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COMPARING ESG RANKINGS AND 2050 TEMPERATURE SCORES VIA FUZZY GROUP DECISION-MAKING

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Abstract

ESG represents a social responsibility metric that defines the level of societal acceptance, sustainable development, and corporate social responsibility and is used for investment across different industries. ESG analysis has been criticized for its lack of comparability due to differences across rating agencies, which can be attributed to heterogeneity of subjects, diverse themes, many scales, and the complexity of content. This paper proposes a comprehensive ESG assessment model that uses fuzzy logic and group decision-making to increase the credibility and precision of ESG assessments, especially with respect to climate change goals such as the Paris Agreement, which aims to limit global warming to less than 2°C by the year 2050. The model comprises four stages: (1) identifying subject preferences; (2) extracting latent preference data via the fuzzy inference system; (3) aggregating information via the TOPSIS method to derive ESG rankings; and (4) comparing the proposed method's ESG score rankings with harvest rankings, GDM rankings and temperature score (2050) rankings to assess conformity to climate goals. This research includes 24 firms from the ESG Book, Kaggle and Harvest Fund (2022) and reveals significant gaps between ESG ratings and climate change targets. Some of the high ESG companies were not aligned with the temperature change mitigation goals, which indicates possible gaps in conventional assessments. The proposed method integrates various preferences, reveals the underlying patterns, and increases the accountability of ESG ratings. Future work should focus on unexplored ESG aspects, such as rating issues and corporate misconduct, to increase the accuracy of ESG ratings.

INTRODUCTION

The inconsistent nature of environmental social governance (ESG) ratings creates major obstacles for investors in reaching climate targets and supporting responsible investment practices. ESG metrics serve as essential evaluation tools to measure corporate sustainability while directing investment choices. ESG ratings face major inconsistencies between different rating agencies, which creates investor confusion and weakens the credibility of sustainability assessment.

The significance of ESG performance has been extensively proven. A study by Chen, Song, and Gao [1] revealed that ESG metrics are positively correlated with corporate financial performance (CFP), especially in large firms operating within high-risk settings. Organizations that implement strong ESG practices build stakeholder trust while creating sustainable operations, which leads to better financial results. according to Grewal, Riedl, and Serafeim

2018 [2], ESG performance functions as a vital factor that determines corporate reputation and investment attraction because investors focus on portfolio alignment with sustainable ethical practices. Strong ESG performance enables companies to secure substantial investment while developing a favorable corporate image in the market.

Despite these benefits, the effectiveness of ESG ratings in reflecting real-world sustainability efforts remains limited. One of the most pressing challenges is the divergence in ratings provided by different agencies. For example, a single company may receive vastly different ESG scores depending on the rating agency, due to variations in criteria, weighting, and data interpretation Berg, Kölbel, and Rigobon [3].This inconsistency not only creates confusion for investors but also hinders the ability of companies to benchmark their sustainability performance accurately. Furthermore, current ESG rating systems often fail to capture critical aspects of sustainability, such as corporate misconduct, climate alignment, and the nuanced preferences of diverse stakeholders Escrig-Olmedo *et al.* [4]. These limitations highlight the need for a more robust and transparent ESG assessment framework that can provide reliable and comparable ratings.

The development of ESG ratings is further complicated by the heterogeneity of subjects, diverse themes and complexity of content, which makes it difficult to achieve consistency across evaluations Tamimi and Sebastianelli [5]. For example, the lack of transparency in evaluation methodologies and the subjective judgment of decision-makers often skew the results of ESG ratings, resulting in less trustworthy outcomes Escrig-Olmedo *et al.* [4]. Furthermore, the increasing emphasis on climate change and the Paris Agreement's target of limiting global warming to below 2°C by 2050 has raised the need for ESG assessments that are in line with global climate objectives Küfeoğlu 2024 [6]. However, many high ESG-rated companies are not aligned with temperature change mitigation goals, which shows potential gaps in conventional assessments by Li and Xu [7].

This paper seeks to address these challenges by proposing a holistic ESG assessment model that employs fuzzy logic and GDM. Fuzzy logic is used to capture the inherent uncertainty and subjectivity in ESG evaluations, whereas GDM synthesizes the preferences of various stakeholders to achieve a more balanced and representative assessment. The proposed model seeks to close the gap between heterogeneous stakeholder preferences and decision-making, thus providing a more accurate and credible evaluation of ESG performance. Furthermore, the model ensures that ESG assessments are in line with global climate goals, such as the Paris Agreement's goal of limiting global warming to below 2°C by 2050, thus ensuring that companies' sustainability efforts are useful in the fight against climate change.

This research makes three essential contributions to the field. The research presents an original ESG assessment framework that resolves the problems found in current rating systems. The research demonstrates the practical use of the model by analyzing 24 companies through a case study that compares the proposed method to traditional ESG ratings and temperature scores. The research demonstrates how ESG evaluations should match climate goals by providing investors and policymakers with an improved assessment tool for corporate sustainability.

The research combines fuzzy logic with group decision-making to improve ESG assessment credibility and precision, which supports better investment choices and sustainable development. The proposed model establishes a method for standardized ESG evaluations that provides transparency and consistency while matching global sustainability targets. This research advances the objectives of responsible investment and sustainable development through its implementation.

1. Literature Review

2.1 Business Performance and ESG Performance

Stakeholders, including government authorities and non-governmental organizations, have shown increasing interest in studying ESG factors since 2022 by Hamdi, Guenich, and Ben Saada [8]. ESG practices serve as essential tools to support sustainable development while helping investors make better decisions. The adoption of global standards together with current practices and voluntary disclosure systems enables businesses to increase their reporting and develop both short-term and long-term value Shen 2023 [9]. ESG performance serves as a vital indicator that business managers and government authorities use to make strategic decisions according to Wu and Li 2023 [10]. Studies have repeatedly shown that organizations that perform well in terms of ESG metrics achieve better financial stability. Research conducted by Suttipun [11], revealed that financial instability has an inverse relationship with ESG performance because organizations with better ESG performance show reduced financial risk and instability. Research indicates that businesses should monitor ESG performance because it leads to sustainable development.

The COVID-19 pandemic has demonstrated how ESG practices remain essential because companies with good ESG performance have experienced minimal financial damage throughout the crisis, thus showing that ESG practices help organizations remain resilient in times of economic instability Al Amosh and Khatib [12]. Research by Ahmad *et al.* [13] shows that ESG scores, together with governance and company size, act as performance-enhancing tools to increase financial stability for firms during crisis situations. Research by Luo, Wei, and He [14] has shown that organizations that perform well in ESGs gain better access to credit because their ESG performance reduces risk, improves operational effectiveness and decreases information asymmetry Research by Lian, Li, and Cao [15] shows that ESG performance leads to corporate green innovation because it removes financing barriers and leads to better human resource management and improved managerial practices. The DEA technique analysis by Cheng *et al.* [16] of 1,108 Chinese companies confirmed a positive relationship between ESG efficiency and financial performance.

2. Inconsistency and discrepancies in ESG scores

The increasing importance of ESG metrics has driven researchers to study inconsistent ESG ratings. The authors of Escrig-Olmedo *et al.* [17], solved this problem through their fuzzy multicriteria decision-making tool, which represented the preferences of various investors during ESG evaluations created an integrated multicriteria decision-making (MCDM) framework that uses the interval type-2 fuzzy analytic hierarchy process (IT2FAHP) together with the interval type-2 fuzzy combined compromise solution (IT2F-CoCoSo) to evaluate corporate companies' sustainable performance. The research evaluated five medical corporations by identifying Pfizer as the company with the best ESG performance while developing important ESG criteria. The method used by K. Yu *et al.* [18], demonstrated stability and efficiency through sensitivity and comparison analyses, which validated its effectiveness as an ESG assessment tool. The remaining inconsistencies in ESG ratings present major difficulties for the field. The authors of Escrig-Olmedo *et al.* [4] studied preference data from different subjects across multiple fields.

