boldsymbol{D}_n \\ c_{11}\dots c_{1m_1} & \cdots & c_{j1}\dots c_{jm_j} & \cdots & c_{n1}\dots c_{nm_n} \end{array} \\ \begin{array}{c} \boldsymbol{D}_1 \begin{array}{c} c_{11} \\ c_{12} \\ \vdots \\ c_{1m_1} \end{array} \\ \vdots \\ \boldsymbol{D}_i \begin{array}{c} c_{i1} \\ c_{i2} \\ \vdots \\ c_{im_i} \end{array} \\ \vdots \\ \boldsymbol{D}_n \begin{array}{c} c_{n1} \\ c_{n2} \\ \vdots \\ c_{nm_n} \end{array} \end{array} & \begin{bmatrix} \boldsymbol{T}_c^{11} & \cdots & \boldsymbol{T}_c^{1j} & \cdots & \boldsymbol{T}_c^{1n} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{T}_c^{i1} & \cdots & \boldsymbol{T}_c^{ij} & \cdots & \boldsymbol{T}_c^{in} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{T}_c^{n1} & \cdots & \boldsymbol{T}_c^{nj} & \cdots & \boldsymbol{T}_c^{nn} \end{bmatrix} \end{array}$$

To calculate the complete relationships matrix based on Eq. (2). In this study, first the identity matrix (I_{10*10}) is formed. Then, the identity matrix is subtracted from the normal matrix, and the resulting matrix is inverted. Finally, the normalized matrix is multiplied by the inverse matrix**.**

Step IV: Results analysis

In this step, the sum of the rows and columns of the complete relationship matrix is calculated separately according to Eq. (3).

$$\boldsymbol{T}=[t_{ij}],\quad i,j\in\{1,2,\ldots,n\}$$
$$\boldsymbol{r}=[r_i]_{n\times 1}=\left[\sum_{j=1}^{n}t_{ij}\right]_{n\times 1}\qquad \boldsymbol{c}=[c_j]_{1\times n}=\left[\sum_{i=1}^{n}t_{ij}\right]_{1\times n} \tag{3}$$

Index r_i indicates the sum of the ith row and c_j indicates the sum of the jth column. The r_i+c_j index is obtained from the sum of the ith row and the jth column $(i=j)$. This index shows the importance of the ith criterion. Similarly, the r_i-c_j index is the result of the difference of the sum of the ith row and the jth column and indicates the effectiveness of the i criterion. In general, if r_i-c_j is positive $(i=j)$, the ith criterion is one of the categories of causal or effectual criteria. If r_i-c_j is negative $(i=j)$, the ith criterion is part of the group of influential criteria. The causal diagram can be drawn based on the mentioned two indicators, known as a network relationship map. According to this map, deciding how the criteria can be improved is possible.

Step V: Normalization of the complete relationship matrix of criteria ($T_C^{\propto}$) and calculation of weighted supermatrix

The normalization of T_C with the total degree of influence and effectiveness of criteria to acquire $T_C^{\propto}$.

$$T_C^{\alpha}=\begin{array}{cc} & \begin{array}{ccccc} \boldsymbol{D}_1 & & \boldsymbol{D}_j & & \boldsymbol{D}_n \\ c_{11}\ldots c_{1m_1} & \cdots & c_{j1}\ldots c_{jm_j} & \cdots & c_{n1}\ldots c_{nm_n}\end{array} \\ \begin{array}{c} \boldsymbol{D}_1\ \begin{array}{c}c_{11}\\c_{12}\\\vdots\\c_{1m_1}\end{array} \\ \vdots \\ \boldsymbol{D}_i\ \begin{array}{c}c_{i1}\\c_{i2}\\\vdots\\c_{im_i}\end{array} \\ \vdots \\ \boldsymbol{D}_n\ \begin{array}{c}c_{n1}\\c_{n2}\\\vdots\\c_{nm_n}\end{array}\end{array} & \begin{bmatrix} \boldsymbol{T}_c^{\alpha 11} & \cdots & \boldsymbol{T}_c^{\alpha 1j} & \cdots & \boldsymbol{T}_c^{\alpha 1n} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{T}_c^{\alpha i1} & \cdots & \boldsymbol{T}_c^{\alpha ij} & \cdots & \boldsymbol{T}_c^{\alpha in} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{T}_c^{\alpha n1} & \cdots & \boldsymbol{T}_c^{\alpha nj} & \cdots & \boldsymbol{T}_c^{\alpha nn}\end{bmatrix}\end{array}$$

An example of how to normalize $T_C^{\propto 11}$ is described as follows: Other $T_c^{\propto nm}$ are calculated similarly.

