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Profiling Investors Under Climate and Environmental Stress: A Novel Fuzzy Decision-Making Model Bridging Ecology and Social Psychology

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ABSTRACT

This study examines the impact of climate change and environmental risks on investment decisions, focusing on human behavior. The fundamental problem is that decision-makers' perceptions of environmental stressors and social factors distort resource allocation through uncertainty and behavioral biases. Therefore, the key points to analyze are which criteria most strongly determine the investor profile and which institutional/investor profiles are more resilient under crisis conditions. A fundamental shortcoming in the literature is that studies focusing on a single variable, often limited to data specific to developed markets, fail to produce a consensus on the most critical stressors. To address this gap, a new multi-criteria decision-making model encompassing economic, financial, ecological, and social psychology dimensions is proposed. Expert weights are calibrated using machine learning based on demographic characteristics. Criteria weights and their interactions are calculated using the criteria importance assessment (CIMAS) method; five investor risk profiles are ranked using additive ratio assessment (ARAS); and all assessments are conducted using Koch Snowflake fuzzy sets, which provide a more detailed and flexible representation of uncertainty. The study contributes to the literature by determining which criteria are prioritized and which risk profile is most appropriate using a new and applicable fuzzy decision model. The proposed model (i) preserves the nuance of judgments by reducing information loss compared to traditional triangular/trapezoidal fuzzy numbers and (ii) increases representational fairness by not assuming equal expert weights. The key findings indicate that social acceptance and stakeholder perception are the most important criteria, closely followed by regulatory risk. The most appropriate investor profile during crisis periods is one that complies with social norms and stakeholder pressure.

1. Introduction

Climate change and environmental risks have become one of the most significant factors directly impacting investment decisions today. This is not limited to environmental sensitivity. It also plays a decisive role in risk management, regulations, and long-term strategic orientations in financial markets. Climate change increases uncertainty for investors. Extreme weather events, droughts, and

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floods disrupt production processes, creating significant fragility in supply chains [1]. This intensifies financial risks, particularly in sectors such as energy, agriculture, tourism, and insurance. Furthermore, the economic impact of environmental risks isn't limited to physical damage. Sectors with high carbon emissions face increasing regulatory pressure. Therefore, investors tend to favor environmentally sensitive business models to maintain long-term profitability. The market value of companies with poor environmental performance is increasing. Climate change is redefining long-term investment strategies. Investments in areas such as renewable energy and energy efficiency offer high growth potential in the future [2]. Conversely, businesses in fossil fuel-based sectors also face the risk of losing value. This is causing investors to reevaluate their portfolio diversification decisions.

Decision-makers' perceptions of environmental stressors and social factors are seen as a fundamental element in shaping investment decisions. These perceptions determine not only individual sensitivity but also the direction of organizational strategies and general trends in markets. Environmental stressors such as climate change, natural disaster risk, and energy crises are perceived as direct threats by decision-makers. When managers consider these stressors, they no longer focus solely on short-term returns when evaluating investment projects but also begin to consider long-term resilience [3]. In this context, the use of tools such as scenario analysis, stress testing, and internal carbon pricing increases. Social factors, however, have a more nuanced impact on decision-makers' perceptions. In societies with high environmental awareness, investors and managers act with the understanding that social reactions can have financial consequences. Stakeholder expectations and sustainability norms determine reputation, regulatory compliance, and the cost of accessing finance. Company managers are driven to develop supply chains more resilient to environmental threats and to invest in energy-efficient technologies [4]. This trend strengthens the integration of environmental, social and governance (ESG) criteria into decision processes and encourages prioritizing green solutions in capital allocation.

There is a growing body of literature on the impact of climate change on investment decisions. However, there are several gaps in the literature. Most studies either focus on a single variable or are limited to data specific to developed markets. It is necessary to determine which factors investors and corporate executives consider most critical. The primary reason for this is that investment decisions are shaped by perceptions. However, there is no consensus in the literature on these most critical stressors. Carbon price volatility may be a determining factor for an energy-intensive sector manager. Conversely, extreme weather events may be more significant for a food supply chain investor. These shortcomings directly translate into problems in practice. Institutions cannot clearly determine how much resource to allocate to each risk. Conversely, they may overspend on high-visibility but relatively low-impact risks. As a result, critical vulnerabilities may be neglected. The negative sentiment and uncertainty created by environmental risks can collectively push investors to make poor decisions, influenced by social psychology. Herd behavior, information cascades, and loss aversion accelerate this process. Investors overreact to high visibility but secondary risks. It may underestimate risks that progress slowly but can be devastating. This creates market pricing bias. Identifying the most significant stressors is essential to mitigating these problems. This demonstrates the need for new priority analyses in this area.

The aim of this study is to examine the impact of climate change and environmental risks on investment decisions, focusing on human behavior; to reveal how decision-makers perceive environmental stressors and social factors and how these perceptions are reflected in their decision-making processes. The primary motivation for this research is uncertainty in the literature regarding which criteria are most critical and which risk profile is considered most appropriate in which context.

The proposed model is a multi-criteria decision-making framework: six criteria encompassing economic, financial, ecological, and social psychology dimensions are identified; the opinions of 10 experts are obtained; expert weights are estimated using machine learning using demographic characteristics; criterion weights are calculated using the criteria importance assessment (CIMAS) method; the most appropriate investor profile under crisis conditions is selected using additive ratio assessment (ARAS); and the entire process is enriched with Koch Snowflake fuzzy sets to reduce uncertainty. The questions this study seeks to answer are: (1) Which criteria are most critical in investor profiling in the context of climate and environmental risk, and what is their order of importance? (2) How do environmental stressors and stakeholder perceptions affect investors' risk appetite and expected return thresholds? (3) How should demographically diverse expert opinions be reflected in the criteria weights, and does this reflection improve model performance? (4) To what extent do Koch Snowflake fuzzy sets strengthen the stability of CIMAS and ARAS results under uncertainty? (5) Which profile among five different investor risk profiles is the most appropriate choice under the defined objectives and constraints during crisis periods?

The study contributes to the literature by determining which criteria are prioritized in investor profiling under climate and environmental risk and which risk profile is most appropriate with a new and applicable fuzzy decision model. The proposed model is superior to similar studies in the following aspects: (1) It models uncertainty in a more detailed and flexible way than classical triangular/trapezoidal fuzzy numbers by using Koch Snowflake fuzzy sets, thus reducing information loss in criteria and alternative evaluations; (2) The opinion weights of experts are calibrated according to demographic factors with machine learning, eliminating the bias and representation problems caused by the equal weight assumption frequently seen in the literature; (3) It combines economic, financial, ecological and social psychology dimensions under the same roof, quantifies the interaction between criteria with CIMAS and directly transfers it to the decision set with ARAS, thus making the decision chain end-to-end and consistent.