The analysis shows that rating agencies have limited consistency in their assessment of ESG characteristics, criteria, and attributes across different contexts. The lack of standardization in ESG rating criteria has been identified as a major problem by Escrig-Olmedo *et al.* 2017 [4], who reported that the same company receives different ESG scores from different rating systems. Billio *et al.* 2021 [19] highlighted this problem by pointing out that the absence of standardization in ESG rating criteria leads to confusion and reduces the reliability of ESG assessments.

The differences between ESG ratings create secret dangers for investors together with other stakeholders. ESG evaluations show significant selection bias according to Barkemeyer, Revelli, and Douaud [20], which damages ESG rating credibility and creates stakeholder uncertainty. Balp and Stram Pelli [21] noted that inconsistent corporate sustainability disclosure frameworks, along with variable and complex ESG rating indices and criteria, create difficulties for investors in obtaining reliable assessments.

Research has investigated the relationship between capital ownership preferences and ESG ratings. Wan and Dawod [22] conducted research on this relationship and demonstrated that ownership structures affect ESG ratings while determining investment choices. Xue *et al.* [23] analyzed the causal link between climate change and the ESG performance of organizations through an examination of Chinese manufacturing companies listed from 2009–2021. Research has demonstrated that temperature deviations lead to better ESG performance in businesses, thus demonstrating the need to link ESG practices with climate objectives.

The Paris Agreement's goal to limit global warming to below 2°C requires firms to obtain ESG funding to reduce their carbon emissions as much as possible. ESG investors are increasing in number, while regulatory oversight intensifies, and financial benefits from ESG investments drive sustainable business operations. Advancement remains difficult because of inconsistent terminology and complicated data Tiefenbacher [24].

3 Methodology

Specialized rating agencies and socially developed groups have emerged because of increasing carbon neutrality and sustainability requirements to evaluate companies' ESG performance through its three core components. ESG scores function as financial market participant signals, yet analysts and decision-makers use different interpretations and information sets that produce significant discrepancies. The development of dependable ESG assessments faces challenges because of inconsistent evaluations, so it becomes essential to base ESG performance assessments on analyst and decision-maker preferences according to Jin [25]. The research presents a group decision-making (GDM) approach for ESG evaluation to incorporate stakeholder preferences in the assessment process. The research study evaluates ESG rankings against temperature score (2050) rankings, which assesses companies' support for the Paris Agreement's 2°C global warming limit, as well as the individual rankings of environmental, social and governance components

3.1 Group decision-making

Through its United Nations Principles for Responsible Investment (UNPRI) framework, the organization has established ESG as both a value-based concept and an evaluation instrument that focuses on environmental, social and governance aspects. Environmental aspects include issues such as waste pollution, carbon emissions, greenhouse gases, and compliance with environmental regulations. The social factors include employee conduct and management training and health and safety standards, whereas governance encompasses anti unfair competition and risk management and anticorruption policies.

Stakeholders show different preferences regarding the relative importance of the three ESG dimensions because they have different knowledge bases and investment requirements. The following six scenarios present different approaches to prioritize the dimensions:

Table 1
Numbers of Scenarios/Circumstances and their configuration

Number of Scenarios/Circumstances	Scenarios/Circumstances
1	E≻S≻G
2	E≻G≻S
3	S≻E≻G
4	S≻G≻E
5	G≻S≻E
6	G≻E≻S

This analysis is based on the first scenario (E ≻ S ≻ G), which is in line with the assessment of other scenarios. Here, $w_1, w_2 w_3$ are the weights assigned by subjects to the environmental (E), social (S), and governance (G) dimensions, respectively reference to study of Y. Yu *et al.* [26]. The ESG score of the y^{th} company, as determined by ES1, can be represented as follows:

$$t_{y1} = max \sum_{q=1}^{3} v_{yq}^{*} w_q$$

$$t.n. = w_1 \geq w_2 \geq w_3 \qquad \text{(Eq.1)}$$

$$\sum_{q=1}^{3} w_q = 1$$

In (Eq.1), t_{y1} represents the C_y ESG value as determined byES_1. v_{yq}^{*} is a normalized value. (Eq. 2) can be used to calculate the normalized value.

$$v_{yq}^{*} = \frac{v_{yq} - \min_{y}\{v_{yq}\}}{\max_{y}\{v_{yq}\} - \min_{y}\{v_{yq}\}} \qquad \text{(Eq. 2)}$$

Here, v_{yq} represents the score of $Comp_y$ on d_y,$y = 1,2, \ldots, m,\ \ j = 1,2,3.$

Principal No. 1. As in previous research of Song *et al.* 2017 [27], stakeholders can perform detailed ESG evaluations of a company, which do not rely on the establishment of exact weights. Accordingly, the C_i ESG score measured for ES1 is shown below.

$$t_{y1} = max\left\{v_{y1}^{*}, \frac{v_{y1}^{*}+v_{y2}^{*}}{2}, \frac{v_{y1}^{*}+v_{y2}^{*}+v_{y3}^{*}}{3}\right\} \qquad \text{(Eq.3)}$$

Here, the technique does not need the precise weights of each indication; thus, the procedure is simpler, and the results are more objective. To create the GDM matrix, the six circumstances of three components (E, S, G) are evaluated according to the above equations.

$$t_{m\times 6} = \begin{bmatrix} t_{y1} & t_{12} & \cdots & t_{16} \\ t_{y2} & t_{22} & \cdots & t_{26} \\ \vdots & \vdots & \cdots & \vdots \\ t_{m1} & t_{m2} & \cdots & t_{m6} \end{bmatrix} \qquad \text{(Eq. 4)}$$

The pth subject's ESG score on the product operator of the y^{th}company is shown by t_{yp}.

3.2 Assessment of Preference Data

The GDM matrix shows the preferences of different people. However, the actual values used in the matrix may hide the underlying preference information. To this end, a fuzzy inference system (FIS) is employed to fuzzify the exact values and obtain the whole preference information. FIS is a widely used method for assessing sustainability quoted by the study of Paula, Gil-Lafuente, and Alvares 2021; Barcellos de Paula, Gil-Lafuente, and Rezende 2021 [28] [29]. The process includes fuzzification, inference, and defuzzification, as shown in Figure 1.

The fuzzy inference system's inference process from fuzzification to defuzzification is shown in Figure 1. The first step is fuzzification. In this paper, an affiliation function is used to fuzzify the precise values. In fuzzification, a clear nonfuzzy number is converted to a membership rank for every linguistic expression in a fuzzy group or set. According to Liu *et al.* [30], Linguistics is a valuable tool for decision makers in a complex decision-making process to convey information on a subject's preference. To fuzzify the precise values, the triangular number is chosen in this paper. Let $j = (j^{\ell}, j^{m}, j^{b})$ be a triangular fuzzy number, and (Eq.5) shows the formula for the appropriate affiliation function.

$$U_J(v) = \begin{cases} 0 & if \quad v \leq j^{\ell} \\ \frac{v - j^{\ell}}{j^{m} - j^{\ell}} & if \quad j^{\ell} < v \leq j^{m} \\ \frac{j^{b} - v}{j^{b} - j^{m}} & if \quad j^{m} < v \leq j^{b} \\ 0 & if \quad j^{b} \leq v \end{cases} \qquad \text{(Eq.5)}$$

In this study, for the fuzzification of the values, five linguistic variables are used to calculate the subject preferences. The variables and scores are illustrated in Table 1. For example, ES_1 is the affiliation of the y^{th} firm (C_y). This is represented in (Eq. 6).

$$\mathcal{U}_y^1 = \frac{u_{BS(t_{y1})}}{t_{y1}} + \frac{u_{SBS(t_{y1})}}{t_{y1}} + \frac{u_{FS(t_{y1})}}{t_{y1}} + \frac{u_{GS(t_{y1})}}{t_{y1}} + \frac{u_{VGS(t_{y1})}}{t_{y1}} \qquad \text{(Eq.6)}$$

Here, "+" denotes the conceptual extension or aggregation of the fuzzy set and its elements, unlike the traditional arithmetic summation operation, whereas $\frac{u_{BS(s_{y1})}}{s_{y1}}$ denotes the affiliation of the elements s_{y1} of the BS.