$$d_{ci}^{11}=\sum_{j=1}^{m_1}t_{cij}^{11}\ ,i=1,2,\ldots,m_1$$

$$\boldsymbol{T}_{\boldsymbol{C}}^{\propto\boldsymbol{11}}=\begin{bmatrix} t_{c11}^{11}/d_{c1}^{11} & \cdots & t_{c1j}^{11}/d_{c1}^{11} & \cdots & t_{c1m1}^{11}/d_{c1}^{11} \\ \vdots & & \vdots & & \vdots \\ t_{ci1}^{11}/d_{ci}^{11} & \cdots & t_{cij}^{11}/d_{ci}^{11} & \cdots & t_{cim1}^{11}/d_{ci}^{11} \\ \vdots & & \vdots & & \vdots \\ t_{cm11}^{11}/d_{cm1}^{11} & \cdots & t_{cm1j}^{11}/d_{cm1}^{11} & \cdots & t_{cm1m1}^{11}/d_{cm1}^{11}\end{bmatrix}=\begin{bmatrix} t_{c11}^{\propto 11} & \cdots & t_{c1j}^{\propto 11} & \cdots & t_{c1m1}^{\propto 11} \\ \vdots & & \vdots & & \vdots \\ t_{ci1}^{\propto 11} & \cdots & t_{cij}^{\propto 11} & \cdots & t_{cim1}^{\propto 11} \\ \vdots & & \vdots & & \vdots \\ t_{cm1\,1}^{\propto 11} & \cdots & t_{cm1j}^{\propto 11} & \cdots & t_{cm1m1}^{\propto 11}\end{bmatrix}$$

Step VI: Calculation of weighted supermatrix

In this step, the transpose of the complete relationship matrix is normalized, $T_C^{\propto}$ is calculated, and the weighted supermatrix $(\boldsymbol{W})$ is obtained.

$$\boldsymbol{W}=(\boldsymbol{T}_c^{\alpha})'=\begin{array}{cc} & \begin{array}{ccccc} \boldsymbol{D}_1 & & \boldsymbol{D}_i & & \boldsymbol{D}_n \\ c_{11}\mathrm{L}\ c_{1m_1} & \cdots & c_{i1}\mathrm{L}\ c_{im_i} & \mathrm{L} & c_{n1}\mathrm{L}\ c_{nm_n}\end{array} \\ \begin{array}{c} \boldsymbol{D}_1\ \begin{array}{c}c_{11}\\c_{12}\\\mathrm{M}\\c_{1m_1}\end{array} \\ \mathrm{M} \\ \boldsymbol{D}_j\ \begin{array}{c}c_{j1}\\c_{j2}\\\mathrm{M}\\c_{jm_j}\end{array} \\ \mathrm{M} \\ \boldsymbol{D}_n\ \begin{array}{c}c_{n1}\\c_{n2}\\\mathrm{M}\\c_{nm_n}\end{array}\end{array} & \begin{bmatrix} \boldsymbol{W}^{11} & \mathrm{L} & \boldsymbol{W}^{i1} & \mathrm{L} & \boldsymbol{W}^{n1} \\ \mathrm{M} & & \mathrm{M} & & \mathrm{M} \\ \boldsymbol{W}^{1j} & \mathrm{L} & \boldsymbol{W}^{ij} & \mathrm{L} & \boldsymbol{W}^{nj} \\ \mathrm{M} & & \mathrm{M} & & \mathrm{M} \\ \boldsymbol{W}^{1n} & \mathrm{L} & \boldsymbol{W}^{in} & \mathrm{L} & \boldsymbol{W}^{nn}\end{bmatrix}\end{array}$$

Step VII: The Limit supermatrix

The limit supermatrix is obtained by raising the weighted supermatrix to powers until it converges and reaches stability. The output of this step will be DANP effective weights.

$$\lim_{Z\to\infty} (\boldsymbol{W}^{\propto})^{Z}$$

Fig. 3 shows the present research's SEM. The abbreviations are defined in Table A1 in the appendix. Finally, an "Importance Index" is defined to show the relative importance of each bias. This index equals the product of each bias's mean value and the sum of correlations with other biases. The higher Importance Index shows that related bias is prevalent among investors and has remarkable relations with other biases.

3.3 Importance index

The Importance index is constituted from the Mean value variable, which shows the average scores of each bias extracted from the survey results. Consequently, an index is defined to show the relative importance of each bias. For each bias, the "Importance Index" equals the product of mean value and the sum of correlations with other biases, showing its relative importance (Eq. 4).

$$Importance\ Index\ for\ i = Mean\ value \times (\sum_{j=0}^{10} C_{ij}) \tag{4}$$

4. Data

The research questionnaire includes 29 Likert-based questions to assess the impact of behavioral biases on decision-making. The ideas for some of the questions are based on Awwad (2017) and Sadighi et al. (2022). In this survey, 512 responses were collected and analyzed from 09/26/2021 until 10/02/2021(Table A1 in the appendix).