The following section reviews the literature. The proposed model is explained in the third section. The results are given in the following section. The final part consists of the conclusion and discussion.

Expected financial return is an essential determinant of the investor profile in an environment where climate change and environmental risks permeate investment decisions. In the context of climate change and environmental risks, this dimension should be considered alongside risk tolerance. Climate risks are recognized to impact the expected returns of financial assets through multiple channels. Ta *et al.,* [5] defined that the fundamental value impact emerges through physical and transition risks on cash flows. Practices such as carbon pricing can increase investment costs and thus significantly impact investor decisions. Value-based motivations play a significant role in investor preferences. In this context, some investors may knowingly accept lower monetary returns for portfolios aligned with sustainability values. Shmelev and Gilardi [6] underlined that a significant portion of institutional investors, however, primarily view ESG integration as a risk management tool. Innovation-focused strategies may be more suitable for investors seeking above-market returns. Furthermore, Xie *et al.,* [7] defined that climate change affects cash flows, discount rates, and risk premiums through macro-financial risk channels. Therefore, expected return is not only a normative choice but also a rational parameter priced in response to regulatory tightening, technological transformation, and demand shifts. Vijai and Wisetsri [8] highlighted that a profiling approach supported by scenario analysis, sensitivity analysis and transition/physical risk stress testing should be adopted to clarify where the investor is positioned in the return-impact trade-off when considered alongside liquidity requirements.

Environmental risk level should be considered an effective and increasingly mandatory criterion when determining the most suitable investor profile. Environmental risks affect both cash flows and discount rates through physical and transition risks. According to Lazar *et al.,* [9], these risks materially alter the expected return and risk premium of financial assets. Physical risks such as floods and droughts put pressure on supply chain continuity, negatively impacting the financial costs of investments. Kim *et al.,* [10] underlined that traditionally, a risk profile is constructed based on market risks such as volatility and maximum drawdown. Environmental risk level, on the other hand, focuses on the investor's exposure to planned and unplanned climate-related shocks. Horn *et al.,* [2] denoted that environmental risk level should be modeled as a separate axis, articulated with the maturity structure, liquidity requirements, and expected financial return target. Using measurable and auditable indicators to operationalize environmental risk level is essential. Fu *et al.,* [11] indicated that governance preferences for institutional and individual investors are also linked to environmental risk level.

Stakeholder perception is an effective criterion in determining the most suitable investor profile. Stakeholder perceptions regarding sustainability and climate performance can significantly influence investment decisions. Hassan *et al.,* [12] identified that in periods of heightened societal sensitivity towards carbon-intensive sectors, stakeholder perception increases the risk premium of investments. Pulido-Moncada *et al.,* [13] demonstrated that stakeholder perception directly contributes to profile determination when operationalized with measurable indicators and clear rules. On the other hand, Hernández-Agüero *et al.,* [13] underlined that stakeholder perception is considered a time-sensitive indicator. Measurements can be affected by seasonal campaigns, information asymmetry, or short-term news flow. González-Moreno *et al.,* [13] concluded that negative stakeholder perceptions reduce investors' effective risk appetite. As a result of this situation, investors begin to adopt a more cautious profile. These dynamics lead to several behavioral shifts in practice, negatively impacting the market. For example, reducing allocations to high-carbon sectors causes these companies to experience liquidity problems.

Regulatory risk is a critical factor in determining the most suitable investor profile, both theoretically and practically. Regulatory risk is the possibility that changes in laws, regulations, standards, and auditing practices could negatively or positively impact asset valuations. Treepongkaruna *et al.,* [14] defined that changes in climate and environmental legislation directly impact cash flows and risk premiums. When regulations reduce information asymmetry and increase market integrity, the risk premium can decrease, and the cost of capital can decline. Jin and Wang [15] denoted that standardized disclosures contribute positively to increased investor confidence. Regulations focused on competition and consumer protection prevent market manipulation. This allows more investors to actively participate in the market. According to Guesmi *et al.,* [16], a lack of regulation has the effect of reducing market efficiency. Lack of regulation means the framework surrounding the rules by which market actors should operate becomes unclear. This leads to a significant number of investors becoming risk averse. Ongsakul *et al.,* [17] highlighted that the simultaneous shift of large numbers of investors to risk averse due to regulatory uncertainty creates problems for the market and the real economy.

The literature demonstrates a lack of clarity regarding which criteria are most critical for investor profiling under climate and environmental risk, and which risk profile is most appropriate in which context. This uncertainty undermines suitability decisions. Inaccurate profiling leads to disruptions in allocating capital to procyclical risk mitigation and transition investments. Future studies should transparently rank and weight the key criteria and empirically validate the most appropriate profile across contexts.

2. Methodology

In this manuscript, where the impact of climate change and environmental risks on investment decisions is examined at the center of human behavior, a decision system is generated. For this purpose, the CIMAS method is used to weight the criteria. However, the traditional CIMAS is expanded to utilize the expertise score derived from the machine learning algorithm for expert weighting. In other words, the machine learning-based CIMAS method is developed. Subsequently, the ARAS method is used to rank the alternatives. In this decision system based on expert judgment, fuzzy logic is used to address uncertainty. Within the scope of fuzzy logic, Koch Snowflake fuzzy sets appropriate to the linguistic structure are integrated to process linguistic expressions. The operation of the decision system is illustrated in Figure 1.

