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Psychological Determinants of Investment Decisions: An Integrated Sierpinski Triangle Fuzzy-based Decision-Making Model for Enhancing Financial Well-Being

Serhat Yüksel[1,2], Gabriela Oana Olaru[3], Serkan Eti[4,*], Hasan Dinçer[1,2]

1 School of Business, Istanbul Medipol University, Istanbul, Turkey
2 Department of Economics and Management, Khazar University, Baku, Azerbaijan
3 School of Business, Istanbul Medipol University, Istanbul, Turkey
4 Faculty of Applied Sciences, Marmara University, Istanbul, Turkey

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ABSTRACT

It is frequently emphasized in the behavioral finance literature that investment decisions cannot be explained solely by economic indicators and rational expectations and that psychological factors also play a significant role in this process. However, the lack of a comparative analysis of the importance of psychological factors influencing investor behavior in the literature and the lack of consensus on which factors are more dominant constitute a fundamental problem. This deficiency leads to significant uncertainties in both theoretical modeling and practical investment strategies, increasing market risks such as irrational price movements, speculative bubbles, and panic selling. In this context, the aim of this study is to determine the relative importance of the fundamental psychological factors influencing investor decisions and, considering these factors, to identify the most appropriate investment alternatives for individuals. This study develops a new integrated decision-making model to answer these research questions. Considering the demographic characteristics of the experts, importance coefficients are calculated using the Euclidean distance-based weighting approach. Criterion weights are then determined using the Entropy method, and the MABAC and MAIRCA methods are applied to rank investment alternatives. Additionally, fractal fuzzy sets based on the Sierpinski triangle are integrated into the proposed model to model uncertainty more effectively. The study's contributions to the literature are highlighted in three dimensions: (1) psychological factors, often overlooked in the literature, are included in the criteria set; (2) expert weights are differentiated based on demographic characteristics rather than assumed to be equal; and (3) expert opinions are modeled more flexibly and precisely using new fractal number-based fuzzy sets. The findings indicate that trust is the most critical psychological factor, followed by loss aversion. In terms of investment alternatives, stocks stand out as the most suitable option, while bonds/deposits and gold are other important alternatives, with cryptocurrencies and real estate ranking next.

* *Corresponding author.*
E-mail address: seti@marmara.edu.tr

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1. Introduction

The influence of psychological factors on investment choices suggests that individuals do not act solely in accordance with economic indicators, mathematical models, and rational expectations. Behavioral factors such as cognitive biases, emotional reactions, and social interactions can also influence decision-making processes. In the behavioral finance literature, concepts such as overconfidence, loss aversion, the framing effect, and the herding effect are particularly prominent as fundamental psychological dynamics that divert investors' choices away from rationality [1]. Investors often act with a sense of confidence based on their own perceptions rather than objectively assessing risks, or they make more cautious choices by prioritizing losses over potential gains. This can lead to irrational price fluctuations in the markets, speculative bubbles, or panic selling. The impact of psychological factors on investment decisions has critical consequences not only for individual investors' portfolio strategies but also for the overall functioning of financial markets. Therefore, considering these factors is crucial for understanding market volatility, predicting investor behavior, and developing risk management strategies [2]. However, the involvement of psychological factors in the decision-making process increases uncertainty beyond rational predictions. This, in turn, poses additional risks to financial stability. Therefore, examining investment preferences from a psychological perspective is essential for understanding the multidimensional nature of individuals' economic behavior and developing sustainable financial decision-making mechanisms.

Psychological factors have a multifaceted impact on investors' decision-making processes, and this influence often goes beyond rational financial theories. Confidence is one of the most fundamental factors shaping investors' market perspectives. High levels of confidence encourage investors to take more risks and pursue new opportunities. Low levels of confidence, on the other hand, can lead to overly cautious behavior and missed opportunities. Furthermore, the tendency to make quick decisions, especially in highly volatile markets, results in impulsive decisions based on intuitive thinking rather than in-depth analysis [3]. This often reinforces irrational price movements. Social influence arises when investors consider the preferences of those around them rather than individual judgments. This tendency, known as herd behavior, can sometimes lead to artificially inflated markets or sudden crashes. Furthermore, risk perception develops differently among investors, and the same investment instrument may be perceived by some as associated with high uncertainty and the possibility of loss. On the other hand, for others, this represents a high-return opportunity. Therefore, these psychological factors do not influence investor decisions in a single direction; on the contrary, they can lead to very different and sometimes contradictory outcomes. While a sense of confidence can sometimes guide investors toward opportunities, social influence can push them to participate in mass movements rather than rational analysis [4]. Risk perception, on the other hand, can shift investor behavior between extreme risk aversion and excessive risk taking. This multifaceted nature demonstrates that investment choices cannot be explained solely by economic rationality; psychological dimensions play a central role in decision-making, providing a critical framework for understanding the heterogeneous nature of investor behavior.

The diversity of psychological factors influencing investor decisions necessitates determining which of these factors are more critical and prioritized. However, the existing literature lacks a clear consensus on this issue. While studies generally demonstrate that psychological factors play a significant role in investment behavior, they fail to specify the order of priority or relative weights among these factors [5]. This presents several challenges, both theoretically and practically. Theoretically, behavioral finance models aimed at explaining investor behavior remain incomplete because they fail to reveal the relative importance of these factors and fail to fully reflect the heterogeneous nature of investment decisions. Practically, uncertainty about which factors are more dominant can lead to inaccurate risk assessments by portfolio managers, policymakers, and individual investors. Similarly, these situations can lead to irrational investment strategies and exacerbate market instability. Furthermore, this gap in the literature creates a fragmented view due to the focus on different factors in different studies, hindering the development of a generally accepted theoretical framework. Indeed, while existing research acknowledges the existence and impact of these factors, systematic comparisons of which psychological element is more prioritized and influential than others are extremely limited [6]. This creates a critical research gap in the literature, hindering a deeper understanding of the multidimensional nature of investor behavior. Therefore, new research focusing on the priority analysis of psychological factors will not only offer a theoretical contribution in academic terms but will also contribute to market stability by increasing the predictability of investment decisions. With the help of this issue, these considerations will also serve to prevent investors from being exposed to irrational risks.

The primary objective of this study is to examine the role of emotional and psychological factors influencing individuals' investment decisions and to determine which investment instruments are optimal for them when these factors are considered. The motivation for this study stems from the fact that, while the impact of psychological factors on investment decisions is generally acknowledged in the literature, the relative importance of these factors and their relationship with investment instruments have not been adequately analyzed. To address this gap, eight different psychological factors are identified as criteria following a comprehensive literature review, and five different financial products are selected as investment alternatives that individuals can choose. The proposed decision-making model in the study is developed to measure the relative impact of psychological factors on investment choices and determine the most appropriate investment alternative. In this context, the initial stage involves gathering opinions from ten different experts on the subject. Taking their demographic characteristics into account, their importance weights are calculated using the Euclidean distance-based weighting approach. Subsequently, the objective weights of the criteria are determined using the Entropy technique, and the MABAC method is applied to rank the investment alternatives. To test the consistency of the results, the MAIRCA technique is used to re-rank the alternatives, and a comparative evaluation is conducted. On the other hand, Sierpinski triangle fuzzy sets are developed and integrated into the model to better handle uncertainty. In line with this methodological framework, the study seeks to answer the following research questions: (1) What are the psychological factors that are most effective in investors' decision-making processes? (2) How do the importance levels of these psychological factors differ from each other? (3) Which investment instrument(s) are most suitable for individuals when psychological factors are considered? (4) What similarities or differences are there between the results obtained with different multi-criteria decision-making techniques? (5) What innovative contributions does the proposed decision-making model make to the literature in explaining investor behavior?