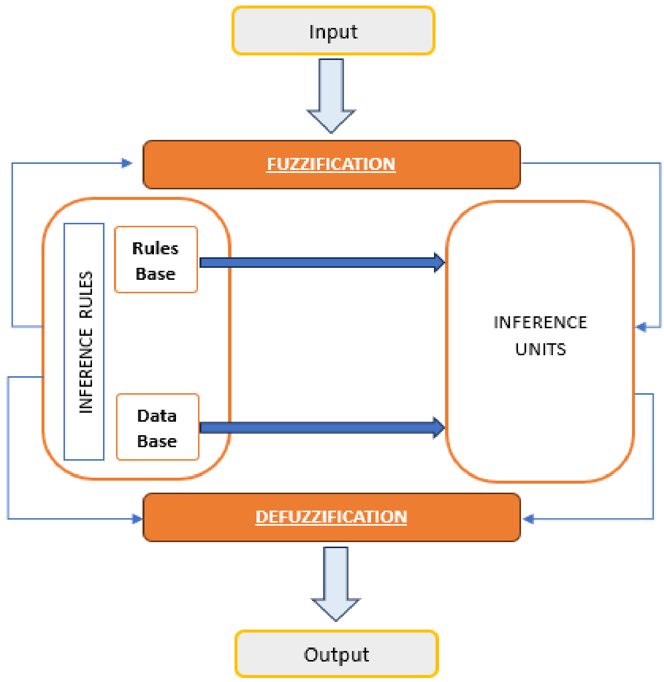

Figure 1. FIS flow chart.

Table 2
Linguistic Terms/Variables and Score

Linguistic Terms/Variables	Affiliation/Membership Score
Bad Sustainability (BS)	(0, 0, 0.25)
Somewhat Bad Sustainability (SBS)	(0, 0.25, 0.5)
Fair Sustainability (FS)	(0.25, 0.5, 0.75)
Good Sustainability (GS)	(0.5, 0.75, 1)
Very Good Sustainability (VGS)	(0.75, 1, 1)

Usually, the "if-then" rule is used for analysis to obtain the affiliation. In this research, to aggregate the fuzzy value, the "product sum" fuzzy operator ($\mathbb{R}(\blacksquare,\oplus)$) is used to aggregate the performance information "Lu, Yu, and Qu 2023 [31]". as shown by (Eq.7).

$$\mathbb{R} = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{11} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix} \times \begin{pmatrix} j_1 \\ j_2 \\ \vdots \\ j_n \end{pmatrix} \qquad \text{(Eq. 7)}$$

In (Eq.7), the fuzzy evaluation value and degree of importance are represented by "x" and "j", respectively. In the inference unit and fuzzification processing, initially, the affiliation tool converts the precise values into triangular fuzzy values, and fuzzy rules are used to build fuzzy results for BS, SBS, FS, GS, and VGS.

The preliminary assessment results of each company are shown by $ES_1 = (t_{11}, t_{21}, \ldots\ldots t_{m1})^T$ new fuzzy matrixes that are developed by using an affiliation function to connect linguistic terms to rating levels, as shown in Eq (8). To combine the developed fuzzy matrix, the fuzzy operator ($\mathbb{R}(\blacksquare,\oplus)$) is used for "product sum". In this research, to express the significance of preferences, the affiliation operator is applied. The affiliation function is illustrated in (Eq.9).

$$F_1 = \begin{bmatrix} (t_{11,}u_{BS}(t_{11})) & (t_{11,}u_{SBS}(t_{11})) \\ (t_{21,}u_{BS}(t_{21})) & (t_{21,}u_{SBS}(t_{21})) \\ \vdots & \vdots \\ (t_{m1,}u_{BS}(t_{m1})) & (t_{m1,}u_{SBS}(t_{m1})) \\ \cdots & (t_{11,}u_{VGS}(t_{11})) \\ \cdots & (t_{21,}u_{VGS}(t_{21})) \\ \cdots & \vdots \\ \cdots & (t_{m1,}u_{VGS}(t_{m1})) \end{bmatrix} \quad \text{(Eq.8)}$$

$$ES_1^* = \left(u_{BS}(t_{11}) \times \frac{u_{BS}(t_{11})}{t_{11}}\right)\left(u_{SBS}(t_{11}) \times \frac{u_{SBS}(t_{11})}{t_{11}}\right) + \cdots + \left(u_{VGS}(t_{m1}) \times \frac{u_{VGS}(t_{11})}{t_{m1}}\right) \quad \text{(Eq.9)}$$

The fuzzy assessment values are developed by the revision of the initial matrix of the GDM via (Eq.8) and (Eq.9). The updated GDM matrix is calculated and illustrated below with preference data.

$$t'_{m\times6} = \begin{bmatrix} t'_{11} & t'_{12} & \cdots & t'_{16} \\ t'_{21} & t'_{22} & \cdots & t'_{26} \\ \vdots & \vdots & \cdots & \vdots \\ t'_{m1} & t'_{m2} & \cdots & t'_{m6} \end{bmatrix} \quad \text{(Eq.10)}$$

The newly generated fuzzy values of C_y are represented by t'_{yp} and can be numerically written as $t'_{yp} = ES^*_{yp} \times u(t_{yp})$.

Ultimately, through the defuzzification process, the newly generated fuzzy numbers are defuzzied by applying (Eq.11). In reference to Gong, Jiang, and Hou [32], the GDM is modified, and the mean value is calculated.

$$t''_{yp} = \frac{t'^{l}_{yp} + t'^{m}_{yp} + t'^{b}_{yp}}{3} \quad \text{(Eq. 11)}$$

$$t''_{m\times6} = \begin{bmatrix} t''_{11} & t''_{12} & \cdots & t''_{16} \\ t''_{21} & t''_{22} & \cdots & t''_{26} \\ \vdots & \vdots & \cdots & \vdots \\ t''_{m1} & t''_{m2} & \cdots & t''_{m6} \end{bmatrix} \quad \text{(Eq. 12)}$$

3.3 Integrated evaluation analysis

The original group decision-making matrix is modified by applying a fuzzy inference system, generating a revised group decision matrix that includes detailed preference information. $t'' = [t''_{yp}]_{m\times6}$. The TOPSIS tool is applied to aggregate the gathered group decision-making data. As a result, the generated ESG assessment is the farthest from the (NIS) negative ideal solution and the nearest to (PIS) positive ideal solution (PIS). Shown below:

$$PIS: \hat{t}_p^{Max} = max(t''_{1p}, t''_{2p}, \ldots., t''_{mp}) \quad \text{(Eq. 13)}$$

$$NIS: \hat{t}_p^{Min} = min(t''_{1p}, t''_{2p}, \ldots., t''_{mp}) \quad \text{(Eq. 14)}$$

In (Eq.13) and (Eq.14), $\hat{t}_p^{Max}$ and $\hat{t}_p^{Min}$ represent the maximum and minimum ESG values granted by ES_p, respectively. Additionally, the distance between C_y and PIS and NIS is represented by Eq. (13) and Eq. (14), which are based on (Eq.13) and (Eq.14).

$$D_y^+ = \sqrt{\sum_{P=1}^{6} (t''_{yp} - \hat{t}_p^{Max})^2} \quad \text{(Eq. 15)}$$

$$D_y^- = \sqrt{\sum_{P=1}^{6} (t''_{yp} - \hat{t}_p^{Min})^2} \quad \text{(Eq. 16)}$$

The distances between C_y and the positive ideal solution (PIS) and negative ideal solution (NIS) are represented by (Eq.15) and (Eq.16), respectively. Furthermore, the ultimate assessment value of the ESG is calculated by using the relative proximity coefficient and expressed in (Eq.17).

$$D_y = \frac{D_y^-}{D_y^- + D_y^+} \quad \text{(Eq. 17)}$$

It is more effective to use D_y integrated multisubject preference information, which reflects real evaluation scenarios, ensuring that the outcomes are widely accepted by most subjects, ultimately achieving group consensus.