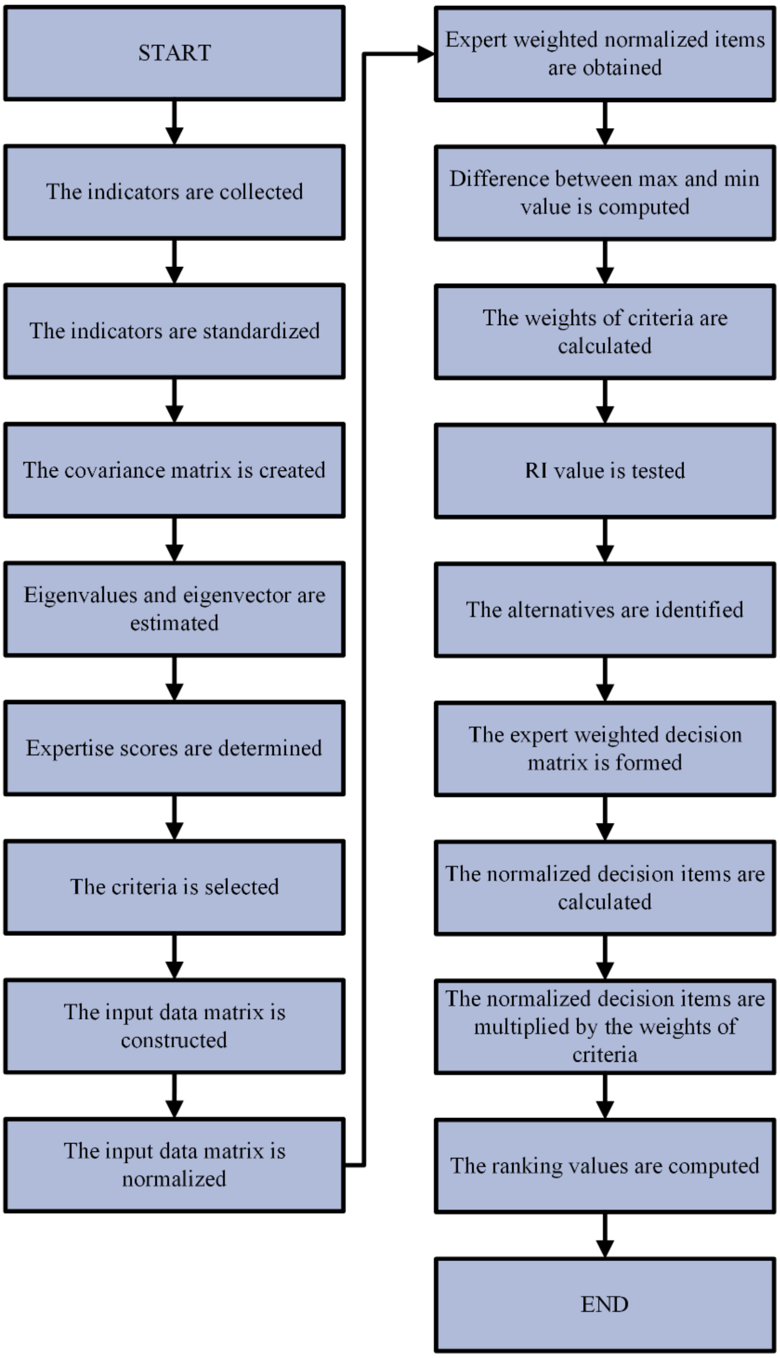

Fig. 1. The Operation of the Decision System

2.1 Koch Snowflake Fuzzy Sets (KSFSs)

Fuzzy set theory, which allows for processing with words, is being updated to address uncertainty structures. To analyze linguistic uncertainty more comprehensively, KSFSs, based on the Koch Snowflake fractal, a special case of fractal geometry, has recently been favored. This is primarily because linguistic expressions are like this fractal's properties of boundless perimeter and bounded area. In other words, while the meaning of linguistic expressions is limited, their content is expansive [18]. Where $\mathfrak{S}$ is a universe of discourse, a KSFS $(\widetilde{\mathcal{F}})$ is defined as in Equation (1).

$$\tilde{\mathcal{F}} = \left\{\langle u, \left(s_{\tilde{\mathcal{F}}}(u), t_{\tilde{\mathcal{F}}}(u)\right)\rangle | u \in \mathfrak{S}\right\} \quad (1)$$

Wherein $s_{\tilde{\mathcal{F}}}: \mathfrak{S} \rightarrow [0,1]$ and $t_{\tilde{\mathcal{F}}}: \mathfrak{S} \rightarrow [0,1]$ present the degrees of membership and non-membership, respectively. These degrees are satisfied with the condition in Equation (2).

$$0 \leq s_{\tilde{\mathcal{F}}}^{\mathfrak{p}} + t_{\tilde{\mathcal{F}}}^{\mathfrak{p}} \leq 1; \forall u \in \mathfrak{S} \quad (2)$$

Wherein $\mathfrak{p}$ equals to $\frac{\log 4}{\log 3} \cong 1.26$, the dimension of Koch Snowflake fractal.

Let $\widetilde{\mathcal{F}_1}$ and $\widetilde{\mathcal{F}_2}$ be two KSFNs, then basic arithmetic operators are computed using Equations (3) – (6).

$$\widetilde{\mathcal{F}_1} + \widetilde{\mathcal{F}_2} = \left(\begin{array}{c} \sqrt[\mathfrak{p}]{\dfrac{s_{\widetilde{\mathcal{F}_1}}^{\mathfrak{p}} + s_{\widetilde{\mathcal{F}_2}}^{\mathfrak{p}} - s_{\widetilde{\mathcal{F}_1}}^{\mathfrak{p}} s_{\widetilde{\mathcal{F}_2}}^{\mathfrak{p}} - (1-\xi) s_{\widetilde{\mathcal{F}_1}}^{\mathfrak{p}} s_{\widetilde{\mathcal{F}_2}}^{\mathfrak{p}}}{1-(1-\xi) s_{\widetilde{\mathcal{F}_1}}^{\mathfrak{p}} s_{\widetilde{\mathcal{F}_2}}^{\mathfrak{p}}}}, \\ \dfrac{t_{\widetilde{\mathcal{F}_1}} t_{\widetilde{\mathcal{F}_2}}}{\sqrt[\mathfrak{p}]{\xi + (1-\xi)\left(t_{\widetilde{\mathcal{F}_1}}^{\mathfrak{p}} + t_{\widetilde{\mathcal{F}_2}}^{\mathfrak{p}} - t_{\widetilde{\mathcal{F}_1}}^{\mathfrak{p}} t_{\widetilde{\mathcal{F}_2}}^{\mathfrak{p}}\right)}} \end{array} \right) \quad (3)$$

$$\widetilde{\mathcal{F}_1} \times \widetilde{\mathcal{F}_2} = \left(\begin{array}{c} \dfrac{s_{\widetilde{\mathcal{F}_1}} s_{\widetilde{\mathcal{F}_2}}}{\sqrt[\mathfrak{p}]{\xi + (1-\xi)\left(s_{\widetilde{\mathcal{F}_1}}^{\mathfrak{p}} + s_{\widetilde{\mathcal{F}_2}}^{\mathfrak{p}} - s_{\widetilde{\mathcal{F}_1}}^{\mathfrak{p}} s_{\widetilde{\mathcal{F}_2}}^{\mathfrak{p}}\right)}}, \\ \sqrt[\mathfrak{p}]{\dfrac{t_{\widetilde{\mathcal{F}_1}}^{\mathfrak{p}} + t_{\widetilde{\mathcal{F}_2}}^{\mathfrak{p}} - t_{\widetilde{\mathcal{F}_1}}^{\mathfrak{p}} t_{\widetilde{\mathcal{F}_2}}^{\mathfrak{p}} - (1-\xi) t_{\widetilde{\mathcal{F}_1}}^{\mathfrak{p}} t_{\widetilde{\mathcal{F}_2}}^{\mathfrak{p}}}{1-(1-\xi) t_{\widetilde{\mathcal{F}_1}}^{\mathfrak{p}} t_{\widetilde{\mathcal{F}_2}}^{\mathfrak{p}}}} \end{array} \right) \quad (4)$$