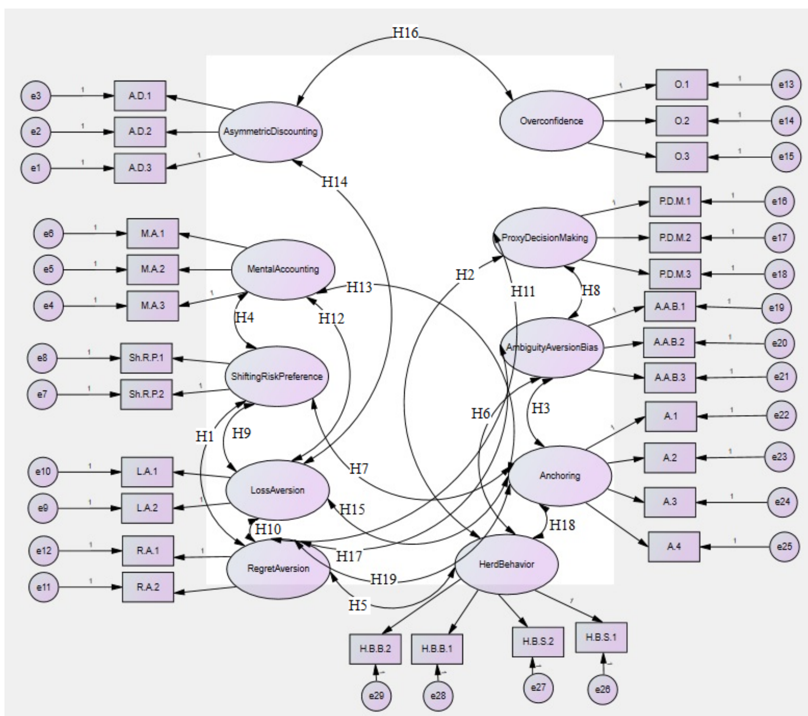

Fig. 3. SEM of the study

The survey started on 09/26/2021 and ended on 10/02/2021. Table A1 in the appendix shows the questionnaire and results for each question. Table 3 illustrates the demographic characteristics of the sample for each question. Table 3 illustrates the demographic characteristics of the sample. The results of the Kolmogorov-Smirnov test show that p-values for every question and field were equal to 0.000. Hence, our data is not normally distributed, and the Bootstrapping method should be used alongside SEM. The Cronbach's Alpha for our data equals 0.818, showing its reliability. The Spearman correlation coefficient test results show that for each question, the correlation is significant at the 0.01 level (in the 2-tailed method). Moreover, two experts reviewed the questionnaire before the survey and approved the validity of the questions. Thus, the validity of our data is supported using these two methods.

5. Results and discussion

5.1 Mutual interrelations between behavioral biases

The model's fit indices are shown in Table 4. According to the results, our model passes the requirements. Table A2 in the appendix shows the regression weights between each field of behavioral biases and its related questions. Table 5 shows the results of testing 19 relationships between different fields of behavioral biases using our SEM model.

Table 3
Demographic Characteristics of the sample

Criteria	Choices	Count	Percent
Age	*Less than 25*	107	20.9%
	25-45	350	68.4%
	More than 45	55	10.7%
Gender	Male	438	85.5%
	Female	74	14.5%
Marital Status	Single	256	50.0%
	Married	256	50.0%
The Year that Respondent Started Stock Trading	1400	5	0.98%
	1399	142	27.7%
	1398 or 1397	214	41.8%
	Before 1397	151	29.5%
Performance since TEDPIX All-Time-High	Less than 25% Loss or Profit	172	33.6%
	Loss Between 25% and 40%	132	25.8%
	More than 40% Loss	185	36.1%
	No Precise Calculation	23	4.5%
Attitude toward Risk	Risk-Averse	89	17.4%
	Neutral	108	21.1%
	Risk-Taker	315	61.5%
Main Analysis Method	Fundamental	149	29.1%
	Technical	181	35.3%
	Sentimental	63	12.3%
	Other Methods	30	5.9%
	No Method	89	17.4%

The relationship is statistically significant if the P-value for a relationship is less than 0.05. The results confirm all our research hypotheses. The following explanations are based on the results of Table 5.

- **Regret aversion and shifting risk preference:** The relation between regret aversion and shifting risk preference is significant, and their correlation is 0.388. According to Kahneman & Tversky (1979), investors are prone to selling stocks that have increased in value because prices may decrease, and they may lose their profit and regret it. Moreover, they avoid selling stocks that have decreased in value to avoid regrets caused by realizing the potential loss.
- **Proxy decision-making and herd behavior:** The relation between proxy decision-making and herd behavior is significant, and the correlation between them is 0.551. The identified relationship is rational because of the similarity in the definition of these two fields.

Table 4
Model's fit indices

Index	Result	Good Range	Acceptable Range	Reference
CMIN	1032	Smaller the better	Smaller the better	(Marsh & Hocevar, 1985)
CMIN/DF	2.883	CMIN/DF < 3	CMIN/DF < 5	(Marsh & Hocevar, 1985)
GFI	0.873	GFI > 0.9	GFI > 0.85	(Doll et al., 1994)
AGFI	0.846	AGFI > 0.9	AGFI > 0.8	(Doll et al., 1996)
RMSEA	0.061	RMSEA < 0.06	RMSEA < 0.08	(MacCallum et al., 1998)