This manuscript makes an important contribution to the literature by proposing a new integrated decision-making model aimed at determining the relative importance of psychological factors in investors' decision-making processes and the most appropriate investment alternatives considering these factors. The proposed model offers several advantages over previously developed decision-making models in the literature. (1) The model utilizes fractal number-based Sierpinski triangle fuzzy sets. This new set approach provides a more flexible and precise representation capability compared to fuzzy sets such as triangular, trapezoidal or spherical that are widely used in the literature. Especially in decision-making environments with high uncertainty, the multi-layered structure of Sierpinski-based sets allows for more accurate modeling of the nuances in expert opinions, which increases the originality and theoretical contribution of the model. (2) The weights of the experts in the study are differentiated according to their demographic characteristics. The assumption of equal weighting of experts in most models in the literature has long been criticized as a methodological limitation. However, experts have different education levels, work experience and professional backgrounds; Therefore, ignoring these differences can undermine the accuracy of the evaluation process. The method developed in this study ensures that the opinions of experts with more work experience and a more comprehensive academic background are considered with a higher coefficient, thus largely addressing this criticism in the literature. (3) Third, the model's criterion set is comprised of psychological factors. Previous studies generally prioritize economic or technical factors, often ignoring the psychological dynamics of investors' decision-making processes. However, psychological factors are highly decisive in explaining the irrational aspects of investment behavior. The inclusion of these factors in the analysis of this model fills a significant gap in the literature and provides a significant advantage over existing models.

Multiple factors influence individuals' stock market and other investment decisions. Risk perception is a prominent factor influencing investment decisions. In this context, risk perception is defined as an individual's subjective assessment of how risky they perceive a risk [7]. Furthermore, research by Bhutto *et al.,* [8] suggested that individuals tend to act in a herd-like manner when making investment decisions and that risk perception is a key factor influencing this behavior. Studies on risk reduction in investment decisions, where risk perception plays a key role, are also available in the literature. For example, Ahmad *et al.,* [9] stated that Robo Advisors play a significant role in risk reduction and determined that their use helps reduce the impact of cognitive biases. Consequently, the expected return on investment decisions is a second factor influencing investors' decisions, leading them to seek safer investments [10]. Bastianello and Peng [11] emphasized in their research that investors expect high market returns on their short-term investments. Still, the opposite is true in the long term, with long-term return expectations being the primary determinant. Löfgren and Nordblom [12] made a distinct contribution to the literature by investigating investment return expectations and sustainable investments. Their research revealed that investors prefer sustainability but do not invest appropriately to meet these preferences, thus approaching return-focused studies from a different perspective.

Another factor influencing investment decisions is the duration of the investment. Indeed, while investors' risk aversion is a determining factor in long-term investments, their current market knowledge is crucial for short-term investments [13]. In this context, Lei and Mathers [14] found in their research that short-term investors tend to be more likely to invest domestically, and that these investors have low financial knowledge, low income, and high-risk aversion. Furthermore, investment duration is directly shaped by investors' labor income, consumption-savings balance, leisure preferences, and borrowing constraints [15]. Investors' sense of confidence significantly influences their investment decisions and investment durations. Therefore, positive environmental, social, and governance (ESG) performance has been found to strengthen investor confidence [16]. Besides *et al.,* [17] also highlighted this phenomenon, stating that green-linked portfolios reinforce investors' sense of financial confidence, particularly during times of crisis, thereby strengthening the impact of ESG-based investments. Conversely, it has been found that overconfidence triggers irrational decisions, particularly during times of crisis, while well-informed investors maintain a sense of confidence and develop rational decisions [18].

At this point, investors' tendency to make quick decisions also emerges as a key factor influencing investment decisions. Indeed, the fear of missing out, also known as FOMO, has been highlighted in research as a significant factor influencing investors' rapid and rational decisions for the sake of short-term gains [19]. Nam *et al.,* [20] argued that mobile investment apps, thanks to real-time data and notifications, increase investors' tendency to make impulsive decisions due to anxiety, overconfidence, and the pursuit of short-term gains. They propose AI-based, data-driven support mechanisms. For example, a study conducted on the Nepalese stock exchange suggests that psychological biases lead investors to make impulsive and potentially unhealthy decisions [21]. Furthermore, while the tendency to make quick decisions influences investors, loss aversion also influences their decisions, negatively impacting market efficiency [22]. The behavioral finance literature suggests that investors struggle to accept losses and, consequently, hold onto investments for extended periods, even when experiencing losses, and sell profitable investments prematurely [23]. Budiman *et al.,* [24] also found in their research on the Indonesian stock market that loss aversion negatively impacts investment decisions and affects market efficiency.

Investors' tendency to act collectively is a factor that influences the investment process and leads to instability, particularly in emerging markets [25]. In this context, empirical findings from a study conducted by Vieito *et al.,* [26] indicated that investors exhibit herding behavior during periods of cyclical volatility. Furthermore, findings from another study covering the last two decades suggest that herding behavior persisted in the A-share market before the global financial crisis but subsequently weakened. Moreover, this research, which finds that both herding and reverse herding behaviors emerged in the post-crisis period, is important for understanding the tendency to act collectively and its causes [27]. While acquiring information based on need during the investment process fosters a positive attitude, information overload or insufficient information can also create a negative attitude [28]. Therefore, investors' capacity to access information and their ability to analyze it also influence investment decisions. New media platforms can provide investors with an alternative means of accessing information. For example, a study conducted in China demonstrated that combining TikTok search data with machine learning and deep learning models could predict the Shanghai Composite Index with high accuracy [29]. Another study on new media examined stock exchange websites, emphasizing that elements such as design, navigation, and ergonomics facilitate access to information, allowing investors to access accurate information [30].

The literature review has identified numerous risk factors that influence investment decisions. Among these factors, risk perception, return expectations, investment duration, confidence, the tendency to make quick decisions, loss aversion, herd behavior, and the ability to access information stand out among the topics addressed within a broad framework. However, an analysis of recent studies reveals that these factors are often evaluated independently, rather than within the framework of a holistic model. Similarly, while there are limited studies that have thoroughly analyzed the impact of emotions such as anger, fear, or hope on investment decisions, the failure to analyze these effects using multi-criteria decision-making methods has also been identified as a shortcoming. In this context, our study aims to address this deficiency by developing a model that goes beyond investors' decision-making processes and incorporates emotional factors.

2. Methodology

This manuscript proposes a two-stage model to find answers for these questions. For the first stage of the model, the Euclidean distance-based weighting model is used, while for the second stage, the entropy-based MABAC method is used. Finally, the validity and consistency of the rankings are tested. In addition to the sensitivity analysis, the MAIRCA method is used for comparative analysis. The steps of the two-stage model are presented in Figure 1.

In the analysis process, fuzzy sets are used to perform calculations with linguistic expressions as words. Fuzzy sets are extended by combining them with other concepts. This manuscript includes the integration of fuzzy sets with the Sierpinski triangle, which is a special case of Fractal geometric shape.

In the subheadings of this section, Sierpinski triangle fuzzy sets, Euclidean distance-based weighting model, entropy-based MABAC and MAIRCA methods are introduced.

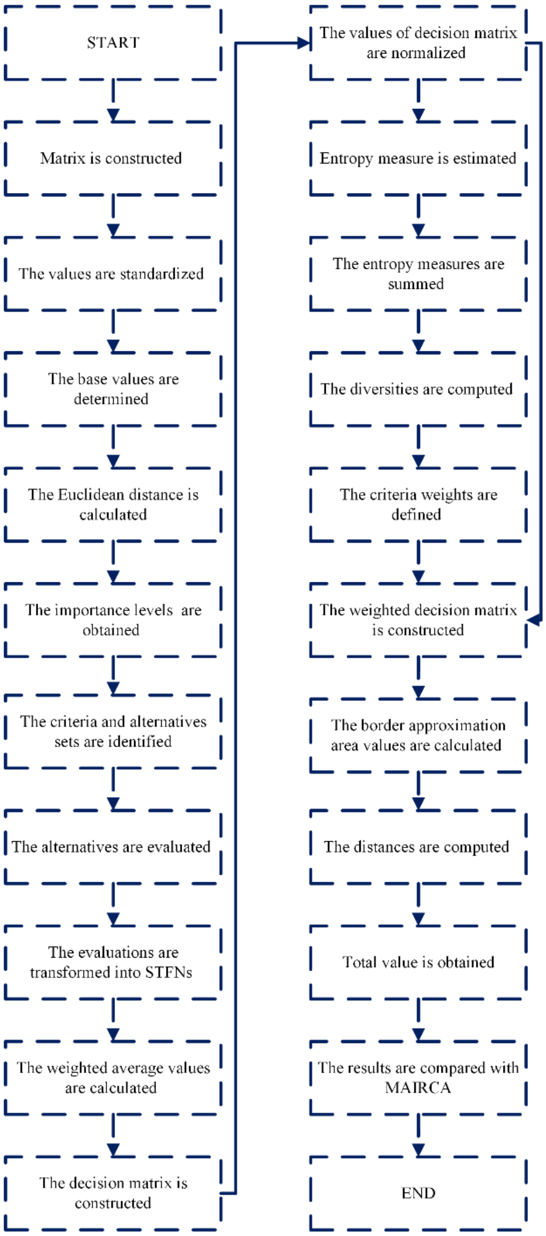

Fig. 1. The Steps of the Two-stage Model

2.1 Sierpinski Triangle Fuzzy Sets (STFSs)

A Sierpinski triangle fuzzy set ($\tilde{\mathcal{A}}$) is descripted with Equation (1).