$$\daleth \odot \tilde{\mathcal{F}} = \left(\begin{array}{c} \sqrt[\mathfrak{p}]{\dfrac{\left[1+(\xi-1) s_{\tilde{\mathcal{F}}}^{\mathfrak{p}}\right]^{\daleth} - \left(1 - s_{\tilde{\mathcal{F}}}^{\mathfrak{p}}\right)^{\daleth}}{\left[1+(\xi-1) s_{\tilde{\mathcal{F}}}^{\mathfrak{p}}\right]^{\daleth} - (\xi-1)\left(1 - s_{\tilde{\mathcal{F}}}^{\mathfrak{p}}\right)^{\daleth}}}, \\ \dfrac{\sqrt[\mathfrak{p}]{\xi}\, t_{\tilde{\mathcal{F}}}^{\daleth}}{\sqrt[\mathfrak{p}]{\left[1+(\xi-1)\left(1 - t_{\tilde{\mathcal{F}}}^{\mathfrak{p}}\right)\right]^{\daleth} + (\xi-1) t_{\tilde{\mathcal{F}}}^{\daleth\mathfrak{p}}}} \end{array} \right) \quad (5)$$

$$\tilde{\mathcal{F}}^{\daleth} = \left(\begin{array}{c} \dfrac{\sqrt[\mathfrak{p}]{\xi}\, s_{\tilde{\mathcal{F}}}^{\daleth}}{\sqrt[\mathfrak{p}]{\left[1+(\xi-1)\left(1 - s_{\tilde{\mathcal{F}}}^{\mathfrak{p}}\right)\right]^{\daleth} + (\xi-1) s_{\tilde{\mathcal{F}}}^{\daleth\mathfrak{p}}}}, \\ \sqrt[\mathfrak{p}]{\dfrac{\left[1+(\xi-1) t_{\tilde{\mathcal{F}}}^{\mathfrak{p}}\right]^{\daleth} - \left(1 - t_{\tilde{\mathcal{F}}}^{\mathfrak{p}}\right)^{\daleth}}{\left[1+(\xi-1) t_{\tilde{\mathcal{F}}}^{\mathfrak{p}}\right]^{\daleth} - (\xi-1)\left(1 - t_{\tilde{\mathcal{F}}}^{\mathfrak{p}}\right)^{\daleth}}} \end{array} \right) \quad (6)$$

Moreover, the score and accuracy values are computed by Equations (7) and (8), respectively.

$$score(\tilde{\mathcal{F}}) = s^{\mathfrak{p}} - t^{\mathfrak{p}} \quad (7)$$

$$acc(\tilde{\mathcal{F}}) = s^{\mathfrak{p}} + t^{\mathfrak{p}} \quad (8)$$

2.2 Machine Learning based CIMAS

CIMAS is a technique developed to calculate criterion importance. One of the greatest advantages of CIMAS is that the reliability of the results can be tested. The results are verified with a second percentile evaluation. Another advantage is that it does not assign equal importance to experts [19]. In traditional CIMAS methods, experts' opinions are weighted according to their years of experience. Thus, the method offers an alternative solution to the criticism of equal importance in literature.

However, determining the importance of opinions based solely on years of experience remains weak. This manuscript introduces the CIMAS method, which uses machine learning and expertise scoring, integrated with KSFNs.

Firstly, indicators of experts' expertise are collected such as age, experience, number of projects etc. From these indicators, a matrix is constructed as in Equation (9).

$$\mathcal{E} = \begin{bmatrix} e_{11} & \cdots & e_{1\hbar} \\ \vdots & \ddots & \vdots \\ e_{d1} & \cdots & e_{d\hbar} \end{bmatrix} \tag{9}$$

Wherein d and $\hbar$ represent the numbers of experts and indicators, respectively. These indicators are standardized by Equations (10) and (11).

$$c_{ij} = e_{ij} - \bar{e}_j \tag{10}$$

$$r_{ij} = \frac{c_{ij}}{\sqrt{\sum_{i=1}^{d} c_{ij}^2}} \tag{11}$$

Wherein $\bar{e}_j$ is the arithmetic mean for j^{th} indicator. Next, the covariance coefficients between the standardized indicators are estimated using Equation (12).

$$cov_{ij} = \frac{\sum_{t=1}^{d}(r_{ti}-\bar{r}_i)(r_{tj}-\bar{r}_j)}{d} \tag{12}$$

The covariance matrix is created as in Equation (13) from the covariance coefficients.

$$\mathcal{C} = \begin{bmatrix} cov_{11} & \cdots & cov_{1\hbar} \\ \vdots & \ddots & \vdots \\ cov_{\hbar 1} & \cdots & cov_{\hbar\hbar} \end{bmatrix} \tag{13}$$

The eigenvalues are computed by solving Equation (14) and then, the maximum eigenvalue is selected for maximum variance or minimum loss information of indicators.

$$\det(\mathcal{C} - \mathrm{I}\lambda) = 0 \tag{14}$$

The eigenvector for the maximum eigenvalue is determined by solving Equation (15).

$$\big(\mathcal{C} - \mathrm{I}(\max\lambda)\big)v = 0 \tag{15}$$

Using this eigenvector, the latent variable for experts is obtained with the help of Equation (16). Later, this new latent variable's elements are normalized via Equation (17). These normalized elements are defined as expertise scores.

$$s_i = \sum_{j=1}^{\hbar} e_{ij}\, v_j \tag{16}$$

$$E^i = \frac{s_i}{\sum_{i=}^{d} s_i} \tag{17}$$

After defining the expertise scores, the criteria set is determined, and these experts assess the criteria. The opinions are transformed into KSFNs regarding Figure 2.