- **Ambiguity aversion bias and anchoring:** The relationship between these fields is significant, and their correlation is 0.409. This relationship can be justified because past prices lower the ambiguity in analyzing investments. Thus, investors take past prices as reference points to avoid ambiguity and adjust their decisions using them.
- **Mental accounting and shifting risk preference:** The relation between these biases is significant, and their correlation is 0.538. When investors show shifting risk preference, their decisions for each stock are based on their purchase price and not the realities of the market. Thus, according to the definition, this relationship is rational.
- **Herd behavior and regret aversion:** The relationship between these fields is significant, and their correlation is 0.608. Pompian (2006) discussed that because regrets caused by abnormal decisions that result in loss are more than regrets investors feel when their wrong decision has been normal, investors tend to show herd behavior to avoid regret. Hence, the relationship between these biases can be justified.
- **Ambiguity aversion bias and herd behavior:** The relation between these fields is significant, and their correlation is 0.496. To avoid ambiguity, investors show herd behavior because they think that if most traders are doing something, it is rational to do it, and the associated risk is low.
- **Mental accounting and loss aversion:** The relation between these fields is significant, and their correlation is 0.268. Because

investors who do mental accounting are usually obsessed with not losing money in any of their separate investments, the relationship between these fields is rational.

- **Mental accounting and anchoring:** The relation between these fields is significant, and their correlation is 0.210. Because investors who do mental accounting consider reference points when making decisions (for example, their purchase price), the relationship between these fields can be justified based on their definitions.
- **Asymmetric discounting and loss aversion:** The relation between these biases is significant, and their correlation is 0.317. The discount rate investors who do asymmetric discounting consider for their invested money that is decreased in value is less than the rate they consider for the increased value increase. Thus, there is a relationship between loss aversion and asymmetric discounting.
- **Loss aversion and anchoring:** The relation between loss aversion and anchoring is significant, and their correlation is 0.273. This relationship exists because investors with loss aversion bias are obsessed with their purchase price and consider it a reference point for their decisions, which is similar to the definition of anchoring.
- **Shifting risk preference and anchoring:** The relation between these biases is significant, and their correlation is 0.877. When investors show shifting risk preference, they consider their purchase price as a reference point for their decisions, similar to the anchoring definition.
- **Proxy decision-making and ambiguity aversion bias:** The relation between these biases is significant, and their correlation is 0.328. Thus, when investors let other people make decisions on their behalf, they feel less ambiguity because they are more confident about other people's predictions.

Table 5
Relations between fields

Hypothesis	Field 1	Field 2	Covariance Estimate	S.E.	C.R.	P	Correlation Estimate	Confirmation?	Reference
H1	Shifting risk preference	Regret aversion	0.127	0.046	2.742	0.006	0.388	Yes	(Kahneman & Tversky, 1979)
H2	Proxy decision making	Herd behavior	0.504	0.067	7.558	***	0.551	Yes	Current research
H3	Ambiguity aversion bias	Anchoring	0.058	0.019	3.028	0.002	0.409	Yes	Current research
H4	Mental accounting	Shifting risk preference	0.178	0.046	3.890	***	0.538	Yes	Current research
H5	Herd behavior	Regret aversion	0.387	0.059	6.577	***	0.608	Yes	(Pompian, 2006)
H6	Ambiguity aversion bias	Herd behavior	0.118	0.035	3.340	***	0.496	Yes	Current research
H7	Shifting risk preference	Anchoring	0.204	0.040	5.079	***	0.877	Yes	Current research
H8	Proxy decision making	Ambiguity aversion bias	0.094	0.032	2.989	0.003	0.328	Yes	Current research
H9	Shifting risk preference	Loss aversion	0.076	0.033	2.324	0.020	0.731	Yes	Current research
H10	Loss aversion	Regret aversion	0.058	0.026	2.231	0.026	0.339	Yes	Current research
H11	Proxy decision making	Regret aversion	0.409	0.067	6.110	***	0.529	Yes	Current research
H12	Mental accounting	Loss aversion	0.047	0.022	2.160	0.031	0.268	Yes	Current research
H13	Mental accounting	Anchoring	0.082	0.027	2.976	0.003	0.210	Yes	Current research
H14	Asymmetric discounting	Loss aversion	0.068	0.029	2.306	0.021	0.317	Yes	Current research
H15	Loss aversion	Anchoring	0.033	0.016	2.131	0.033	0.273	Yes	Current research
H16	Asymmetric discounting	Overconfidence	0.082	0.031	2.645	0.008	0.168	Yes	Current research
H17	Ambiguity aversion bias	Regret aversion	0.062	0.024	2.545	0.011	0.308	Yes	(Gazel, 2014)
H18	Anchoring	Herd behavior	0.177	0.034	5.207	***	0.390	Yes	Current research
H19	Anchoring	Regret aversion	0.114	0.035	3.307	***	0.298	Yes	Current research

- **Shifting risk preference and loss aversion:** The relation between these biases is significant, and their correlation is 0.731. By definition, investors who show shifting risk preference keep stocks decreased in value to avoid realizing losses. Thus, this relationship is rational.
- **Loss aversion and regret aversion:** The relation between these fields is significant, and their correlation is 0.339. Losing money causes regret, and the regret caused by losing money is more than positive feelings caused by gaining profits or negative

emotions caused by missing profitable investment options. Therefore, the relationship between these fields is rational.