$$\tilde{\mathcal{A}} = \{\langle x, (\xi_{\tilde{\mathcal{A}}}(x), \varphi_{\tilde{\mathcal{A}}}(x)) | x \in \mathcal{X}\} \tag{1}$$

Wherein assume that $\mathcal{X}$ be a discourse. In addition, $\xi: \mathcal{X} \to [0,1]$ and $\varphi: \mathcal{X} \to [0,1]$ are membership and non-membership degrees of x to $\tilde{\mathcal{A}}$. Also, the items of STFS met the condition in Equation (2) [31].

$$0 \leq \xi_{\tilde{\mathcal{A}}}^{\psi}(x) + \varphi_{\tilde{\mathcal{A}}}^{\psi}(x) \leq 1 \tag{2}$$

Wherein ψ is the dimension of Sierpinski triangle fractal and considered $\frac{\log(3)}{\log(2)}$. Moreover, the indeterminacy degree is determined by Equation (3)

$$\rho_{\tilde{\mathcal{A}}}(x) = \sqrt[\psi]{1 - \xi_{\tilde{\mathcal{A}}}^{\psi}(x) - \varphi_{\tilde{\mathcal{A}}}^{\psi}(x)} \tag{3}$$

Assume $\widetilde{\mathcal{X}}$ and $\widetilde{\mathcal{Y}}$ be two STFNs. So, basic operators are identified with the help of Equations (4) - (8) [32].

$$\widetilde{\mathcal{X}} \oplus \widetilde{\mathcal{Y}} = \left(\sqrt[\psi]{\frac{\xi_{\widetilde{\mathcal{X}}}^{\psi}+\xi_{\widetilde{\mathcal{Y}}}^{\psi}-\xi_{\widetilde{\mathcal{X}}}^{\psi}\xi_{\widetilde{\mathcal{Y}}}^{\psi}-(1-a)\xi_{\widetilde{\mathcal{X}}}^{\psi}\xi_{\widetilde{\mathcal{Y}}}^{\psi}}{1-(1-a)\xi_{\widetilde{\mathcal{X}}}^{\psi}\xi_{\widetilde{\mathcal{Y}}}^{\psi}}}, \frac{\varphi_{\widetilde{\mathcal{X}}}\varphi_{\widetilde{\mathcal{Y}}}}{\sqrt[\psi]{a+(1-a)\left(\varphi_{\widetilde{\mathcal{X}}}^{\psi}+\varphi_{\widetilde{\mathcal{Y}}}^{\psi}-\varphi_{\widetilde{\mathcal{X}}}^{\psi}\varphi_{\widetilde{\mathcal{Y}}}^{\psi}\right)}} \right) \tag{4}$$

$$\widetilde{\mathcal{X}} \otimes \widetilde{\mathcal{Y}} = \left(\frac{\xi_{\widetilde{\mathcal{X}}}\xi_{\widetilde{\mathcal{Y}}}}{\sqrt[\psi]{a+(1-a)\left(\xi_{\widetilde{\mathcal{X}}}^{\psi}+\xi_{\widetilde{\mathcal{Y}}}^{\psi}-\xi_{\widetilde{\mathcal{X}}}^{\psi}\xi_{\widetilde{\mathcal{Y}}}^{\psi}\right)}}, \sqrt[\psi]{\frac{\varphi_{\widetilde{\mathcal{X}}}^{\psi}+\varphi_{\widetilde{\mathcal{Y}}}^{\psi}-\varphi_{\widetilde{\mathcal{X}}}^{\psi}\varphi_{\widetilde{\mathcal{Y}}}^{\psi}-(1-a)\varphi_{\widetilde{\mathcal{X}}}^{\psi}\varphi_{\widetilde{\mathcal{Y}}}^{\psi}}{1-(1-a)\varphi_{\widetilde{\mathcal{X}}}^{\psi}\varphi_{\widetilde{\mathcal{Y}}}^{\psi}}} \right) \tag{5}$$

$$\beta \odot \widetilde{\mathcal{X}} = \left(\sqrt[\psi]{\frac{\left[1+(a-1)\xi_{\widetilde{\mathcal{X}}}^{\psi}\right]^{\beta}-\left(1-\xi_{\widetilde{\mathcal{X}}}^{\psi}\right)^{\beta}}{\left[1+(a-1)\xi_{\widetilde{\mathcal{X}}}^{\psi}\right]^{\beta}-(a-1)\left(1-\xi_{\widetilde{\mathcal{X}}}^{\psi}\right)^{\beta}}}, \frac{\sqrt[\psi]{a}\varphi_{\widetilde{\mathcal{X}}}^{\beta}}{\sqrt[\psi]{\left[1+(a-1)\left(1-\varphi_{\widetilde{\mathcal{X}}}^{\psi}\right)\right]^{\beta}+(a-1)\varphi_{\widetilde{\mathcal{X}}}^{\beta\psi}}} \right) \tag{6}$$

$$\widetilde{\mathcal{X}}^{\beta} = \left(\frac{\sqrt[\psi]{a}\xi_{\widetilde{\mathcal{X}}}^{\beta}}{\sqrt[\psi]{\left[1+(a-1)\left(1-\xi_{\widetilde{\mathcal{X}}}^{\psi}\right)\right]^{\beta}+(a-1)\xi_{\widetilde{\mathcal{X}}}^{\beta\psi}}}, \sqrt[\psi]{\frac{\left[1+(a-1)\varphi_{\widetilde{\mathcal{X}}}^{\psi}\right]^{\beta}-\left(1-\varphi_{\widetilde{\mathcal{X}}}^{\psi}\right)^{\beta}}{\left[1+(a-1)\varphi_{\widetilde{\mathcal{X}}}^{\psi}\right]^{\beta}-(a-1)\left(1-\varphi_{\widetilde{\mathcal{X}}}^{\psi}\right)^{\beta}}} \right) \tag{7}$$

$$\widetilde{\mathcal{X}}^{C} = (\varphi_{\widetilde{\mathcal{X}}}, \xi_{\widetilde{\mathcal{X}}}) \tag{8}$$

Wherein a is positive value and generally equals to 1. β is positive number. Moreover, let $\tilde{\mathcal{A}} = (\xi_{\tilde{\mathcal{A}}}, \varphi_{\tilde{\mathcal{A}}})$ be a STFN. Then, the score and accuracy values of $\tilde{\mathcal{A}}$ are estimated with the help of Equations (9) and (10), respectively.

$$SF(\tilde{\mathcal{A}}) = \xi_{\tilde{\mathcal{A}}}^{\psi}(x) - \varphi_{\tilde{\mathcal{A}}}^{\psi}(x) \tag{9}$$

$$AF(\tilde{\mathcal{A}}) = \xi_{\tilde{\mathcal{A}}}^{\psi}(x) + \varphi_{\tilde{\mathcal{A}}}^{\psi}(x) \tag{10}$$

Let's assume $\tilde{\mathcal{A}}_i$ is a sequence of STFNs. Then, the Sierpinski triangle fuzzy weighted and the Sierpinski triangle fuzzy weighted geometric averages are computed using Equations (11) and (12), respectively.