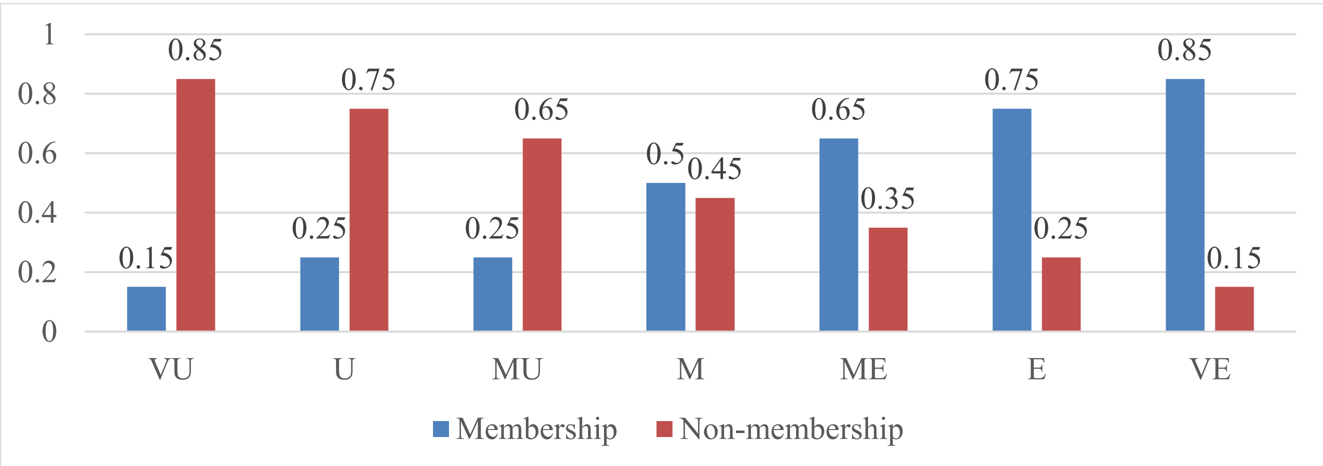

Fig. 2. Linguistic Scales

With transformed evaluation numbers, the input data matrix is constructed as in Equation (18). The number of columns in this matrix is the number of criteria, with each column representing a criterion. The number of rows corresponds to the number of experts, and each row contains the expert's assessment.

$$\mathrm{A} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{d1} & \cdots & a_{dn} \end{bmatrix} \tag{18}$$

Afterwards, the items of input data matrix are normalized according to type of criterion. Equation (19) is used for beneficial criteria and Equation (20) is used for cost criteria.

$$\mathfrak{y}_{ij} = \left(\mathscr{s}_{a_{ij}}, \mathscr{t}_{a_{ij}}\right) \tag{19}$$

$$\mathfrak{y}_{ij} = \left(\mathscr{t}_{a_{ij}}, \mathscr{s}_{a_{ij}}\right) \tag{20}$$

The expert weighted normalized items are obtained via Equation (21). In other words, unlike traditional CIMAS, the normalized items are multiplied by the proposed expertise score. This multiplication operator is defined in Equation (5).

$$z_{ij} = \mathfrak{y}_{ij} E^{i} \tag{21}$$

The difference between the maximum and minimum values of score values of expert weighted normalized items for each criterion is calculated with Equation (22). The score value is identified in Equation (7).

$$\delta_j = \max_i score(z_{ij}) - \min_i score(z_{ij}) \tag{22}$$

Finally, the differences are normalized by Equation (23). These normalized differences are defined as the weights of criteria.

$$\omega_j = \frac{\delta_j}{\sum_{j=1}^{n} \delta_j} \tag{23}$$

In the second stage of CIMAS, the reliability of the results is tested. For this, experts evaluate for second time. In this second assessment, experts score the criteria, and the total score should be 100. The criteria scores are then averaged. Using the average score and normalized differences, the RI value is calculated with Equation (24).

$$RI = \frac{\sum_{j=1}^{n} \left|100\omega_j - AV_j\right|}{100} \tag{24}$$

Wherein AV is average score. Moreover, RI result should be lower than 0.1. Otherwise, the weight results are not reliable.

2.3 ARAS

The ARAS method is a technique that ranks alternatives. The biggest advantage of this method is its ease of calculation. It compares alternatives based on the optimal value. This manuscript introduces the ARAS method integrated with KSFNs [20].

Firstly, the alternatives are selected, and the experts evaluate the alternatives regarding to Figure 2. Then, the assessments are transformed into KSFNs, KSFNs are multiplied by expertise scores using Equation (5). Next, the expert-weighted KSFNs are summed by Equation (3). So, the expert weighted decision items are obtained. From these expert weighted decision items, decision matrix is formed as in Equation (25).

$$\mathcal{B} = \begin{bmatrix} b_{01} & \cdots & b_{0n} \\ \vdots & \ddots & \vdots \\ b_{m1} & \cdots & b_{mn} \end{bmatrix} \tag{25}$$

Wherein m is the number of alternatives. b_{0j} the optimal items. These optimal items are determined as maximum items for beneficial criterion or minimum items for cost criterion. Using score values of the expert weighted decision items, the normalized decision items are calculated. Equation (26) is used for beneficial criteria. Equation (27) is used for cost criteria.

$$\mathfrak{z}_{ij} = \frac{score(b_{ij})}{\sum_{i=0}^{m} score(b_{ij})} \tag{26}$$

$$\mathfrak{z}_{ij} = \frac{\left(\frac{1}{score(b_{ij})}\right)}{\sum_{i=0}^{m}\left(\frac{1}{score(b_{ij})}\right)} \tag{27}$$

Afterwards, the weighted items are estimated by multiplying the weights of criteria. Using Equation (28), normalized decision items are multiplied by the weights of criteria and summed.

$$\mathfrak{r}_i = \sum_{j=1}^{n} \mathfrak{z}_{ij}\omega_j \tag{28}$$

Finally, the ranking values for alternatives are computed with the help of Equation (29).

$$\mathcal{K}_i = \frac{\mathfrak{r}_i}{\mathfrak{r}_0} \tag{29}$$

3. Results

The analysis results about the impact of climate change and environmental risks on investment decisions are presented in this section. These results are given as tables and figures.

3.1 Weighting of Criteria

Firstly, the indicators about expertise scores of experts are determined such as age, experience years, the number of projects managed and number of certificates. These indicators' values of ten experts are shared in Table 1.

Table 1
Indicators

Experts	Age	Experience (Years)	Number of Projects	Number of Certificates
Expert_1	51	32	3	4
Expert_2	53	32	3	4
Expert_3	57	37	4	5
Expert_4	47	27	2	4
Expert_5	47	26	2	3
Expert_6	49	29	3	4
Expert_7	48	27	2	3
Expert_8	47	27	2	4
Expert_9	48	28	2	4
Expert_10	49	30	3	4

According to indicators in Table 1, the average age, experience years, the number of projects managed and the number of certificates of ten experts equal to 49.6, 29.5, 2.6, and 3.9, respectively. In addition, these experts have the least 26 experience years. Next, these indicators are standardized with Equation (10) and (11). The standardized indicators are summarized in Table 2.