Table 6
Importance Index

Behavioral Biases	Asymmetric discounting	Mental accounting	Shifting risk preference	Loss aversion	Over-confidence	Proxy decision making	Ambiguity aversion bias	Anchoring	Herd behavior	Regret aversion	Mean value (0 to 4)	Importance Index
Asymmetric discounting	0	0	0	0.317	0.168	0	0	0	0	0	2.009	**0.974**
Mental accounting	0	0	0.538	0.268	0	0	0	0.21	0	0	2.295	**2.331**
Shifting risk preference	0	0.538	0	0.731	0	0	0	0.877	0	0.388	2.505	**6.347**
Loss aversion	0.317	0.268	0.731	0	0	0	0	0.273	0	0.339	2.995	**5.775**
Overconfidence	0.168	0	0	0	0	0	0	0	0	0	1.641	**0.276**
Proxy decision making	0	0	0	0	0	0	0.328	0	0.551	0.529	1.729	**2.434**
Ambiguity aversion bias	0	0	0	0	0	0.328	0	0.409	0.496	0.308	2.170	**3.344**
Anchoring	0	0.21	0.877	0.273	0	0	0.409	0	0.39	0.298	2.411	**5.924**
Herd behavior	0	0	0	0	0	0.551	0.496	0.39	0	0.608	1.658	**3.391**
Regret aversion	0	0	0.388	0.339	0	0.529	0.308	0.298	0.608	0	2.049	**5.061**

- **Proxy decision-making and regret aversion:** The relation between these biases is significant, and their correlation is 0.529. Because investors who do Proxy decision-making are less confident in their predictions, they think they will face less regret if they let others make decisions on their behalf.
- **Asymmetric discounting and overconfidence:** These biases' relationship is significant, and their correlation is 0.168. Investors who do asymmetric discounting tend to sell stocks that have gained profit as soon as possible and reinvest the money. Thus, they trade frequently similar to overconfident investors, and the relationship between these biases is rational. However, the correlation is relatively low because of other aspects of the definition of asymmetric discounting.
- **Ambiguity aversion bias and regret aversion:** The relation between these biases is significant, and their correlation is 0.308. Gazel(2014) argued that risk-averse investors are more prone to regret aversion. They avoid ambiguity to avoid future regrets, and this relationship is rational.
- **Anchoring and herd behavior:** The relation between anchoring and herd behavior is significant, and their correlation is 0.390. This relationship is justifiable because investors with less experience are more prone to herd behavior and anchoring. A lack of knowledge causes these investors to consider previous prices as reference points or do herd behavior instead of rationally analyzing stocks.
- **Anchoring and regret aversion:** The relation between anchoring and regret aversion is significant, and their correlation is 0.298. Regret-averse investors tend to do anchoring because the reference prices help them be sure about their decisions to avoid future regrets. For example, last year's lowest price ensures them about the amount of risk associated with their decision.

5.2 The Importance Index

Shifting risk preference, anchoring, loss aversion, and regret aversion have the highest Importance indices among studied behavioral biases based on correlations of behavioral biases, shown in Table 6. Thus, investors must understand these biases and their financial functions. Herd behavior, ambiguity aversion bias, proxy decision-making, and mental accounting are the subsequent behavioral biases based on importance indices. Although understanding these biases is necessary, they are not as crucial as the first group for investors. Also, asymmetric discounting and overconfidence have the least importance indices .

5.3 .DANP method results

The results of the implementation of step II have been shown in Table 7.

Table 7
The normalized matrix for the DANP technique

	Asymmetric discounting	Mental accounting	Shifting risk preference	Loss aversion	Over-confidence	Proxy decision making	Ambiguity aversion bias	Anchoring	Herd behavior	Regret aversion
Asymmetric discounting	0	0	0	0.125	**0.066**	0	0	0	0	0
Mental accounting	0	0	0.212	0.106	0	0	0	0.083	0	0
Shifting risk preference	0	0.212	0	0.288	0	0	0	**0.346**	0	0.153
Loss aversion	0.125	0.106	0.288	0	0	0	0	0.108	0	0.134
Over-confidence	**0.066**	0	0	0	0	0	0	0	0	0
Proxy decision making	0	0	0	0	0	0	0.129	0	0.217	0.209
Ambiguity aversion bias	0	0	0	0	0	0.129	0	0.161	0.196	0.122
Anchoring	0	0.083	**0.346**	0.108	0	0	0.161	0	0.154	0.118
Herd behavior	0	0	0	0	0	0.217	0.196	0.154	0	0.240
Regret aversion	0	0	0.153	0.134	0	0.209	0.122	0.118	0.240	0

The results of step III (calculation of the total relationships matrix) have been shown in Table 8.