$$STFWA(\tilde{\mathcal{A}}_i) = \left(\begin{array}{c} \sqrt[\psi]{\frac{\prod_{i=1}^{t}\left(1+(a-1)\xi_i^{\psi}\right)^{w_i}-\prod_{i=1}^{t}\left(1-\xi_i^{\psi}\right)^{w_i}}{\prod_{i=1}^{t}\left(1+(a-1)\xi_i^{\psi}\right)^{w_i}-(a-1)\prod_{i=1}^{t}\left(1-\xi_i^{\psi}\right)^{w_i}}}, \\ \frac{\sqrt[\psi]{a}\prod_{i=1}^{t}(\varphi_i)^{w_i}}{\sqrt[\psi]{\prod_{i=1}^{t}\left(1+(a-1)\left(1-\varphi_i^{\psi}\right)\right)^{w_i}+(a-1)\prod_{i=1}^{t}(\varphi_i)^{\psi w_i}}} \end{array} \right) \tag{11}$$

$$STFWG(\tilde{\mathcal{A}}_i) = \left(\begin{array}{c} \frac{\sqrt[\psi]{a}\prod_{i=1}^{t}(\xi_i)^{w_i}}{\sqrt[\psi]{\prod_{i=1}^{t}\left(1+(a-1)\left(1-\xi_i^{\psi}\right)\right)^{w_i}+(a-1)\prod_{i=1}^{t}(\xi_i)^{\psi w_i}}}, \\ \sqrt[\psi]{\frac{\prod_{i=1}^{t}\left(1+(a-1)\varphi_i^{\psi}\right)^{w_i}-\prod_{i=1}^{t}\left(1-\varphi_i^{\psi}\right)^{w_i}}{\prod_{i=1}^{t}\left(1+(a-1)\varphi_i^{\psi}\right)^{w_i}-(a-1)\prod_{i=1}^{t}\left(1-\varphi_i^{\psi}\right)^{w_i}}} \end{array} \right) \tag{12}$$

Wherein w represents the weights of fuzzy numbers and $\sum_{i=1}^{t} w_i = 1$. t is the amount of STFNs. Some distance metrices such as Euclidean and Taxicab between any two STFNs are determined with the help of Equations (13) and (14), respectively.

$$\mathcal{D}(\widetilde{\mathcal{X}}, \widetilde{\mathcal{Y}}) = \sqrt{\left(\left(\xi_{\widetilde{\mathcal{X}}}^{\psi} - \xi_{\widetilde{\mathcal{Y}}}^{\psi}\right)^2 + \left(\varphi_{\widetilde{\mathcal{X}}}^{\psi} - \varphi_{\widetilde{\mathcal{Y}}}^{\psi}\right)^2 + \left(\rho_{\widetilde{\mathcal{X}}}^{\psi} - \rho_{\widetilde{\mathcal{Y}}}^{\psi}\right)^2\right)} \tag{13}$$

$$\mathcal{T}(\widetilde{\mathcal{X}}, \widetilde{\mathcal{Y}}) = \left|\xi_{\widetilde{\mathcal{X}}}^{\psi} - \xi_{\widetilde{\mathcal{Y}}}^{\psi}\right| + \left|\varphi_{\widetilde{\mathcal{X}}}^{\psi} - \varphi_{\widetilde{\mathcal{Y}}}^{\psi}\right| + \left|\rho_{\widetilde{\mathcal{X}}}^{\psi} - \rho_{\widetilde{\mathcal{Y}}}^{\psi}\right| \tag{14}$$

Moreover, the entropy measure of the STFN is calculated by Equation (15).

$$\mathcal{E}(\widetilde{\mathcal{X}}) = 1 - \left[\left(\xi_{\widetilde{\mathcal{X}}}^{\psi} - \varphi_{\widetilde{\mathcal{X}}}^{\psi}\right)\left(\xi_{\widetilde{\mathcal{X}}}^{\psi} + \varphi_{\widetilde{\mathcal{X}}}^{\psi}\right)\right]^2 \tag{15}$$

2.2 Euclidean Distance-based Weighting Model

Professional backgrounds of DMs may vary due to factors such as age, experience, etc. Therefore, DMs' evaluations are also formed under these factors. For this reason, the source of the differences in evaluations should be included in the analysis. In other words, the importance levels of the evaluations of the DMs should be determined and integrated into the analysis process. Euclidean distance-based weighting model is used to objectively determine the importance levels of DMs [33]. The model performs analysis based on professional factors such as age, experience, etc. The calculation of the model can be summarized as follows.

For the analysis, firstly a matrix containing the professional factors of DMs is constructed as in Equation (16).

$$\mathcal{S} = \left[\mathcal{s}_{ij}\right]_{p\times r} \tag{16}$$

Wherein p is the number of DMs, while r represents the number of professional factors. Then, $\mathcal{s}_{ij}$ refers to value of j^{th} professional factor for DM_i. Next, these values are standardized using Equation (17).

$$z_{ij} = \frac{\mathcal{s}_{ij}-\overline{\mathcal{s}_j}}{\sigma_j} \tag{17}$$

Wherein $\bar{\mathcal{s}}$ and σ are the arithmetic mean and standard deviation, respectively. These statistic parameters are computed with Equations (18) and (19).

$$\overline{\mathcal{s}_j} = \frac{\sum_{i=1}^{p}\mathcal{s}_{ij}}{p} \tag{18}$$

$$\sigma_j^2 = \frac{1}{p}\left(\sum_{i=1}^{p}\left(\mathcal{s}_{ij} - \overline{\mathcal{s}_j}\right)^2\right) \tag{19}$$

Afterwards, the base values are determined according to Equation (20).

$$b_j = \min_{j} z_{ij} \tag{20}$$

Then, the Euclidean distance of the standardized values to the base value is calculated by Equation (21).

$$\mathfrak{E}_i = \sqrt{\sum_{j=!}^{r}\left(z_{ij} - b_j\right)^2} \tag{21}$$

Finally, the importance levels of DMs are obtained with the help of Equation (22).

$$\ell_i = \frac{\mathfrak{E}_i}{\sum_{i=1}^{p}\mathfrak{E}_i} \tag{22}$$

The high value of this value indicates that the importance of DM's evaluation is high.

2.3 Entropy-based MABAC

The MABAC method, developed for ranking alternatives, performs analysis according to the deviation of criterion-weighted evaluations from the geometric mean [17]. The entropy method is integrated to calculate the criteria weights. The entropy method is an objective weighting method [34]. Thus, the results of the MABAC method can be more realistic. Entropy-based MABAC with STFNs are detailed below.

Firstly, the criteria and alternatives sets are identified. Then, the alternatives are evaluated with respect to each criterion. These evaluations are transformed into STFNs in Table 1.

Afterwards, the weighted average values of STFNs of these evaluations are calculated using Equation (11). The weights here are the ℓ values obtained via Equation (22). The decision matrix depicted in Equation (23) is formed, accepting these weighted average items as elements.

$$\widetilde{\mathcal{H}} = \left[\tilde{h}_{ij}\right]_{m\times n} \tag{23}$$

Wherein the sizes of criteria and alternative sets are symbolized by m and n, respectively. Next, these values of decision matrix are normalized with Equations (24) and (25).

$$\tilde{\mathfrak{y}}_{ij} = \tilde{\hbar}_{ij} \quad for\ Beneficial \tag{24}$$
$$\tilde{\mathfrak{y}}_{ij} = \left(\tilde{\hbar}_{ij}\right)^{c} \quad for\ Cost \tag{25}$$

After determining the normalized values, entropy measure for each normalized value is estimated using Equation (15). Next, the entropy measures are summed by Equation (26).

$$\mathfrak{e}_{j} = \sum_{i=1}^{m} \mathcal{E}\left(\tilde{\mathfrak{y}}_{ij}\right) \tag{26}$$

The diversities are computed using Equation (27).

$$\mathfrak{d}_{j} = 1 - \mathfrak{e}_{j} \tag{27}$$

Afterwards, the criteria weights are defined with the help of Equation (28).

$$\mathfrak{p}_{j} = \frac{\mathfrak{d}_{j}}{\sum_{j=1}^{n} \mathfrak{d}_{j}} \tag{28}$$