3.4 Validation of Validity and Scientific Accuracy

After the calculation of the final ESG results, the relationship between the final ESG score (relative proximity coefficient D_y) and the group evaluation values was analyzed via the Pearson correlation coefficient to validate and confirm the effectiveness and scientific precision of the proposed methodology. As shown in (Eq.18).

$$\rho_{fg} = \frac{cov(f,g)}{\sigma_f \sigma_g} \quad \text{(Eq.18)}$$

where "ρ_{fg}" is used for the Pearson correlation coefficient of the ultimate ESG values (final ESG score) and group assessment values. "$cov(f,g)$" represents the computed covariance between the ultimate score of the ESG and the group assessment values. Here, "f" represents the final value of the ESG, "g" represents the group assessment value, and "$\sigma_f \sigma_g$" is the product of the computed standard deviation of the final values of the ESG and the group assessment value.

3.5 Stepwise Procedure

In this research, the fuzzy inference and group decision-making methods are based on the use of the ESG evaluation technique, which requires consideration of the preferences of numerous and multiple subjects. By using this method, both the difficulty of preserving information integrity and the varied desires of heterogeneous subjects in ESG assessment are fully considered. The use of a group decision-making approach for ESG evaluation promotes group consensus among subjects by guaranteeing that the final ranking results meet their diverse needs. By fuzzifying the assessment information, the hidden preferences of agents can be reflected by fuzzy inference, which enhances the consistency of the results with real evaluation values. The steps of the procedure are as follows.

1. In the initial step of this research, we developed a primary matrix of GDMs on the basis of identified decision makers with heterogeneous preferences in a unique sequence among E, S, and G. Six circumstances or scenarios of preferences for decision makers are developed. Using these scenarios, the preference information is incorporated into the initial group decision matrix, $t_{y\times 6} = (t_{y1}, t_{y2}, \dots . t_{y6}), y = 1,2 \dots . m$.
2. In the second step, we analyze the information and find some complexity and multiplicity in the ESG assessment indicators, features of real values, and information concealed by some analysts. Therefore, to find the real result of the research, we apply FIS for fuzzification of initial evaluation values to obtain the preference of the linguistic relation distribution among the subjects' preferences.

$$\mathcal{U}_y^p = \frac{u_{BS(t_{yp})}}{t_{yp}} + \frac{u_{SBS(t_{yp})}}{t_{yp}} + \frac{u_{FS(t_{yp})}}{t_{yp}} + \frac{u_{GS(t_{yp})}}{t_{yp}} + \frac{u_{VGS(t_{yp})}}{t_{yp}}$$

   Now, to aggregate the preferences $t'_{y\times 6} = (t'_{y1}, t'_{y2}, \dots, t'_{y6})$, the "fuzzy weighted sum" is applied to develop a matrix of fuzzy GDMs with preferences. Furthermore, the defuzzification operator is applied, and the fuzzy GDM matrix is reformed into a new group assessment matrix $t''_{y\times 6} = (t''_{y1}, t''_{y2}, \dots, t''_{y6})$.
3. In this step, the TOPSIS method is used for the calculation of the final ESG assessment value and its ranking. To calculate the ESG assessment final score for each subject, the preference assessment information of the six various subjects is aggregated via the TOPSIS method. Then, the selected companies are ranked according to the computed final ESG score in descending order. Companies with high ESG performance are ranked high, and vice versa. These companies also have outstanding performance in environmental, social, and governance.
4. In the fourth step, we used the TOPSIS method to find the companies ranking in terms of the temperature score (2050) contribution to the global climate goal set by the Paris Agreement, and companies with high rankings in terms of ESG were ranked according to the findings using the TOPSIS method. The high temperature score (2050) companies are ranked in low rank in ascending order because of the global climate goal Paris Agreement temperature range. The Paris Agreement aims to limit global warming to well below 2°C, preferably 1.5°C, above preindustrial levels by 2050 and beyond.

4. Research Case:

4.1 Assessment of the Proposal

In this study, we used the ESG score and temperature score climate goal (2050) of 24 companies in different sectors from Harvest Fund's 2022 and *ESG Book* statistics as a sample and used the keywords "Kaggle" and "ESG book" as data sources. The data are presented in Table 3 & 4. The data measure the ESG performance of selected companies in three distinct categories $[(d_1, Enviromental); (d_2, Social); (d_3, Governance)]$ and the temperature score climate goal (2050).

Table 3
ESG initial score

Company	ESG Score	E Score	S Score	G Score	Temperature Score (2050)
Com 1	775	525	317	300	3
Com 2	1142	520	310	310	1.5
Com 3	1103	500	306	305	1.5
Com 4	734	374	254	210	1.5
Com 5	899	290	333	305	1.5
Com 6	1100	700	340	300	2
Com 7	1049	500	300	300	2.7
Com 8	1148	530	313	305	2.7
Com 9	1242	608	313	305	2.7
Com 10	899	444	310	295	1.5
Com 11	774	675	389	355	2
Com 12	1182	569	363	310	2.7
Com 13	838	500	308	295	3
Com 14	1340	280	234	220	1.5
Com 15	1140	255	334	310	2
Com 16	1005	255	301	300	1.5
Com 17	1419	323	301	275	1.5
Com 18	1111	533	300	300	1.5
Com 19	928	535	300	305	2.7
Com 20	1226	480	329	320	3
Com 21	856	504	368	310	2
Com 22	1140	235	285	255	3
Com 23	1133	295	259	220	1.5
Com 24	1129	500	300	205	2.7

Significant diversity exists among ESG assessment subjects (e.g., analysts, researchers, and investors), and they may demonstrate unpredictable evaluation preferences for a business' ESG performance because of the different scenarios they present or discrepancies in their knowledge structures. Owing to the differences in preferences among heterogeneous subjects (e.g., analysts, researchers, and investors), this study proposes the following method to analyze the ESG evaluation problem. The specific steps are as follows:

Step 1: In this step, the ESG data are normalized via (Eq.2), *but the column "Temperature Score (2050)" remains the same for the later step.*

Table 4
Normalized ESG and E, S, and G initial scores

Company	ESG	E	S	G
Com 1	0.0599	0.6237	0.5355	0.6333
Com 2	0.5956	0.6129	0.4903	0.7000
Com 3	0.5387	0.5699	0.4645	0.6667
Com 4	0.0000	0.2989	0.1290	0.0333
Com 5	0.2409	0.1183	0.6387	0.6667
Com 6	0.5343	1.0000	0.6839	0.6333
Com 7	0.4599	0.5699	0.4258	0.6333
Com 8	0.6044	0.6344	0.5097	0.6667
Com 9	0.7416	0.8022	0.5097	0.6667
Com 10	0.2409	0.4495	0.4903	0.6000
Com 11	0.0584	0.9462	1.0000	1.0000
Com 12	0.6540	0.7183	0.8323	0.7000
Com 13	0.1518	0.5699	0.4774	0.6000
Com 14	0.8847	0.0968	0.0000	0.1000
Com 15	0.5927	0.0430	0.6452	0.7000
Com 16	0.3956	0.0430	0.4323	0.6333
Com 17	1.0000	0.1892	0.4323	0.4667
Com 18	0.5504	0.6409	0.4258	0.6333
Com 19	0.2832	0.6452	0.4258	0.6667
Com 20	0.7182	0.5269	0.6129	0.7667
Com 21	0.1781	0.5785	0.8645	0.7000
Com 22	0.5927	0.0000	0.3290	0.3333
Com 23	0.5825	0.1290	0.1613	0.1000
Com 24	0.5766	0.5699	0.4258	0.0000

Step 2. The six scenarios of subject preferences were subsequently evaluated via Song's study. In this step, the primary GDM matrix is calculated via (Eq.3) on the basis of Table 4. The initial GDM matrix is illustrated in tabulation form in table 5.