Table 8
Total relationships matrix

	Asymmetric discounting	Mental accounting	Shifting risk preference	Loss aversion	Overconfidence	Proxy decision making	Ambiguity aversion bias	Anchoring	Herd behavior	Regret aversion
Asymmetric discounting	0.027	0.046	0.098	0.179	0.068	0.027	0.032	0.076	0.040	0.067
Mental accounting	0.046	0.187	0.539	0.366	0.003	0.113	0.147	0.407	0.179	0.264
Shifting risk preference	0.098	0.539	0.776	0.778	0.006	0.292	0.365	0.954	0.450	0.702
Loss aversion	0.179	0.366	0.778	0.422	0.012	0.212	0.251	0.604	0.316	0.531
Over-confidence	0.068	0.003	0.006	0.012	0.005	0.002	0.002	0.005	0.003	0.004
Proxy decision making	0.027	0.113	0.292	0.212	0.002	0.288	0.398	0.348	0.546	0.562
Ambiguity aversion bias	0.032	0.147	0.365	0.251	0.002	0.398	0.307	0.523	0.549	0.525
Anchoring	0.076	0.407	0.954	0.604	0.005	0.348	0.523	0.690	0.608	0.708
Herd behavior	0.040	0.179	0.450	0.316	0.003	0.546	0.549	0.608	0.493	0.722
Regret aversion	0.067	0.264	0.702	0.531	0.004	0.562	0.525	0.708	0.722	0.616

The result of steps IV and V, as an unweighted supermatrix, has been shown in Table 9.

Table 9
The unweighted supermatrix

	Asymmetric discounting	Mental accounting	Shifting risk preference	Loss aversion	Over-confidence	Proxy decision making	Ambiguity aversion bias	Anchoring	Herd behavior	Regret aversion
Asymmetric discounting	0.041	0.070	0.149	0.272	0.103	0.040	0.048	0.115	0.060	0.101
Mental accounting	0.020	0.083	0.239	0.163	0.001	0.050	0.066	0.181	0.080	0.117
Shifting risk preference	0.020	0.109	0.157	0.157	0.001	0.059	0.074	0.192	0.091	0.141
Loss aversion	0.049	0.100	0.212	0.115	0.003	0.058	0.068	0.165	0.086	0.145
Over-confidence	0.619	0.028	0.059	0.108	0.041	0.016	0.019	0.046	0.024	0.040
Proxy decision making	0.010	0.041	0.105	0.076	0.001	0.103	0.143	0.125	0.196	0.202
Ambiguity aversion bias	0.010	0.048	0.118	0.081	0.001	0.128	0.099	0.169	0.177	0.169
Anchoring	0.015	0.083	0.194	0.123	0.001	0.071	0.106	0.140	0.123	0.144
Herd behavior	0.010	0.046	0.115	0.081	0.001	0.140	0.141	0.156	0.126	0.185
Regret aversion	0.014	0.056	0.149	0.113	0.001	0.120	0.112	0.151	0.154	0.131

5.3.1 Calculation of the weighted supermatrix

The result of step VI, as a weighted supermatrix, has been represented in Table 10.

Table 10
The weighted supermatrix

	Asymmetric discounting	Mental accounting	Shifting risk preference	Loss aversion	Over-confidence	Proxy decision making	Ambiguity aversion bias	Anchoring	Herd behavior	Regret aversion
Asymmetric discounting	0.041	0.020	0.020	0.049	0.619	0.010	0.010	0.015	0.010	0.014
Mental accounting	0.070	0.083	0.109	0.100	0.028	0.041	0.048	0.083	0.046	0.056
Shifting risk preference	0.149	0.239	0.157	0.212	0.059	0.105	0.118	0.194	0.115	0.149
Loss aversion	0.272	0.163	0.157	0.115	0.108	0.076	0.081	0.123	0.081	0.113
Over-confidence	0.103	0.001	0.001	0.003	0.041	0.001	0.001	0.001	0.001	0.001
Proxy decision making	0.040	0.050	0.059	0.058	0.016	0.103	0.128	0.071	0.140	0.120
Ambiguity aversion bias	0.048	0.066	0.074	0.068	0.019	0.143	0.099	0.106	0.141	0.112
Anchoring	0.115	0.181	0.192	0.165	0.046	0.125	0.169	0.140	0.156	0.151
Herd behavior	0.060	0.080	0.091	0.086	0.024	0.196	0.177	0.123	0.126	0.154
Regret aversion	0.101	0.117	0.141	0.145	0.040	0.202	0.169	0.144	0.185	0.131

5.3.2 Limiting of weighted supermatrix

In this step, following $\lim_{Z\to\infty}(\boldsymbol{W}^{\propto})^{Z}$, the weighted supermatrix is brought to the power until it converges. It means that the elements of each of the two columns or each of the two rows are the same. In this research, the weighted matrix is converged to the ninth power. The results are given in Table 11.

Table 11
Limiting supermatrix

	Asymmetric discounting	Mental accounting	Shifting risk preference	Loss aversion	Over-confidence	Proxy decision making	Ambiguity aversion bias	Anchoring	Herd behavior	Regret aversion
Asymmetric discounting	0.0212	0.0212	0.0212	0.0212	0.0212	0.0212	0.0212	0.0212	0.0212	0.0212
Mental accounting	0.0724	0.0724	0.0724	0.0724	0.0725	0.0724	0.0724	0.0724	0.0724	0.0724
Shifting risk preference	0.1597	0.1597	0.1597	0.1597	0.1597	0.1597	0.1597	0.1597	0.1597	0.1597
Loss aversion	0.1182	0.1182	0.1182	0.1182	0.1182	0.1182	0.1182	0.1182	0.1182	0.1182
Over-confidence	0.0035	0.0035	0.0035	0.0035	0.0035	0.0035	0.0035	0.0035	0.0035	0.0035
Proxy decision making	0.0897	0.0897	0.0897	0.0897	0.0897	0.0897	0.0897	0.0897	0.0897	0.0897
Ambiguity aversion bias	0.0998	0.0998	0.0998	0.0998	0.0998	0.0998	0.0998	0.0998	0.0998	0.0998
Anchoring	0.1585	0.1585	0.1585	0.1585	0.1585	0.1585	0.1585	0.1585	0.1585	0.1585
Herd behavior	0.1257	0.1257	0.1257	0.1257	0.1257	0.1257	0.1257	0.1257	0.1257	0.1257
Regret aversion	0.1513	0.1513	0.1513	0.1513	0.1513	0.1513	0.1513	0.1513	0.1513	0.1513