The larger the $\mathfrak{p}$ value of a criterion is, the more important that criterion is. After determining the priority values of the criteria, the process of ranking the alternatives begins. The weighted decision matrix is constructed with Equation (29).

$$\tilde{\mathfrak{x}}_{ij} = \mathfrak{p}_{j} \odot \tilde{\mathfrak{y}}_{ij} \tag{29}$$

Next, the border approximation area values are calculated by Equation (30).

$$\tilde{\mathcal{g}}_{j} = \left(\prod_{i=1}^{m} \tilde{\mathfrak{x}}_{ij}\right)^{1/m} \tag{30}$$

Table 1
Linguistic Numbers

Linguistic terms	ξ	φ
Inadequate	0.1	0.975
Very Poor	0.2	0.9
Poor	0.3	0.8
Medium Poor	0.4	0.65
Medium	0.55	0.5
Medium Good	0.65	0.4
Good	0.8	0.3
Very Good	0.9	0.2
Exceptional	0.975	0.1

Wherein the multiplication and power operations are defined in Equations (5) and (7). Later, the distances between alternative and border approximation areas are computed using Equations (31) – (33).

$$\tau_{ij} = \mathcal{D}\left(\tilde{\mathfrak{x}}_{ij}, \tilde{\mathcal{g}}_{j}\right) \quad if\ \tilde{\mathfrak{x}}_{ij} > \tilde{\mathcal{g}}_{j} \tag{31}$$
$$\tau_{ij} = 0 \quad if\ \tilde{\mathfrak{x}}_{ij} = \tilde{\mathcal{g}}_{j} \tag{32}$$
$$\tau_{ij} = -\mathcal{D}\left(\tilde{\mathfrak{x}}_{ij}, \tilde{\mathcal{g}}_{j}\right) \quad if\ \tilde{\mathfrak{x}}_{ij} < \tilde{\mathcal{g}}_{j} \tag{33}$$

Finally, ς_{i} value is obtained with Equation (34).

$$\varsigma_{i} = \sum_{j=1}^{n} \tau_{ij} \tag{34}$$

The alternatives are ranked from largest to smallest according to the ς value. The alternative with the maximum ς is considered the optimal alternative.

2.4 MAIRCA

The MAIRCA method is a decision model that ranks alternatives according to the total gap between theoretical and actual evaluations. In theoretical evaluation, the method is based on uniform distribution [35]. MAIRCA with STFNs is introduced below.

Firstly, the criteria and alternatives sets are identified. Then, the alternatives are evaluated with respect to each criterion. These evaluations are transformed into STFNs in Table 1. Afterwards, the weighted average values of STFNs of these evaluations are calculated using Equation (11). The weights here are the ℓ values obtained via Equation (22). The decision matrix depicted in Equation (23) is formed, accepting these weighted average items as elements. According to the uniform distribution, the preference probabilities of the alternatives are calculated with Equation (35).

$$\mathrm{P}_i = \frac{1}{m} \tag{35}$$

Afterwards, the theoretical evaluation matrix is created using Equations (36).

$$\mathrm{t}_{\mathbb{p}_{ij}} = \mathrm{P}_i \mathfrak{p}_j \tag{36}$$

Then, the actual evaluation matrix is constructed with Equations (37) and (38).

$$\mathrm{t}_{\mathbb{r}_{ij}} = \mathrm{t}_{\mathbb{p}_{ij}} \left(\frac{SF(\tilde{\hbar}_{ij}) - \min_j SF(\tilde{\hbar}_{ij})}{\max_j SF(\tilde{\hbar}_{ij}) - \min_j SF(\tilde{\hbar}_{ij})} \right) \quad for\ Beneficial \tag{37}$$

$$\mathrm{t}_{\mathbb{r}_{ij}} = \mathrm{t}_{\mathbb{p}_{ij}} \left(\frac{SF(\tilde{\hbar}_{ij}) - \max_j SF(\tilde{\hbar}_{ij})}{\min_j SF(\tilde{\hbar}_{ij}) - \max_j SF(\tilde{\hbar}_{ij})} \right) \quad for\ Cost \tag{38}$$

Next, the values of gap matrix are computed by Equation (39).

$$\mathcal{G}_{ij} = \mathrm{t}_{\mathbb{p}_{ij}} - \mathrm{t}_{\mathbb{r}_{ij}} \tag{39}$$

Finally, $\mathcal{Q}$ values are estimated with the help of Equation (40).

$$\mathcal{Q}_i = \sum_{j=1}^{n} \mathcal{G}_{ij} \tag{40}$$

3. Results

The purpose of this study is to examine the effects of basic emotions such as anger, fear, and hope on individuals' investment decisions and to systematically model these effects using multi-criteria decision-making methods. The study aims to reveal how psychological factors, beyond rational decision-making processes, shape investors' investment choices. The outputs of this manuscript are shared in this section with tables and figures. The section includes the subheadings of Euclidean distance-based weighting, entropy-based MABAC, comparison analysis with MAIRCA, and sensitivity analysis.

3.1 Euclidean Distance-based Weighting

In this study, opinions are obtained from 10 different subject-matter experts to enhance the reliability and validity of the decision-making process. During the expert selection process, individuals with academic knowledge in the relevant field, professional experience, and competence in investment decisions are preferred. Communication with these experts is facilitated through meetings organized on various online platforms to overcome time and space constraints. During the meetings, structured questions are posed on the eight psychological factors (criteria) and five financial products (alternatives) identified in the study, and systematic feedback is obtained from each expert. The questions are designed to reveal the experts' assessments of the relative importance of the criteria and their preferences among investment alternatives. This method allows for the collection of individual opinions within a standardized framework and makes them suitable for analysis. Furthermore, conducting the process online facilitates participation and access to a broader expert profile, despite the experts' geographical locations. This approach strengthens the methodological robustness of the study and contributes to more reliable, multidimensional, and comprehensive results by integrating the perspectives of experts with diverse backgrounds. The age, income, experience and management period information related to the professional background of these 10 DMs are presented in Table 2.

As can be seen from Table 2, the average age of DMS is 51.1 years old and the minimum experience as manager of DMs is 11 years. Next, the information of DMs is standardized using Equations (17) – (19). The standardized information of DMs is displayed in Table 3.

Table 2
Professional Factors

DM	Age	Income	Total Experience	Experience as Manager
DM1	56	2750	35	20
DM2	48	2450	29	14
DM3	53	2550	31	16
DM4	43	1850	23	13
DM5	55	2700	34	18
DM6	56	2850	37	19
DM7	56	2800	36	14
DM8	53	2550	31	15
DM9	43	2100	22	11
DM10	48	2400	28	12

Table 3
Standardized Information Values

DM	Age	Income	Total Experience	Experience as Manager
DM1	0.990	0.826	0.894	1.680
DM2	-0.626	-0.165	-0.325	-0.420
DM3	0.384	0.165	0.081	0.280
DM4	-1.637	-2.149	-1.544	-0.770
DM5	0.788	0.661	0.691	0.980
DM6	0.990	1.157	1.300	1.330
DM7	0.990	0.992	1.097	-0.420
DM8	0.384	0.165	0.081	-0.070
DM9	-1.637	-1.322	-1.747	-1.470
DM10	-0.626	-0.331	-0.528	-1.120

Afterwards, Equation (20) is used and the base values according to standardized information values are determined as in Table 4.

Table 4
Base Values

Age	Income	Total Experience	Experience as Manager
-1.637	-2.149	-1.747	-1.470

After determining the base value for each professional factor, the Euclidean distance of the standardized information values to these values are calculated by Equation (21). The Euclidean distances of DMs are summarized in Table 5.

Table 5
Euclidean Distances

Experts	$\mathfrak{E}$
DM1	5.714
DM2	2.842
DM3	3.980
DM4	0.729
DM5	5.072
DM6	5.912
DM7	5.094
DM8	3.839
DM9	.826
DM10	2.436

Finally, the importance level for each DM is obtained by normalizing distances. Equation (22) is used for this process. According to importance levels of DMs in Figure 2, DM6 and DM1 have the most important evaluations with 0.162 and 0.157, respectively.