Table 5
Computed initial/primary GDM matrix.

Company	ES_1	ES_2	ES_3	ES_4	ES_5	ES_6
Com 1	0.6237	0.6285	0.5975	0.5975	0.6333	0.6333
Com 2	0.6129	0.6565	0.6011	0.6011	0.7000	0.7000
Com 3	0.5699	0.6183	0.5670	0.5670	0.6667	0.6667
Com 4	0.2989	0.2989	0.2140	0.1538	0.1661	0.1538
Com 5	0.4746	0.4746	0.6387	0.6527	0.6667	0.6667
Com 6	1.0000	1.0000	0.8419	0.7724	0.8167	0.7724
Com 7	0.5699	0.6016	0.5430	0.5430	0.6333	0.6333
Com 8	0.6344	0.6505	0.6036	0.6036	0.6667	0.6667
Com 9	0.8022	0.8022	0.6595	0.6595	0.7344	0.6667

Com 10	0.5133	0.5247	0.5133	0.5452	0.6000	0.6000
Com 11	0.9821	0.9821	1.0000	1.0000	1.0000	1.0000
Com 12	0.7753	0.7502	0.8323	0.8323	0.7502	0.7661
Com 13	0.5699	0.5849	0.5491	0.5491	0.6000	0.6000
Com 14	0.0968	0.0984	0.0656	0.0656	0.1000	0.1000
Com 15	0.4627	0.4627	0.6452	0.6726	0.7000	0.7000
Com 16	0.3695	0.3695	0.4323	0.5328	0.6333	0.6333
Com 17	0.3627	0.3627	0.4323	0.4495	0.4667	0.4667
Com 18	0.6409	0.6409	0.5667	0.5667	0.6371	0.6333
Com 19	0.6452	0.6559	0.5792	0.5792	0.6667	0.6667
Com 20	0.6355	0.6468	0.6355	0.6898	0.7667	0.7667
Com 21	0.7215	0.7143	0.8645	0.8645	0.7143	0.7823
Com 22	0.2208	0.2208	0.3290	0.3312	0.3333	0.3333
Com 23	0.1452	0.1301	0.1613	0.1613	0.1301	0.1306
Com 24	0.5699	0.5699	0.4978	0.4258	0.3319	0.3319

Step 3. The exact numbers of the initial group decision-making matrix need linguistic evaluation and the degree of affiliation. Therefore, in this step, we used fuzzification. In fuzzification processing, the precise dataset of Table 5 is converted into relevant linguistic evaluations and affiliation/membership degrees based on Table 2, and (Eq.4) and (Eq.5) are used. This is due to the substantial amount of computed data and the same computation procedure. We use ES_1 as an example to illustrate the data in Table 6.

Table 6
Linguistic evaluation and degree of affiliation/membership

Company	BS	SBS	FS	GS	VGS
Com 1	0.0000	0.0000	0.5054	0.4946	0.0000
Com 2	0.0000	0.0000	0.5484	0.4516	0.0000
Com 3	0.0000	0.0000	0.7204	0.2796	0.0000
Com 4	0.0000	0.8043	0.1957	0.0000	0.0000
Com 5	0.0000	0.1018	0.8982	0.0000	0.0000
Com 6	0.0000	0.0000	0.0000	0.0000	1.0000
Com 7	0.0000	0.0000	0.7204	0.2796	0.0000
Com 8	0.0000	0.0000	0.4624	0.5376	0.0000
Com 9	0.0000	0.0000	0.0000	0.7914	0.2086
Com 10	0.0000	0.0000	0.9470	0.0530	0.0000
Com 11	0.0000	0.0000	0.0000	0.0717	0.9283
Com 12	0.0000	0.0000	0.0000	0.8989	0.1011
Com 13	0.0000	0.0000	0.7204	0.2796	0.0000
Com 14	0.6129	0.3871	0.0000	0.0000	0.0000
Com 15	0.0000	0.1491	0.8509	0.0000	0.0000
Com 16	0.0000	0.5219	0.4781	0.0000	0.0000
Com 17	0.0000	0.5491	0.4509	0.0000	0.0000
Com 18	0.0000	0.0000	0.4366	0.5634	0.0000

Com 19	0.0000	0.0000	0.4194	0.5806	0.0000
Com 20	0.0000	0.0000	0.4581	0.5419	0.0000
Com 21	0.0000	0.0000	0.1140	0.8860	0.0000
Com 22	0.1168	0.8832	0.0000	0.0000	0.0000
Com 23	0.4194	0.5807	0.0000	0.0000	0.0000
Com 24	0.0000	0.0000	0.7204	0.2796	0.0000

After "fuzzification", "*fuzzy rules*" and inference use (if-then) "if-then" inference rules are applied, and to aggregate the affiliation and linguistic preference information 'Table 6', the product sum is used. The study needs a revised group decision-making matrix. To develop this information, we used the *"reasoning units"* approach. According to the results of "Fuzzification" and "Fuzzy rules", the ESG scores of the 24 listed companies were evaluated. To demonstrate the calculation procedures, we choose ES_1 as an example and combine the fuzzy assessment score of ES_1 as the outcome.

$$F_1 = \begin{bmatrix} BS & \cdots & GS & VGS \\ \vdots & \cdots & \vdots & \vdots \\ BS & \cdots & GS & VGS \\ BS & \cdots & GS & VGS \end{bmatrix} \times \begin{bmatrix} 0 & \cdots & 0 & 0 \\ \vdots & \cdots & \vdots & \vdots \\ 0.6237 & \cdots & 0.1452 & 0.5699 \\ 0 & \cdots & 0 & 0.5699 \end{bmatrix}$$

$$ES_1^*(t_{y1}) = \left(BS \times u_{BS}(t_{y1})\right) + \cdots + \left(GS \times u_{GS}(t_{y1})\right) + \left(VGS \times u_{VGS}(t_{y1})\right)$$

$$ES_1^*(t_{1,1}) = (BS \times 0) + \cdots + (GS \times 0.6237) + (VGS \times 0)$$

$$\vdots$$

$$ES_1^*(t_{24,1}) = (BS \times 0) + \cdots + (GS \times 0.5699) + (VGS \times 0.5699)$$

An alternative technique for creating the Revised Group Evaluation Score is the "Additive Subtractive Balancing" method, which is shown in Table 7. Tables 2 and 5 must be consulted while using this method. The lowest nonzero affiliation function (0.25) of all linguistic variables from Table 1 is added to the initial base value of Table 3 to obtain the right-side values of each revised group evaluation score in Table 7.