5.3.3 The final weights of the criteria

The resulting criteria weights are the same number extracted from the limiting supermatrix, shown in Table 12 .

Table 12
The final weight and rank of the criteria

criteria	weight	rank
Asymmetric discounting	0.0212	9
Mental accounting	0.0724	8
Shifting risk preference	0.1597	1
Loss aversion	0.1182	5
Over-confidence	0.0035	10
Proxy decision making	0.0897	7
Ambiguity aversion bias	0.0998	6
Anchoring	0.1585	2
Herd behavior	0.1257	4
Regret aversion	0.1513	3

6. Managerial insights

Behavioral biases play a significant role in the decision-making of investors. These biases cause irrational fluctuations in financial markets and decrease market efficiency. They cause investors to lose money and perform poorly in the market, and may deprive good firms of being funded enough. Increasing investors' level of knowledge about behavioral biases is an appropriate way to achieve the right decisions, such as better risk management in portfolios, more accurate predictions, and resilient trading strategies. Moreover, asset managers sometimes have to make decisions affected by behavioral biases because they have to satisfy the desires of their clients. This research reveals that increasing the knowledge of investors and managers about shifting risk preference, anchoring, loss aversion, and regret aversion is more critical than other biases because they are prevalent among investors, and ignoring them in the decision-making process will also eliminate the existence of many other biases. However, In recent years, novel approaches in intelligence systems of decision-making (e.g., algorithmic trading and Robo-advisors) have been developed to overcome the challenges discussed in the current study since they are not affected by psychological parameters.

7. Conclusion

Psychological factors, including behavioral biases, affect investors' decisions significantly and cause anomalies in financial markets. To reduce the role of behavioral biases in investors' decisions, understanding their mutual relations is essential. The current research investigated how a specific behavioral bias can lead to other biases. Results show that behavioral biases are highly correlated, and an increase in the intensity of one of the fields has a similar impact on others. Therefore, it is essential to conduct a comprehensive study of important biases. The results showed that loss aversion, regret aversion, and anchoring have significant interrelations with other biases. Thus, focusing on these biases causes us to distinguish other biases correctly. Artificial intelligence (AI) helps investors quickly analyze and correctly predict volatile financial market conditions. Their analysis can help investors make decisions based on standard analysis methods instead of heuristic shortcuts, emotions, and biases.

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Appendix

Table A1
Values for all questions and fields

#	Index in SEM	Question or Field	Mean	Std. Deviation	Kurtosis	Skewness
1	A.D.1	I am a short-term investor in TSE.	2.662	1.420	-1.156	0.295
2	A.D.2	I prefer immediate profits (even if they are insignificant) to long-term profits.	2.628	1.530	-1.349	0.364
3	A.D.3	I believe gaining profits immediately and in the short term is better than gaining profits in the long term.	3.736	1.321	-0.632	-0.724
		Asymmetric discounting	3.009	1.159	-0.934	-0.020
4	M.A.1	I tend to treat different parts of my portfolio separately. (For example, I assess the profit or loss of stocks I have bought using my wage separately.)	2.992	1.409	-1.162	0.001
5	M.A.2	It matters to me if the stock I have is related to the profits or the initial capital.	3.455	1.441	-1.078	-0.452
6	M.A.3	I take more risks on the profits I have gained in the market.	3.437	1.447	-1.085	-0.455
		Mental accounting	3.294	1.084	-0.600	-0.340
7	Sh.R.P.1	I tend to keep stocks whose value has decreased for long periods to avoid selling with a loss.	3.613	1.410	-0.927	-0.613
8	Sh.R.P.2	I tend to sell stocks whose value has increased. (in comparison to the stocks decreased in value.)	3.396	1.289	-0.893	-0.340
		Shifting risk preference	3.504	1.007	-0.206	-0.342
9	L.A.1	I am more concerned about a substantial loss than missing a substantial gain.	3.718	1.249	-0.542	-0.659
10	L.A.2	In investments, not losing is more important than not gaining profit.	4.271	1.094	1.496	-1.518
		Loss aversion	3.995	0.899	0.041	-0.711
11	R.A.1	I blame myself so much when I miss a substantial gain in the market.	3.210	1.268	-0.909	-0.222
12	R.A.2	When I am suffering from loss, I will feel better if I know that others are suffering from loss like me.	2.886	1.407	-1.228	-0.005
		Regret aversion	3.048	1.067	-0.528	-0.048
13	O.1	On average, I predict future prices of stocks better than others.	3.076	1.130	-0.450	-0.068
14	O.2	I make risky trades because I can understand and predict the market well.	2.599	1.188	-0.810	0.237
15	O.3	I trade frequently and excessively.	2.246	1.322	-0.574	0.765
		Overconfidence	2.640	0.895	0.029	0.431
16	P.D.M.1	I trust in the analysis of Telegram channels or stockbrokers or others more than my analysis.	2.498	1.351	-1.029	0.387
17	P.D.M.2	I feel a higher level of confidence when I ask friends or colleagues about their opinions.	3.279	1.183	-0.459	-0.448
18	P.D.M.3	I trade signals spread through Telegram channels, Instagram pages, or other social media. (Signal means purchase or sell suggestion.)	2.408	1.372	-1.101	0.460
		Proxy decision making	2.728	0.999	-0.468	0.278
19	A.A.B.1	When market performance is poor, I do not increase my investments in the market.	3.736	1.248	-0.500	-0.686
20	A.A.B.2	I prefer investing in the real estate sector to investing in the stock market. (Because real estate prices are less volatile than stock market prices.)	2.500	1.501	-1.222	0.474
21	A.A.B.3	I do not invest in TSE if uncertainty is high and the market faces significant fluctuations.	3.273	1.360	-1.112	-0.200
		Ambiguity aversion bias	3.169	0.948	-0.561	0.058
22	A.1	When I trade, I consider the purchase price a reference point for the decisions.	3.679	1.112	-0.284	-0.595