3.2 Entropy-based MABAC

Psychological factors influencing investors' decision-making processes have a multidimensional structure and give rise to different investment behaviors. *Risk perception* (RPTC) shapes the fundamental direction of investment strategies by determining individuals' propensity to take or avoid risk. Relatedly, *return expectation* (RTEP) guides investors' choices based on their short- and long-term expected returns, directly influencing how they perceive the risk-return balance. *Investment duration* (INDT) differentiates decisions based on how long an investor plans to hold a particular asset, creating a distinction between short-term speculative tendencies and long-term strategic approaches. *Confidence* (CNFN) encompasses both an individual's confidence in their own knowledge and competence and their belief in the stability of the markets, significantly influencing investors' preferences for risky or safe instruments. *The tendency to make quick decisions* (QKDN), particularly prominent in uncertain market conditions, can lead investors to react intuitively to sudden fluctuations, displacing rational analysis. *Loss aversion* (LSAN) causes investors to exhibit cautious or defensive behavior in their decisions because they prioritize potential losses more strongly than potential gains. On the other hand, *social influence or herd behavior* (HDBV) leads individuals to adopt similar strategies by following the investment preferences of the majority, which can trigger irrational price movements in the markets. Finally, *information access and analysis capability* (INCS) determine investors' capacity to evaluate market data, interpret news, and conduct technical or fundamental analysis. Different levels of this capacity lead to heterogeneous decision-making behaviors among investors. Taken together, these factors reveal that investment decisions are shaped not only by economic rationality but also by psychological tendencies and cognitive processes.

Investment alternatives vary depending on their risk-return balance, liquidity level, and economic conditions. While *stocks* (STCK) involve high risk, they offer high return potential, making them an important tool for investors seeking short- and medium-term gains. In contrast, *bonds and deposits* (BNDP) stand out with their low risk and low return levels, making them an attractive option for individuals seeking safer and more stable investments. *Gold* (GOLD)is particularly preferred for its "safe haven" nature during periods of economic uncertainty and crisis and is generally seen as a medium-term investment vehicle. *Cryptocurrencies* (CRNC), which have grown in popularity in recent years, are characterized by very high volatility and speculative nature, offering high short-term gain potential but also carrying a high risk of loss. *Real estate* (RLST), on the other hand, offers a long-term and relatively safer investment alternative, but has limited liquidity and is therefore disadvantageous in meeting short-term cash needs. Each of these investment instruments shapes investors' decision-making processes in line with different psychological factors and risk perceptions. Therefore, it plays a decisive role in the diversification of investment preferences and the heterogeneity of investor behavior. In the next step of analysis, the financial risk management strategies are evaluated with respect to each criterion using the linguistic terms in Table 1. The evaluations are expressed in Table 6.

Afterwards, these evaluations in Table 6 are transformed into STFNs regarding to Table 1. Using the importance levels of DMs in Figure 2 and Equation (11), the weighted average values of these STFNs are calculated. The decision matrix is given in Table 7.

Table 6
Evaluation

	RPTC	RTEP	INDT	CNFN	QKDN	LSAN	HDBV	INCS
STCK	E	G	G	G	MG	G	VG	G
BNDP	E	VG	G	M	VG	M	G	G
GOLD	MG	VG	G	MG	MG	M	M	MG
CRNC	MG	MG	MG	M	MG	M	MG	M
RLST	MG	MG	M	G	G	G	MG	MG
	RPTC	RTEP	INDT	CNFN	QKDN	LSAN	HDBV	INCS
STCK	VG	G	G	G	MG	MG	G	G
BNDP	G	G	G	MG	MG	G	VG	MG
GOLD	MG	MG	M	MG	G	M	MG	M
CRNC	E	MG	MG	M	MG	M	MG	G
RLST	VG	MG	G	M	M	M	MG	M
	RPTC	RTEP	INDT	CNFN	QKDN	LSAN	HDBV	INCS
STCK	VG	VG	G	MG	VG	MG	MG	G
BNDP	G	G	VG	M	VG	VG	M	VG
GOLD	G	G	G	M	G	MG	M	M
CRNC	MG	VG	MG	MG	M	G	G	G
RLST	MG	G	G	G	M	G	G	M
	RPTC	RTEP	INDT	CNFN	QKDN	LSAN	HDBV	INCS
STCK	E	G	VG	MG	G	MG	MG	MG
BNDP	G	G	G	VG	G	VG	G	MG
GOLD	MG	MG	M	M	G	M	G	G
CRNC	G	MG	G	MG	MG	G	M	MG
RLST	VG	MG	G	G	M	M	M	M
	RPTC	RTEP	INDT	CNFN	QKDN	LSAN	HDBV	INCS
STCK	E	VG	VG	MG	G	G	VG	VG
BNDP	VG	VG	MG	MG	G	M	G	MG
GOLD	E	MG	G	MG	MG	M	G	MG
CRNC	G	G	G	MG	G	M	M	M
RLST	MG	G	MG	MG	G	MG	M	MG
	RPTC	RTEP	INDT	CNFN	QKDN	LSAN	HDBV	INCS
STCK	E	E	G	G	G	MG	VG	G
BNDP	E	G	G	VG	G	M	VG	G
GOLD	MG	MG	G	G	G	MG	G	MG
CRNC	VG	G	MG	G	M	MG	M	M
RLST	E	VG	G	M	MG	G	MG	G
	RPTC	RTEP	INDT	CNFN	QKDN	LSAN	HDBV	INCS
STCK	E	VG	VG	MG	VG	VG	G	VG
BNDP	VG	G	M	VG	G	VG	G	MG
GOLD	VG	VG	G	MG	MG	M	G	G
CRNC	MG	G	G	M	M	MG	G	G
RLST	VG	MG	G	MG	M	MG	G	M
	RPTC	RTEP	INDT	CNFN	QKDN	LSAN	HDBV	INCS
STCK	VG	G	MG	G	G	MG	G	MG
BNDP	E	G	M	MG	G	MG	VG	VG
GOLD	VG	MG	M	M	M	MG	G	G
CRNC	MG	G	MG	MG	G	M	M	MG
RLST	MG	G	G	MG	MG	MG	M	MG

Table 6
Continued

	RPTC	RTEP	INDT	CNFN	QKDN	LSAN	HDBV	INCS
STCK	VG	E	MG	MG	MG	VG	MG	MG
BNDP	G	VG	MG	M	VG	MG	M	MG
GOLD	E	MG	M	G	G	M	G	MG
CRNC	VG	MG	M	M	M	G	MG	M
RLST	VG	VG	MG	G	M	MG	MG	MG
	RPTC	RTEP	INDT	CNFN	QKDN	LSAN	HDBV	INCS
STCK	E	E	VG	MG	MG	VG	VG	MG
BNDP	E	VG	M	MG	MG	G	MG	M
GOLD	VG	G	MG	G	M	G	G	MG
CRNC	VG	G	M	M	M	G	M	M
RLST	MG	MG	MG	MG	MG	M	G	MG

Table 7
Decision Matrix

	RPTC		RTEP		INDT		CNFN		QKDN		LSAN		HDBV		INCS	
STCK	.961	.000	.910	.000	.834	.000	.737	.000	.800	.000	.780	.000	.850	.000	.815	.000
BNDP	.941	.000	.847	.000	.742	.000	.754	.000	.824	.000	.747	.000	.820	.000	.775	.000
GOLD	.858	.000	.784	.000	.753	.000	.680	.000	.709	.000	.614	.000	.743	.000	.686	.000
CRNC	.813	.000	.785	.000	.699	.000	.643	.000	.657	.000	.654	.000	.658	.000	.669	.000
RLST	.840	.000	.774	.000	.744	.000	.689	.000	.677	.000	.715	.000	.689	.000	.653	.000

Next, the values in Table 7 are normalized with Equations (24) and (25). Since all the criteria in this manuscript are beneficial, the normalized matrix and the decision matrix are the same according to Equation (25). After that, the entropy measure for each normalized value is estimated using Equation (15) and then, the entropy measures are summed by Equation (26). Next, the diversities are computed with Equation (27). The results are illustrated in Table 8.