Table 7
Modified assessment group fuzzy group score

Company	ES_1			ES_2			ES_3			ES_4			ES_5			ES_6		
Com 1	0.3737	0.6237	0.8737	0.3785	0.6285	0.8785	0.3475	0.5975	0.8475	0.3475	0.5975	0.8475	0.3833	0.6333	0.8833	0.3833	0.6333	0.8833
Com 2	0.3629	0.6129	0.8629	0.4065	0.6565	0.9065	0.3511	0.6011	0.8511	0.3511	0.6011	0.8511	0.4500	0.7000	0.9500	0.4500	0.7000	0.9500
Com 3	0.3199	0.5699	0.8199	0.3683	0.6183	0.8683	0.3170	0.5670	0.8170	0.3170	0.5670	0.8170	0.4167	0.6667	0.9167	0.4167	0.6667	0.9167
Com 4	0.0489	0.2989	0.5489	0.0489	0.2989	0.5489	0.0000	0.2140	0.4640	0.0000	0.1538	0.4038	0.0000	0.1661	0.4161	0.0000	0.1538	0.4038
Com 5	0.2246	0.4746	0.7246	0.2246	0.4746	0.7246	0.3887	0.6387	0.8887	0.4027	0.6527	0.9027	0.4167	0.6667	0.9167	0.4167	0.6667	0.9167
Com 6	0.7500	1.0000	1.0000	0.7500	1.0000	1.0000	0.5919	0.8419	1.0000	0.5224	0.7724	1.0000	0.5667	0.8167	1.0000	0.5224	0.7724	1.0000
Com 7	0.3199	0.5699	0.8199	0.3516	0.6016	0.8516	0.2930	0.5430	0.7930	0.2930	0.5430	0.7930	0.3833	0.6333	0.8833	0.3833	0.6333	0.8833
Com 8	0.3844	0.6344	0.8844	0.4005	0.6505	0.9005	0.3536	0.6036	0.8536	0.3536	0.6036	0.8536	0.4167	0.6667	0.9167	0.4167	0.6667	0.9167
Com 9	0.5522	0.8022	1.0000	0.5522	0.8022	1.0000	0.4095	0.6595	0.9095	0.4095	0.6595	0.9095	0.4844	0.7344	0.9844	0.4167	0.6667	0.9167
Com 10	0.2633	0.5133	0.7633	0.2747	0.5247	0.7747	0.2633	0.5133	0.7633	0.2952	0.5452	0.7952	0.3500	0.6000	0.8500	0.3500	0.6000	0.8500
Com 11	0.7321	0.9821	1.0000	0.7321	0.9821	1.0000	0.7500	1.0000	1.0000	0.7500	1.0000	1.0000	0.7500	1.0000	1.0000	0.7500	1.0000	1.0000
Com 12	0.5253	0.7753	1.0000	0.5002	0.7502	1.0000	0.5823	0.8323	1.0000	0.5823	0.8323	1.0000	0.5002	0.7502	1.0000	0.5161	0.7661	1.0000
Com 13	0.3199	0.5699	0.8199	0.3349	0.5849	0.8349	0.2991	0.5491	0.7991	0.2991	0.5491	0.7991	0.3500	0.6000	0.8500	0.3500	0.6000	0.8500
Com 14	0.0000	0.0968	0.3468	0.0000	0.0984	0.3484	0.0000	0.0656	0.3156	0.0000	0.0656	0.3156	0.0000	0.1000	0.3500	0.0000	0.1000	0.3500
Com 15	0.2127	0.4627	0.7127	0.2127	0.4627	0.7127	0.3952	0.6452	0.8952	0.4226	0.6726	0.9226	0.4500	0.7000	0.9500	0.4500	0.7000	0.9500
Com 16	0.1195	0.3695	0.6195	0.1195	0.3695	0.6195	0.1823	0.4323	0.6823	0.2828	0.5328	0.7828	0.3833	0.6333	0.8833	0.3833	0.6333	0.8833
Com 17	0.1127	0.3627	0.6127	0.1127	0.3627	0.6127	0.1823	0.4323	0.6823	0.1995	0.4495	0.6995	0.2167	0.4667	0.7167	0.2167	0.4667	0.7167
Com 18	0.3909	0.6409	0.8909	0.3909	0.6409	0.8909	0.3167	0.5667	0.8167	0.3167	0.5667	0.8167	0.3871	0.6371	0.8871	0.3833	0.6333	0.8833
Com 19	0.3952	0.6452	0.8952	0.4059	0.6559	0.9059	0.3292	0.5792	0.8292	0.3292	0.5792	0.8292	0.4167	0.6667	0.9167	0.4167	0.6667	0.9167
Com 20	0.3855	0.6355	0.8855	0.3968	0.6468	0.8968	0.3855	0.6355	0.8855	0.4398	0.6898	0.9398	0.5167	0.7667	1.0000	0.5167	0.7667	1.0000
Com 21	0.4715	0.7215	0.9715	0.4643	0.7143	0.9643	0.6145	0.8645	1.0000	0.6145	0.8645	1.0000	0.4643	0.7143	0.9643	0.5323	0.7823	1.0000
Com 22	0.0000	0.2208	0.4708	0.0000	0.2208	0.4708	0.0790	0.3290	0.5790	0.0812	0.3312	0.5812	0.0833	0.3333	0.5833	0.0833	0.3333	0.5833
Com 23	0.0000	0.1452	0.3952	0.0000	0.1301	0.3801	0.0000	0.1613	0.4113	0.0000	0.1613	0.4113	0.0000	0.1301	0.3801	0.0000	0.1306	0.3806
Com 24	0.3199	0.5699	0.8199	0.3199	0.5699	0.8199	0.2478	0.4978	0.7478	0.1758	0.4258	0.6758	0.0819	0.3319	0.5819	0.0819	0.3319	0.5819

Similarly, the lowest nonzero affiliation function (0.25) from Table 2 is deducted from the initial base value in Table 7 to determine the left-side values of each revised group evaluation score in Table 7. If the calculated values exceed the upper bound 1 defined in Table 2, they are capped at 1. Conversely, if the resulting value is negative, it is set to 0.

For example, the ES_1 value for Com1 is 0.6237 in Table 5, so the revised group evaluation score is calculated for ES_1 for Com1 as follows:
Right-hand side value, 0.6237+0.25= 0.8737
The left-hand side value is 0.6237-0.25= 0.3737.

However, the revised group assessment scores of ES_1 for Com1 are 0.3737, 0.6237 and 0.8737.

Finally, through the "***Defuzzification"*** process, the revised group assessment fuzzy score is defuzzied via equation (11). The resulting updated GDM matrix is a new group decision-making matrix along the comprehensive preference score via defuzzification of the fuzzy numbers, as illustrated in Table 8.

Table 8
Revised assessment score

Company	ES_1	ES_2	ES_3	ES_4	ES_5	ES_6
Com 1	0.6237	0.6285	0.5975	0.5975	0.6333	0.6333
Com 2	0.6129	0.6565	0.6011	0.6011	0.7000	0.7000
Com 3	0.5699	0.6183	0.5670	0.5670	0.6667	0.6667
Com 4	0.2989	0.2989	0.2260	0.1859	0.1941	0.1859
Com 5	0.4746	0.4746	0.6387	0.6527	0.6667	0.6667
Com 6	0.9167	0.9167	0.8113	0.7649	0.7945	0.7649
Com 7	0.5699	0.6016	0.5430	0.5430	0.6333	0.6333
Com 8	0.6344	0.6505	0.6036	0.6036	0.6667	0.6667
Com 9	0.7848	0.7848	0.6595	0.6595	0.7344	0.6667
Com 10	0.5133	0.5247	0.5133	0.5452	0.6000	0.6000
Com 11	0.9047	0.9047	0.9167	0.9167	0.9167	0.9167
Com 12	0.7669	0.7501	0.8049	0.8049	0.7501	0.7607
Com 13	0.5699	0.5849	0.5491	0.5491	0.6000	0.6000
Com 14	0.1479	0.1489	0.1271	0.1271	0.1500	0.1500
Com 15	0.4627	0.4627	0.6452	0.6726	0.7000	0.7000
Com 16	0.3695	0.3695	0.4323	0.5328	0.6333	0.6333
Com 17	0.3627	0.3627	0.4323	0.4495	0.4667	0.4667
Com 18	0.6409	0.6409	0.5667	0.5667	0.6371	0.6333
Com 19	0.6452	0.6559	0.5792	0.5792	0.6667	0.6667
Com 20	0.6355	0.6468	0.6355	0.6898	0.7611	0.7611
Com 21	0.7215	0.7143	0.8263	0.8263	0.7143	0.7715
Com 22	0.2305	0.2305	0.3290	0.3312	0.3333	0.3333
Com 23	0.1801	0.1701	0.1909	0.1909	0.1701	0.1704
Com 24	0.5699	0.5699	0.4978	0.4258	0.3319	0.3319