#	Index in SEM	Question or Field	Mean	Std. Deviation	Kurtosis	Skewness
23	A.2	I compare current stock prices with last year's highest and lowest prices and use this comparison when I trade in the market.	3.361	1.321	-0.928	-0.390
24	A.3	I will sell my share if it reaches last year's high.	3.443	1.385	-1.104	-0.412
25	A.4	If the price of a stock is higher than last year, I will probably not buy it.	3.160	1.378	-1.166	-0.110
		Anchoring	3.411	0.868	-0.192	-0.207
26	H.B.S.1	If a group of investors sells a company's shares, I also will sell them.	2.822	1.391	-1.217	0.132
27	H.B.B.1	If the majority buys a company's shares, I may invest a portion of my money in shares of that company.	3.013	1.292	-0.989	-0.168
28	H.B.B.2	Buyers' queue for a company's shares persuades one to buy that company's shares.	2.404	1.417	-1.068	0.529
29	H.B.S.2	Sellers' queue for a company's shares persuades one to sell that company's shares.	2.392	1.409	-0.996	0.558
		Herd behavior	2.658	1.049	-0.651	0.214
		Herd behavior (when buying)	2.709	1.154	-0.765	0.222
		Herd behavior (when selling)	2.607	1.170	-0.843	0.268

Table A2
Regression weights among fields of behavioral biases and relevant questions

Question	Field	Regression weight estimate	S.E.	C.R.	P	Standardized Regression weight estimate
A.D.3	Asymmetric Discounting	1.000				0.695
A.D.2	Asymmetric Discounting	1.282	0.112	11.478	***	0.770
A.D.1	Asymmetric Discounting	0.999	0.089	11.246	***	0.646
M.A.3	Mental Accounting	1.000				0.514
M.A.2	Mental Accounting	1.670	0.234	7.126	***	0.863
M.A.1	Mental Accounting	0.903	0.115	7.881	***	0.477
Sh.R.P.2	Shifting Risk Preference	1.000				0.346
Sh.R.P.1	Shifting Risk Preference	1.027	0.197	5.210	***	0.325
L.A.2	Loss Aversion	1.000				0.214
L.A.1	Loss Aversion	4.219	1.671	2.524	0.012	0.799
O.1	Overconfidence	1.000				0.473
O.2	Overconfidence	1.925	0.365	5.273	***	0.867
O.3	Overconfidence	1.058	0.152	6.969	***	0.428
P.D.M.1	Proxy Decision Making	1.000				0.781
P.D.M.2	Proxy Decision Making	0.427	0.059	7.208	***	0.381
P.D.M.3	Proxy Decision Making	0.925	0.085	10.887	***	0.711
A.A.B.1	Ambiguity Aversion Bias	1.000				0.219
A.A.B.2	Ambiguity Aversion Bias	3.402	0.948	3.590	***	0.623
A.A.B.3	Ambiguity Aversion Bias	2.821	0.785	3.595	***	0.569
A.1	Anchoring	1.000				0.473
A.2	Anchoring	1.066	0.174	6.128	***	0.424
A.3	Anchoring	1.566	0.218	7.183	***	0.597
A.4	Anchoring	1.274	0.193	6.614	***	0.486
H.B.S.2	Herd Behavior	1.024	0.093	11.017	***	0.638
H.B.S.1	Herd Behavior	1.000				0.631
H.B.B.1	Herd Behavior	0.964	0.086	11.219	***	0.655
H.B.B.2	Herd Behavior	1.121	0.096	11.644	***	0.696
R.A.2	Regret Aversion	0.815	0.136	5.998	***	0.429
R.A.1	Regret Aversion	1.000				0.589