By standardizing indicators, unitary importance is eliminated. Then, the covariance coefficients between the standardized indicators are estimated by Equation (12). So, the covariance matrix formed in Equation (13) is obtained. The covariance matrix is illustrated in Table 3.

Table 2
Standardized Indicators

Experts	Age	Experience (Years)	Number of Projects	Number of Certificates
Expert_1	0.144	0.247	0.191	0.059
Expert_2	0.350	0.247	0.191	0.059
Expert_3	0.762	0.741	0.667	0.646
Expert_4	-0.268	-0.247	-0.286	0.059
Expert_5	-0.268	-0.346	-0.286	-0.528
Expert_6	-0.062	-0.049	0.191	0.059
Expert_7	-0.165	-0.247	-0.286	-0.528
Expert_8	-0.268	-0.247	-0.286	0.059
Expert_9	-0.165	-0.148	-0.286	0.059
Expert_10	-0.062	0.049	0.191	0.059

Table 3
Covariance Matrix

Experts	Age	Experience (Years)	Number of Projects	Number of Certificates
Age	0.100	0.098	0.090	0.070
Experience (Years)	0.098	0.100	0.094	0.078
Number of Projects	0.090	0.094	0.100	0.073
Number of Certificates	0.070	0.078	0.073	0.100

Afterwards, the eigenvalues of covariance matrix are found by solving Equation (14). These eigenvalues are .35267, .03603, .001167, and .010133. So, the maximum eigenvalue is .35267. The eigenvector for the maximum eigenvalue is estimated by solving Equation (15). The items of the eigenvector are displayed in Table 4.

Table 4
Eigenvector

Eigenvector
0.510324
0.526534
0.5086
0.451284

The indicators in Table 1 are multiplied by the eigenvector in Table 4 using Equation (16). Later, the new latent variable's elements are normalized via Equation (17). The expertise scores are presented in Figure 3.

After that, the criteria set is determined such as expected financial return (EFNRT), risk level (RSLEV), environmental risk level (EVRKL), social acceptance and stakeholder perception (SCPKC), compliance/future regulatory risk (CNFRG), and long-term sustainability (LTMSY). These criteria are evaluated by ten experts. Next, the opinions are transformed into KSFN using Figure 2 and the input data matrix is constructed. The input data matrix is shown in Table 5.

Afterwards, the input data matrix is normalized using Equation (19) since the criteria are beneficial. Next, the expert weighted normalized items are obtained with the help of Equation (20). The expert weighted normalized matrix is expressed in Table 6.

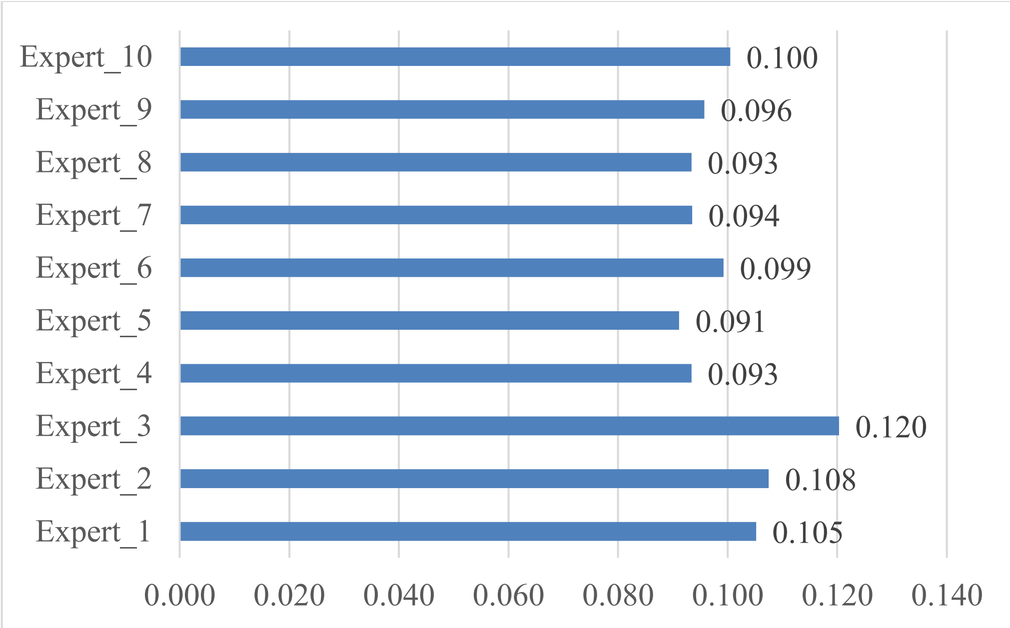

Fig. 3. Expertise Scores

Table 5
Input Data Matrix

Expert	EFNRT		RSLEV		EVRKL		SCPKC		CNFRG		LTMSY	
Expert_1	0.5	0.45	0.15	0.85	0.5	0.45	0.75	0.25	0.15	0.85	0.15	0.85
Expert_2	0.65	0.35	0.25	0.75	0.25	0.75	0.25	0.65	0.65	0.35	0.25	0.75
Expert_3	0.25	0.65	0.75	0.25	0.65	0.35	0.65	0.35	0.15	0.85	0.65	0.35
Expert_4	0.85	0.15	0.25	0.75	0.25	0.65	0.75	0.25	0.5	0.45	0.25	0.65
Expert_5	0.85	0.15	0.65	0.35	0.85	0.15	0.85	0.15	0.75	0.25	0.15	0.85
Expert_6	0.65	0.35	0.65	0.35	0.25	0.75	0.65	0.35	0.85	0.15	0.25	0.75
Expert_7	0.15	0.85	0.75	0.25	0.25	0.65	0.85	0.15	0.75	0.25	0.5	0.45
Expert_8	0.5	0.45	0.25	0.65	0.85	0.15	0.15	0.85	0.5	0.45	0.85	0.15
Expert_9	0.25	0.75	0.85	0.15	0.25	0.75	0.15	0.85	0.85	0.15	0.5	0.45
Expert_10	0.25	0.65	0.15	0.85	0.65	0.35	0.85	0.15	0.25	0.65	0.15	0.85