Step 4. To calculate the ESG assessment value of 24 companies, the PIS and NIS values are needed. Therefore, in this step, we measured the PIS and NIS values from Table 8 via Eq. (13) and Eq. (14), respectively.

$\hat{t}_p^{Max} = (0.9167, 0.9167, 0.9167, 0.9167, 0.9167, 0.9167)$

$\hat{t}_p^{Min} = (0.1479, 0.1489, 0.1271, 0.1271, 0.1500, 0.1500)$

Now, we compute the relative proximity coefficient or final ESG score (the proposed ESG score) via Eq. (15), Eq. (16), and Eq. (17). In Table 9, the computed ESG score is given.

Table 9
ESG Score for 24 Companies

Company	ESG Score	Company	ESG Score
Com 1	0.6190	Com 13	0.5593
Com 2	0.6475	Com 14	0.0000
Com 3	0.6015	Com 15	0.5940
Com 4	0.1287	Com 16	0.4591
Com 5	0.5820	Com 17	0.3658
Com 6	0.8627	Com 18	0.6085
Com 7	0.5739	Com 19	0.6311
Com 8	0.6389	Com 20	0.7004
Com 9	0.7332	Com 21	0.7937
Com 10	0.5256	Com 22	0.2099
Com 11	1.0000	Com 23	0.0535
Com 12	0.8127	Com 24	0.4101

To authenticate the accuracy of the proposed method, the final ESG score (relative proximity coefficient D_y) and the group evaluation values were analyzed via the Pearson correlation coefficient via Eq.18. The common statistical technique for bivariate correlation coefficient research is Pearson's correlation coefficient. The common statistics and their indications are shown in the following table 10.

Table 10
Common Pearson's correlation coefficient and their indications

ρ Values Rang	Indications
0.90 to 1.00	Very Strong Correlation
0.70 to 0.89	Strong Correlation
0.50 to 0.69	Moderate Correlation
0.30 to 0.49	Weak Correlation
0.00 to 0.29	Very or Extremely Weak or Zero Correlation

Table 11
The Pearson correlation coefficient (**ρ**) results

	ES_1	ES_2	ES_3	ES_4	ES_5	ES_6
Pearson Correlation coefficient (**ρ**)	0.9504	0.9506	0.9814	0.9790	0.9659	0.9639

The Pearson correlation coefficient (ρ) results or ESG evaluation score values are calculated by applying the proposed method in Table 11, which shows the very high and strongest correlation from ES1 to ES6. The proposed method ranking can be seen as more suitable for heterogeneous subjects.

4.2 DISCUSSION:

4.2.1 *Ranking comparisons of the three methods:*

The initial data (Table 3) are contrasted with ESG assessment values. The ESG initial score (normalized form) and general GDM demonstrate the advantages of the proposed method in this article. The calculated rankings and ESG assessment values are listed in Table 1

Table 12 ESG scores of diverse methods and stacking

Company	Harvest method		GDM method		Proposed Method	
	Initial Score	Ranking	GDM Scores	Ranking	Score	Ranking
Com 1	0.0599	22	0.5975	9	0.6190	10
Com 2	0.5956	7	0.6011	8	0.6475	7
Com 3	0.5387	13	0.5670	11	0.6015	12
Com 4	0.0000	24	0.1537	22	0.1287	22
Com 5	0.2409	18	0.4746	16	0.5820	14
Com 6	0.5343	14	0.7724	2	0.8627	2
Com 7	0.4599	15	0.5430	14	0.5739	15
Com 8	0.6044	6	0.6036	7	0.6389	8
Com 9	0.7416	3	0.6595	5	0.7332	5
Com 10	0.2409	18	0.5133	15	0.5256	17
Com 11	0.0584	23	0.9821	1	1.0000	1
Com 12	0.6540	5	0.7502	3	0.8127	3
Com 13	0.1518	21	0.5491	13	0.5593	16
Com 14	0.8847	2	0.0656	24	0.0000	24
Com 15	0.5927	8	0.4627	17	0.5940	13
Com 16	0.3956	16	0.3695	18	0.4591	18
Com 17	1.0000	1	0.3627	19	0.3658	20
Com 18	0.5504	12	0.5667	12	0.6085	11
Com 19	0.2832	17	0.5792	10	0.6311	9
Com 20	0.7182	4	0.6355	6	0.7004	6
Com 21	0.1781	20	0.7143	4	0.7937	4
Com 22	0.5927	8	0.2208	21	0.2099	21
Com 23	0.5825	10	0.1301	23	0.0535	23
Com 24	0.5766	11	0.3319	20	0.4101	19

Currently, the correlation between ESG evaluation scores measured by three different techniques, e.g., Harvest, Group Decision Making, and the proposed method, needs to be calculated. In this study, we used Spearman's rank correlation coefficient. The results of the evaluation are calculated via the equation below and are shown in Table 13.

$$r_s = 1 - \frac{6\sum_{y=1}^{m}(b_y)^2}{n(n^2-1)}$$

In the above equation, the ranking difference of y^{th} company (Com_y) is represented as "b_y", where "n" denotes the number of listed companies. The Spearman's rank correlation coefficient analysis results shown in Table 13 indicate that the proposed method outperforms the other two techniques. The proposed method shows a 9.17% improvement over the harvest data ranking and a 0.02% increase over the GDM. Harvest and *ESG Book* data analysis revealed negative values compared with those of the GDM and proposed methods.

Table 13
Spearman's ranking correlation coefficient

Method	Environmental	Social	governance	average	Impact	
Harvest	-0.1343	-0.0891	-0.0270	-0.0835		
GDM	0.8265	0.8143	0.7617	0.8009	+9.15%	
Proposed Method	0.7926	0.8404	0.8226	0.8186	+9.17%	+0.02%

4.2.2 *Other Comparisons*

The same tool is applied to compute the relationship between the component value and final score within different sample sizes of different datasets to verify and investigate the influence of the dataset and sample size on the proposed method.

Table 14
Spearman's rank correlation coefficient using different sample sizes and different datasets

Method	Samples Size	environmental	social	governance	average	impact	
Harvest	24	-0.1343	-0.0891	-0.027	-0.0835		
GDM		0.8265	0.8143	0.7617	0.8009	+9.15%	
Proposed Method		0.7926	0.8404	0.8226	0.8186	+9.17%	+0.02%
Harvest	30	0.0905	0.8033	0.7864	0.5601		
GDM		0.4154	0.7241	0.6013	0.5802	+2.01%	
Proposed method		0.479	0.7237	0.608	0.6036	+4.35%	+2.33%

The above investigation shown in Table 14 reveals that different sample sizes and different datasets have no effect on the proposed method. For various samples, it performs more effectively than the harvest approach does, and a slice/miner improvement than group decision-making depends on the accuracy of the data.