Table 8
Total Entropies and Diversities

	RPTC	RTEP	INDT	CNFN	QKDN	LSAN	HDBV	INCS
$\mathfrak{e}$	0.512	0.694	0.822	0.889	0.840	0.881	0.808	0.858
$\mathfrak{d}$	0.488	0.306	0.178	0.111	0.160	0.119	0.192	0.142

In the end of Entropy method, the criteria weights are defined with the help of Equation (28). The study identifies confidence as the most important criterion. This issue stands out as one of the fundamental determinants of investors' decision-making processes. Trust expresses investors' faith in both their own knowledge and analytical abilities and in the financial markets, directly impacting the level of rationality of their decisions. A high level of confidence allows investors to take more risks, pursue new investment opportunities, and adhere to long-term strategies. A low level of confidence, on the other hand, can lead to overly cautious behavior, missed investment opportunities, and increased vulnerability to market fluctuations. Therefore, trust can be a source of stability or instability in investment choices not only at the individual level but also in the market. Loss aversion is identified as the second most critical factor. This explains why investors focus more on potential losses than on potential gains. As Prospect Theory suggests, individuals experience the pain of losses more strongly than the pleasure they derive from gains of the same magnitude. This leads investors to develop risk-averse strategies, be overly affected by short-term fluctuations, and sometimes make irrational selling decisions. This dynamic relationship between confidence and loss aversion provides a critical framework for understanding investor behavior. On the one hand, overconfidence can drive markets into speculative bubbles, while on the other, loss aversion can trigger panic selling. Therefore, the prominence of these two factors as primary criteria clearly demonstrates the crucial role of the psychological dimensions of investment decisions in financial stability and investment strategies.

In the second process, MABAC is performed for ranking. Using the values in Table 7, the weighted decision matrix is constructed with Equation (29). The weighted decision matrix is presented in Table 9.

Table 9
Weighted Decision Matrix

	RPTC		RTEP		INDT		CNFN		QKDN		LSAN		HDBV		INCS	
STCK	.689	.000	.468	.009	.283	.113	.171	.344	.246	.173	.197	.268	.307	.101	.237	.211
BNDP	.644	.000	.398	.020	.230	.179	.177	.335	.260	.149	.183	.289	.286	.118	.216	.235
GOLD	.522	.001	.346	.042	.235	.199	.151	.380	.201	.218	.137	.405	.241	.146	.178	.280
CRNC	.475	.002	.346	.040	.210	.203	.139	.422	.180	.274	.149	.350	.201	.213	.172	.306
RLST	.502	.002	.339	.038	.231	.170	.154	.360	.188	.274	.170	.352	.215	.187	.166	.321

Afterwards, the border approximation area for each criterion is calculated using Equation (30). The result is given in Table 10.

Table 10
Border Approximation Areas

RPTC		RTEP		INDT		CNFN		QKDN		LSAN		HDBV		INCS	
.560	.002	.376	.031	.237	.175	.158	.370	.213	.222	.166	.336	.247	.157	.192	.273

Later, the distances between values in Table 9 and Table 10 are computed using Equations (31) – (33). The distances are summarized in Table 11.

Table 11
Distances

	RPTC	RTEP	INDT	CNFN	QKDN	LSAN	HDBV	INCS
STCK	0.219	0.121	0.046	0.028	0.038	0.067	0.056	0.054
BNDP	0.139	0.027	-0.005	0.037	0.055	0.048	0.036	0.033
GOLD	-0.060	-0.036	-0.020	-0.011	-0.013	-0.078	0.012	-0.010
CRNC	-0.130	-0.036	-0.025	-0.063	-0.045	-0.015	-0.045	-0.031
RLST	-0.090	-0.045	-0.009	0.013	-0.045	-0.022	-0.028	-0.046

Finally, the distances in Table 11 are summed with the help of Equation (34). The ranking results are presented in Figure 2.

Figure 2 indicates that stocks emerged as the most suitable investment alternative. Thanks to their high return potential and capital appreciation, stocks occupy a central position in investors' portfolios, offering advantages in terms of value appreciation and capitalization, particularly in long-term strategies. Bonds, deposits, and gold were also identified as other important alternatives for investors. Bonds and deposits, due to their low risk and stable returns, are prominent among risk-averse individuals seeking secure investments. Gold, thanks to its "safe haven" and value preservation properties, is particularly preferred during periods of high uncertainty during times of crisis. In contrast, cryptocurrencies and real estate are ranked next. While cryptocurrencies are considered more limited investment vehicles due to their high volatility and speculative nature, real estate becomes a less desirable option due to its low liquidity and long-term commitment. These findings reveal that it is a rational approach for investors to create a balanced portfolio by focusing on stocks, bonds/deposits and gold, while other alternatives should be considered as complementary or speculative investment instruments.

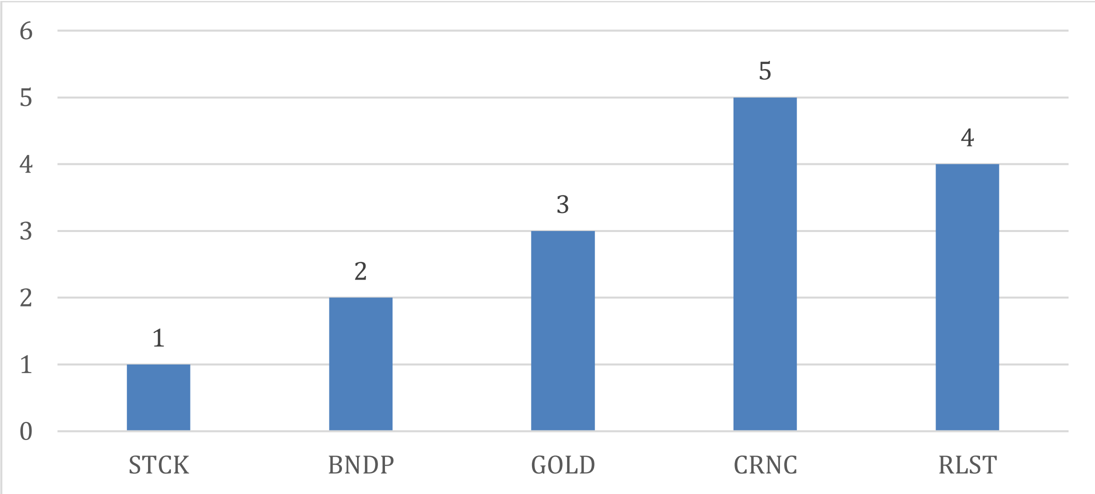

Fig. 2. Ranking Results

3.3 Comparison Analysis with MAIRCA

To test the validity of the ranking results obtained from the manuscript, the evaluations are reanalyzed with the second method. MAIRCA is the second method preferred for this purpose. The preference probabilities of the financial risk management strategies are equal and calculated as 0.2 by Equation (35). Later, the elements of the theoretical evaluation matrix are created using Equation (36). The theoretical evaluation matrix is expressed in Table 12.

Table 12
Theoretical Evaluation Matrix

	RPTC	RTEP	INDT	CNFN	QKDN	LSAN	HDBV	INCS
STCK	0.058	0.036	0.021	0.013	0.019	0.014	0.023	0.017
BNDP	0.058	0.036	0.021	0.013	0.019	0.014	0.023	0.017
GOLD	0.058	0.036	0.021	0.013	0.019	0.014	0.023	0.017
CRNC	0.058	0.036	0.021	0.013	0.019	0.014	0.023	0.017
RLST	0.058	0.036	0.021	0.013	0.019	0.014	0.023	0.017

Afterwards, the actual evaluation matrix is constructed with Equations (37) and (38). For this, the score values of elements in Table 7. Moreover, since all the criteria in this manuscript are beneficial, Equation (37) is preferred. The actual evaluation matrix is exhibited in Table 13.

Table 13
Actual Evaluation Matrix

	RPTC	RTEP	INDT	CNFN	QKDN	LSAN	HDBV	INCS
STCK	0.000	0.000	0.000	0.002	0.003	0.000	0.000	0.000
BNDP	0.008	0.017	0.015	0.000	0.000	0.003	0.004	0.004
GOLD	0.041	0.034	0.013	0.009	0.013	0.014	0.013	0.014
CRNC	0.058	0.033	0.021	0.013	0.019	0.011	0.023	0.015
RLST	0.048	0.036	0.014	0.008	0.017	0.006	0.019	0.017

Next, the gap value between the theoretical and actual evaluation matrices is computed by Equation (39). The gap matrix is shared in Table 14.