Table 6
Expert Weighted Normalized Matrix

	EFNRT		RSLEV		EVRKL		SCPKC		CNFRG		LTMSY	
Expert_1	0.101	0.919	0.026	0.983	0.101	0.919	0.183	0.864	0.026	0.983	0.026	0.983
Expert_2	0.147	0.893	0.046	0.970	0.046	0.970	0.046	0.955	0.147	0.893	0.046	0.970
Expert_3	0.050	0.949	0.203	0.846	0.160	0.881	0.160	0.881	0.029	0.981	0.160	0.881
Expert_4	0.217	0.838	0.041	0.973	0.041	0.961	0.168	0.879	0.092	0.928	0.041	0.961
Expert_5	0.213	0.841	0.130	0.909	0.213	0.841	0.213	0.841	0.165	0.881	0.023	0.985
Expert_6	0.139	0.901	0.139	0.901	0.043	0.972	0.139	0.901	0.227	0.828	0.043	0.972
Expert_7	0.024	0.985	0.168	0.878	0.041	0.961	0.217	0.837	0.168	0.878	0.092	0.928
Expert_8	0.092	0.928	0.041	0.961	0.217	0.838	0.024	0.985	0.092	0.928	0.217	0.838
Expert_9	0.042	0.973	0.221	0.834	0.042	0.973	0.024	0.985	0.221	0.834	0.094	0.926
Expert_10	0.043	0.958	0.025	0.984	0.140	0.900	0.229	0.826	0.043	0.958	0.025	0.984

The score values of the expert weighted normalized matrix are estimated via Equation (7) and then, the maximum and minimum values are determined. The differences between these values are calculated by Equation (22). The results are exhibited in Table 7.

Table 7
Max, Min and Difference Values

	EFNRT	RSLEV	EVRKL	SCPKC	CNFRG	LTMSY
Max	-0.654	-0.646	-0.654	-0.630	-0.634	-0.654
Min	-0.972	-0.970	-0.948	-0.972	-0.969	-0.973
Difference	0.318	0.324	0.294	0.342	0.334	0.319

Finally, the difference values in Table 7 are normalized by Equation (23). The weights of criteria are visualized in Figure 4.

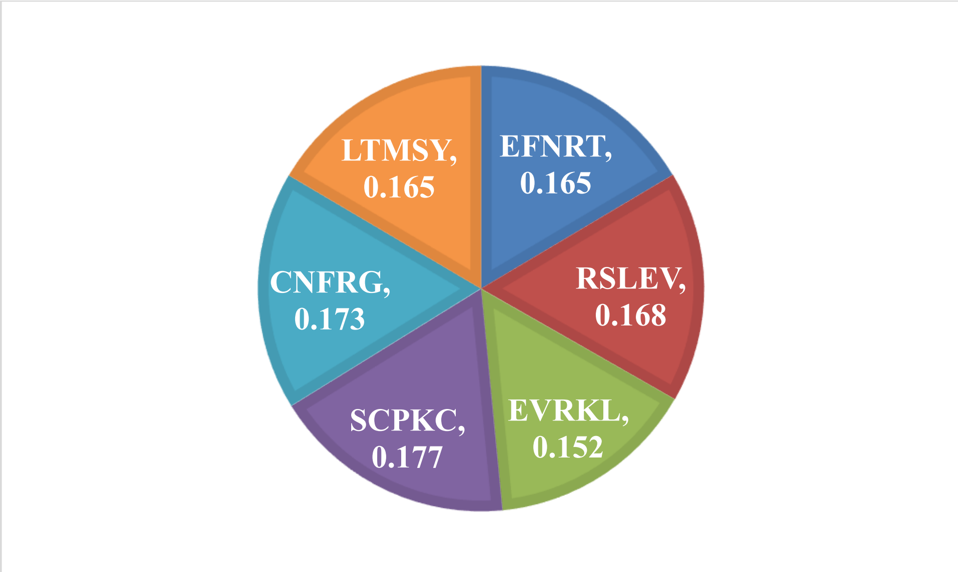

Fig. 4. Weights of Criteria

As can be seen in Figure 4, the most important criterion is social acceptance and stakeholder perception with .177. The second important criterion is compliance/future regulatory risk with .173. In the second stage of CIMAS, the RI value is computed with Equation (24). For this, ten experts evaluate for second time. In process, the average scores of criteria equal to 19, 19, 15, 16, 16, and 15, respectively. So, the RI value is .09. In other words, since the value is lower than 0.1, the result is reliable.

3.2 Ranking of Alternatives

Firstly, the alternatives are identified as profit maximization-focused investor (PMXFS), risk-averse investor (RAVIS), investor compliant with social norms and stakeholder pressure (ICWSN), sustainability-focused idealist investor (SCIDI), and balanced/portfolio diversifying investor (BCPDI). The assessments about alternatives are collected from ten experts. The assessments are illustrated in Table 8.

These assessments are transformed into KSFNs, multiplied by values in Figure 4 and then summed using Equations (5) and (3), respectively. The decision matrix is shown in Table 9.

Items are crisped via score values. After that, the maximum score items are determined as optimal items. Next, using Equation (26), the normalized decision items are obtained since entire criteria are beneficial. The normalized decision matrix is given in Table 10.

Table 8
Assessments

Expert_1	EFNRT	RSLEV	EVRKL	SCPKC	CNFRG	LTMSY	Expert_2	EFNRT	RSLEV	EVRKL	SCPKC	CNFRG	LTMSY
PMXFS	1	4	4	4	4	3	PMXFS	2	3	3	3	4	3
RAVIS	1	2	1	2	4	1	RAVIS	5	3	5	3	3	4
ICWSN	7	7	7	6	6	6	ICWSN	7	7	7	7	7	6
SCIDI	3	2	1	1	3	5	SCIDI	4	2	4	5	2	3
BCPDI	6	4	4	5	4	6	BCPDI	6	7	4	6	4	6
Expert_3	EFNRT	RSLEV	EVRKL	SCPKC	CNFRG	LTMSY	Expert_4	EFNRT	RSLEV	EVRKL	SCPKC	CNFRG	LTMSY
PMXFS	1	3	5	5	2	3	PMXFS	2	3	1	1	1	2
RAVIS	1	2	4	3	2	5	RAVIS	2	2	2	4	1	1
ICWSN	6	7	7	6	6	6	ICWSN	6	7	7	6	7	6
SCIDI	4	4	3	1	5	2	SCIDI	4	4	2	4	1	2
BCPDI	7	4	5	4	6	4	BCPDI	4	4	7	5	5	6
Expert_5	EFNRT	RSLEV	EVRKL	SCPKC	CNFRG	LTMSY	Expert_6	EFNRT	RSLEV	EVRKL	SCPKC	CNFRG	LTMSY
PMXFS	5	1	1	5	2	4	PMXFS	5	2	4	5	5	3
RAVIS	4	2	5	1	2	3	RAVIS	1	3	1	2	1	3
ICWSN	7	7	7	6	6	6	ICWSN	6	7	7	6	6	7
SCIDI	5	2	5	1	1	1	SCIDI	1	2	1	4	4	5
BCPDI	7	4	6	5	5	7	BCPDI	5	5	6	7	5	7
Expert_7	EFNRT	RSLEV	EVRKL	SCPKC	CNFRG	LTMSY	Expert_8	EFNRT	RSLEV	EVRKL	SCPKC	CNFRG	LTMSY
PMXFS	2	1	2	5	2	3	PMXFS	2	2	1	5	3	3
RAVIS	1	1	1	2	2	1	RAVIS	4	1	2	3	2	1
ICWSN	6	7	6	7	7	6	ICWSN	7	7	7	6	6	6
SCIDI	2	2	3	2	1	1	SCIDI	5	3	2	2	2	4
BCPDI	4	5	5	6	6	5	BCPDI	6	5	5	7	6	7
Expert_9	EFNRT	RSLEV	EVRKL	SCPKC	CNFRG	LTMSY	Expert_10	EFNRT	RSLEV	EVRKL	SCPKC	CNFRG	LTMSY
PMXFS	1	2	3	3	3	2	PMXFS	4	4	4	2	2	5
RAVIS	5	2	3	4	2	3	RAVIS	1	5	3	5	1	5
ICWSN	6	6	6	6	7	6	ICWSN	7	6	6	6	7	7
SCIDI	2	1	2	3	4	5	SCIDI	4	1	3	2	5	5
BCPDI	4	6	6	5	7	6	BCPDI	6	4	4	7	5	7

Table 9
Decision Matrix

	EFNRT		RSLEV		EVRKL		SCPKC		CNFRG		LTMSY	
PMXFS	0.971	0.011	0.929	0.017	0.972	0.006	0.997	0.001	0.967	0.008	0.958	0.007
RAVIS	0.976	0.008	0.927	0.025	0.971	0.008	0.967	0.007	0.888	0.043	0.969	0.008
ICWSN	10.000	0.000	10.000	0.000	10.000	0.000	10.000	0.000	10.000	0.000	10.000	0.000
SCIDI	0.992	0.002	0.929	0.023	0.949	0.013	0.960	0.012	0.980	0.006	0.993	0.002
BCPDI	10.000	0.000	10.000	0.000	10.000	0.000	10.000	0.000	10.000	0.000	10.000	0.000

Table 10
Normalized Decision Matrix

	EFNRT	RSLEV	EVRKL	SCPKC	CNFRG	LTMSY
Optimal	0.169	0.175	0.171	0.170	0.173	0.170
PMXFS	0.162	0.159	0.164	0.169	0.166	0.160
RAVIS	0.163	0.158	0.164	0.162	0.146	0.163
ICWSN	0.169	0.175	0.171	0.170	0.173	0.170
SCIDI	0.167	0.158	0.159	0.160	0.169	0.168
BCPDI	0.169	0.175	0.171	0.170	0.173	0.170

Afterwards, the normalized decision items are multiplied by the weights in Figure 4. For multiplication, Equation (28) is used. Finally, the ranking values for alternatives are computed with Equation (29). The results are shared in Table 11.

Table 11
Ranking Values

	Sums	K
Optimal	0.171	
PMXFS	0.1634	0.9545
RAVIS	0.1592	0.9296
ICWSN	0.1712	1.0000
SCIDI	0.1636	0.9556
BCPDI	0.1712	0.9999

According to ranking values in Table 11, the most optimal alternative is investor compliant with social norms and stakeholder pressure with 1.0. The second optimal alternative is balanced/portfolio diversifying investor with .9999. While these values may appear close, the difference is significant. The reason for the closeness is that the values are reduced relative to the optimal value.

4. Conclusions

This study aims to clarify the impact of climate change and environmental risks on investment decisions, focusing on human behavior. To this end, a six-criteria multi-criteria decision-making framework is constructed that incorporates economic, financial, ecological, and social psychology dimensions. In this process, the opinions of 10 experts are collected, and the expert weights are calibrated using machine learning based on demographic characteristics. Additionally, the criteria weights and their interactions are calculated using CIMAS, and five investor risk profiles are ranked using ARAS. The uncertainty in the analysis process is modeled using Koch snowflake fuzzy sets. The findings indicate that social acceptance and stakeholder perception are the most decisive criteria. Regulatory risk also plays a key role in this framework. On the other hand, investor compliance with social norms and stakeholder pressure is the most appropriate investor type to overcome this problem. The study contributes to the literature by (i) reducing information loss by representing uncertainty in a more nuanced way compared to classical triangular/trapezoidal fuzzy numbers, (ii) increasing representation fairness with data-based calibration that does not assume equal expert weights, and (iii) quantitatively integrating the interaction between criteria into the decision chain.

A collective reading of the findings suggests that investment decisions are shaped not only by the narrow risk-return ratio but also by social acceptance and legitimacy. Kateb *et al.,* [21] discussed that the primary criterion of stakeholder perception implies that reputational risk, the cost of accessing finance, and social license to operate dynamics directly impact pricing. Kohli *et al.,* [22] highlighted that the close monitoring of regulatory risk implies that policy uncertainty, carbon pricing, and compliance obligations are determinants of cash flows. In this context, the results are consistent with numerous findings in the behavioral finance, sustainable investment, stakeholder theory, and institutional legitimacy literatures [23, 24]. This confirms the impact of social norms and regulatory signals on risk perception and threshold returns. However, the prioritization established in this study does not imply that other criteria are unimportant. Physical climate risk, supply chain fragility, and technological efficiency capacity may become primary determinants in certain geographies, sectors, and time horizons [25, 26]. Therefore, it should be noted that the weights are context-sensitive and should be recalibrated based on business cycles and stress scenarios.

This study has several limitations in both methodological and theoretical aspects. The current model was created based on the judgments of 10 experts. While this sample size provides a sufficient starting point for interpretability of the results, it may be limited in fully capturing heterogeneity and context-specific differences. Future studies could expand the expert pool and increase geographical and sectoral diversity. The fact that no specific sector or country group was analyzed separately in this study should be considered a factor that limits the external validity and generalizability of the findings. Different sectors and countries respond heterogeneously to climate risks, regulatory pressures, and stakeholder dynamics. Without testing for this heterogeneity, the context-sensitive nature of effect sizes cannot be fully demonstrated. It is recommended that future studies include a balanced sample across sectors and country groups. Comparative designs can be developed for developed and developing economies. In this study, the determination of expert importance weights using a limited number of observable variables is considered a limitation that may affect the external validity and accuracy of the model. The limited variable set may not capture all the context-sensitive factors that shape expert contribution. The variable set should be expanded in future studies. Psychometric indicators such as experts' sector and geography experience, climate literacy and numerical competence, and tolerance for risk and uncertainty can be added to the model.

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Conflicts of Interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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