Table 14
Gap Matrix

	RPTC	RTEP	INDT	CNFN	QKDN	LSAN	HDBV	INCS
STCK	0.058	0.036	0.021	0.011	0.016	0.014	0.023	0.017
BNDP	0.049	0.019	0.006	0.013	0.019	0.011	0.019	0.012
GOLD	0.017	0.002	0.008	0.004	0.006	0.000	0.010	0.003
CRNC	0.000	0.003	0.000	0.000	0.000	0.003	0.000	0.002
RLST	0.010	0.000	0.007	0.005	0.002	0.008	0.003	0.000

Finally, the gap values are summed for each alternative using Equation (40). According to total gap values, these investment alternatives can be ranked. The ranking results of the MAIRCA and MABAC methods are demonstrated in Table 15.

Table 15
Comparative Ranking Results

Alternatives	MABAC	MAIRCA
STCK	1	1
BNDP	2	2
GOLD	3	3
CRNC	5	5
RLST	4	4

In this study, the MABAC and MAIRCA methods are applied separately to rank investment alternatives, and the results obtained from both methods are found to be identical. Indeed, Table 15 shows that the ranking results of these investment alternatives are completely consistent across both methods. The fact that different multi-criteria decision-making methods independently achieve the same ranking significantly increases the reliability of the proposed model. In the multi-criteria decision-making literature, differences between methods often raise questions about model consistency. In this study, the fact that two methods based on different mathematical foundations, MABAC and MAIRCA, achieve the same results demonstrates that the findings are not coincidental but rather possess strong methodological soundness. This not only confirms the internal consistency of the proposed model but also supports the reliability of the criteria used in evaluating investment alternatives. Therefore, the concordance between the methods strengthens the scientific contribution of the study and enhances both the theoretical validity and practical applicability of the proposed approach.

3.4 Sensitivity Analysis

Sensitivity analysis is performed to assess the sensitivity of the ranking results obtained from the manuscript. In other words, the weight of each criterion is increased by 1%, and the analyses are repeated. In other words, in the first case, only the weight of the first criterion is increased by 1% and the updated weights are normalized. The analysis is performed with the new weights. The ranking results of the eight cases created in this way are summarized in Table 16.

A sensitivity analysis is conducted to test the robustness of the model, reevaluating the rankings of investment alternatives under eight different conditions. The primary objective of the sensitivity analysis was to test the reliability of the model by examining whether changes in the criteria weights affected the final ranking results.

Table 16
Sensitivity Analysis

	CS1	CS2	CS3	CS4	CS5	CS6	CS7	CS8
HEDFINS	1	1	1	1	1	1	1	1
INSURE	2	2	2	2	2	2	2	2
DINVPORT	3	3	3	3	3	3	3	3
LITERACY	5	5	5	5	5	5	5	5
WRMSYS	4	4	4	4	4	4	4	4

The findings revealed that the rankings of investment alternatives remained unchanged in all scenarios. This result demonstrates that the proposed model is not only valid under certain conditions but also maintains its consistency under different parameter settings. In the multi-criteria decision-making literature, sensitivity analyses are often applied to reveal the weakest aspects of a model; small changes in the criteria weights that significantly alter the rankings are considered to undermine the reliability of the method. However, in this study, the fact that the same results were obtained even under different conditions demonstrates the model's high level of robustness and robustness. Therefore, the sensitivity analysis findings support both the academic validity and practical applicability of the proposed model, highlighting it as a reliable tool for explaining investor behavior.

4. Conclusions

The main objective of this study is to reveal the relative importance of psychological factors that play a role in investors' decision-making processes and to determine the most appropriate investment alternatives considering these factors. The integrated decision-making model developed for this purpose offers a unique approach by incorporating psychological factors, which are frequently emphasized but not systematically addressed in the behavioral finance literature, into the analysis. In the study, eight different psychological criteria and five investment alternatives were evaluated; expert opinions are weighted according to demographic characteristics, and the obtained data are analyzed using Entropy, MABAC, and MAIRCA methods. The results reveal that trust is the most critical psychological factor, with loss aversion the second most important. In terms of investment alternatives, stocks stand out as the most suitable option, while bonds/deposits and gold are identified as other important instruments. The originality of the study stems from the use of fractal number-based Sierpinski fuzzy sets, the calculation of expert weights by considering demographic differences, and the integration of psychological factors into the analysis as decision criteria. In this respect, the research fills a significant gap in the literature; It contributes to understanding investor behavior from a more comprehensive and multidimensional perspective.

The analysis findings reveal that confidence is the most critical psychological factor, followed by loss aversion, highlighting two fundamental dimensions in understanding investor behavior. Confidence reflects investors' perceptions of both their own knowledge and analytical competence and the stability of market conditions. Lim *et al.,* [36] defined that while high confidence facilitates the evaluation of opportunities, low confidence can lead to missed potential gains due to excessive caution. Therefore, transparent market regulations, improving financial literacy, and strengthening access to information are important strategies to increase investor confidence. Loss aversion, on the other hand, explains individuals' tendency to focus on losses rather than gains, which sometimes leads to irrational selling decisions and excessive risk aversion [37]. Sood *et al.,* [38] denoted that to mitigate the negative effects of this tendency, it is recommended that investors diversify their portfolios with a long-term perspective and develop training programs to identify their behavioral biases. These results confirm the central role of these two psychological factors, frequently emphasized in the literature, in investment decisions. However, Nagrajan and Thirunavukkarasu [39] highlighted that while trust and loss aversion are the most critical factors, risk perception, social influence, the tendency to make quick decisions, and other psychological factors also need to be considered for a holistic understanding of investor behavior. Therefore, the findings of this study not only confirm the literature but also highlight the multidimensional nature of psychological factors, paving the way for the development of comprehensive strategies for investors and policymakers.

It is also identified that stocks stand out as the most suitable investment alternative, followed by bonds/deposits and gold. Stocks, with their high return potential and capital growth opportunities, offer significant advantages to investors, particularly in long-term investment strategies [40]. Bonds and deposits, on the other hand, stand out as a safe choice for risk-averse investors thanks to their low risk and stable returns, acting as a balancing factor in portfolio diversification [41]. Gold, on the other hand, maintains its value as a "safe haven" during times of crisis and serves as an important hedge for investors in uncertain times. The prominence of these three investment instruments is frequently emphasized in the literature, presenting findings consistent with market dynamics [42]. However, these results do not imply that other investment alternatives (cryptocurrencies and real estate) are unimportant. On the contrary, these instruments should be considered regarding specific investor profiles and strategies but should be evaluated from a more speculative or long-term perspective [43, 44]. From a strategic perspective, investors are advised to hold stocks, bonds/deposits, and gold as core components in their portfolios, while positioning cryptocurrencies and real estate as complementary instruments. This approach will both facilitate risk management and contribute to the creation of a portfolio structure that is more resilient to market fluctuations.

Despite its significant contributions, this study also has certain theoretical and methodological limitations. First, the psychological factors used in the analyses were selected based on a literature review and may not encompass all possible factors that could influence investor behavior. Furthermore, expert opinions were obtained from a limited sample. Data obtained from broader and more diverse geographical or sectoral samples would increase the generalizability of the results. The proposed model also has some inherent limitations. While Sierpinski-based fractal fuzzy sets offer the potential to model uncertainty in decision-making more flexibly, they can also lead to high computational complexity in implementation. Similarly, while weighting experts based on demographic characteristics increases the specificity of the method, the selection and measurement of demographic variables could be addressed more comprehensively in future studies. To address these limitations, it is recommended that future research include different sets of behavioral factors in the analysis, collect data from larger expert groups, and conduct comparative studies across different countries or investor profiles. Furthermore, the developed model can be integrated with other multi-criteria decision-making methods in the future, supported by AI-based optimization techniques, and enhanced to adapt to dynamic market conditions. This will allow for the creation of more robust, multi-dimensional decision-making models that more accurately reflect investor behavior.

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Conflicts of Interest
The authors declare no conflicts of interest.

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