4.2.3 *Ranking Comparison of the Three Methods with the 2050 Climate Goal (Paris Agreement)*

This study needs to compare the obtained rankings of the three methods with the temperature score 2050 of 24 selected companies. Referring to Table

4, in the temperature score 2050 column, we initially normalized the score via (Eq.2). The results are shown below in Table 15.

Table 15

Temperature score 2050 of 24 companies and normalized score

Company	Temperature Score (2050)	Normalized Temperature Score (2050)	Company	Temperature Score (2050)	Normalized Temperature Score (2050)
Com 1	3	1.0000	Com 13	3	1.0000
Com 2	1.5	0.0000	Com 14	1.5	0.0000
Com 3	1.5	0.0000	Com 15	2	0.3333
Com 4	1.5	0.0000	Com 16	1.5	0.0000
Com 5	1.5	0.0000	Com 17	1.5	0.0000
Com 6	2	0.3333	Com 18	1.5	0.0000
Com 7	2.7	0.8000	Com 19	2.7	0.8000
Com 8	2.7	0.8000	Com 20	3	1.0000
Com 9	2.7	0.8000	Com 21	2	0.3333
Com 10	1.5	0.0000	Com 22	3	1.0000
Com 11	2	0.3333	Com 23	1.5	0.0000
Com 12	2.7	0.8000	Com 24	2.7	0.8000

To obtain the rankings of the companies in terms of the temperature score (2050) of the global climate change goal (Paris Agreement), we used the TOPSIS method to calculate the rankings in ascending order using either the simple temperature score (2050) or the normalized temperature score (2050), and the ranking results were the same. The temperature score (2050) and Raking data are shown in Table 16.

Table 16

Temperature Score (2050) and Raking

Company	Normalized Temperature Score (2050)	Ranking	Company	Normalized Temperature Score (2050)	Ranking
Com 1	1.0000	21	Com 13	1.0000	21
Com 2	0.0000	1	Com 14	0.0000	1
Com 3	0.0000	1	Com 15	0.3333	11
Com 4	0.0000	1	Com 16	0.0000	1
Com 5	0.0000	1	Com 17	0.0000	1
Com 6	0.3333	11	Com 18	0.0000	1
Com 7	0.8000	15	Com 19	0.8000	15
Com 8	0.8000	15	Com 20	1.0000	21
Com 9	0.8000	15	Com 21	0.3333	11
Com 10	0.0000	1	Com 22	1.0000	21
Com 11	0.3333	11	Com 23	0.0000	1
Com 12	0.8000	15	Com 24	0.8000	15

In Table 16, the companies are ranked on the basis of the temperature score (2050) and align with the climate goal of the Paris Agreement. The normalized temperature score of 0.0000 suggests that companies have the best alignment with the Paris Agreement, are ranked 1 and have no net warming impact. Conversely, companies with higher scores (such as 1.0000) are less aligned with climate goals because they are causing more warming.

In this part of the study, we compared the above temperature score (2050) rankings with the obtained rankings of the three methods to determine the accuracy of the data. ranking is shown in Table 17.

Table 17
Comparison of the three methods in terms of the temperature score (2050) ranking

Company	Harvest Method		GDM Method		Proposed Method		Normalized Temperature Score (2050)	Ranking
	Initial score	ranking	GDM scores	ranking	score	ranking		
Com 1	0.0599	22	0.5975	9	0.6190	10	1.0000	21
Com 2	0.5956	7	0.6011	8	0.6475	7	0.0000	1
Com 3	0.5387	13	0.5670	11	0.6015	12	0.0000	1
Com 4	0.0000	24	0.1537	22	0.1287	22	0.0000	1
Com 5	0.2409	18	0.4746	16	0.5820	14	0.0000	1
Com 6	0.5343	14	0.7724	2	0.8627	2	0.3333	11
Com 7	0.4599	15	0.5430	14	0.5739	15	0.8000	15
Com 8	0.6044	6	0.6036	7	0.6389	8	0.8000	15
Com 9	0.7416	3	0.6595	5	0.7332	5	0.8000	15
Com 10	0.2409	18	0.5133	15	0.5256	17	0.0000	1
Com 11	0.0584	23	0.9821	1	1.0000	1	0.3333	11
Com 12	0.6540	5	0.7502	3	0.8127	3	0.8000	15
Com 13	0.1518	21	0.5491	13	0.5593	16	1.0000	21
Com 14	0.8847	2	0.0656	24	0.0000	24	0.0000	1
Com 15	0.5927	8	0.4627	17	0.5940	13	0.3333	11
Com 16	0.3956	16	0.3695	18	0.4591	18	0.0000	1
Com 17	1.0000	1	0.3627	19	0.3658	20	0.0000	1
Com 18	0.5504	12	0.5667	12	0.6085	11	0.0000	1
Com 19	0.2832	17	0.5792	10	0.6311	9	0.8000	15
Com 20	0.7182	4	0.6355	6	0.7004	6	1.0000	21
Com 21	0.1781	20	0.7143	4	0.7937	4	0.3333	11
Com 22	0.5927	8	0.2208	21	0.2099	21	1.0000	21
Com 23	0.5825	10	0.1301	23	0.0535	23	0.0000	1
Com 24	0.5766	11	0.3319	20	0.4101	19	0.8000	15

The table shows significant discrepancies between firm rankings based on harvest and *ESG Book* scores, GDM scores, and the proposed method with a temperature score (2050) ranking. Some companies are ranked in Harvest Scores, GDM Scores and the Proposed Method at the top but are ranked lower in the temperature score (2050) Paris Agreement align and vice versa. This variation in ranking highlights that, in the evaluation, the data contain biases and inconsistencies either in the ESG score or in the temperature score (2050) of the Paris Agreement.

5. Conclusion:

This research presents an innovative approach to handle stakeholder preference heterogeneity when performing ESG assessments by integrating group decision making (GDM) with fuzzy inference system (FIS) techniques. The method starts by building a GDM matrix based on the three core ESG dimensions that incorporate diverse stakeholder preferences. The FIS is used to reveal hidden preferences before the TOPSIS method aggregates the GDM matrix to generate the ESG score and ranking results. The method's effectiveness and enhancements are confirmed through the application of Spearman's rank correlation. The results obtained from the analysis are matched against the temperature score (2050) of the Paris Agreement to confirm the alignment of the rankings and data precision.

This study presents important findings to help investment agencies and financial institutions that carry out ESG evaluations and release reports. Through this method, investment agencies can better incorporate stakeholder preference variations for each ESG dimension to achieve more accurate aggregation and decision-making for investment attraction in financial markets. This method resolves stakeholder preference complexity issues, which leads to missing and unbalanced evaluations that equal-weighted scoring methods frequently produce. FIS integration enhances assessment accuracy by revealing hidden preferences while providing broader stakeholder viewpoint representations.

This study reveals ESG ranking discrepancies and variations that demonstrate existing biases and inconsistencies between ESG and temperature score (2050) evaluations. Traditional performance metrics show inconsistent alignment with climate sustainability goals because their variations occur. The research improves the accuracy of the temperature score (2050) by using FIS, which extracts hidden preferences to create a better evaluation tool for investors to assess environmental company commitments.

This research has multiple recognized constraints. ESG evaluation institutions use varying group weights on the basis of their organizational objectives, which produce results that may align with investor interests. The study enhances ESG data interpretability through concealed preference extraction but does not fully address corporate misconduct and data presentation biases. Further research should integrate these elements to create improved models that better represent total ESG performance alongside corporate violations and misconduct while better fulfilling Paris Agreement climate targets.

This research presents an advanced ESG evaluation framework that increases accuracy and reduces rating agency inconsistencies. The reliable ESG score provided by investors enables better choices, which leads investors to select companies with superior sustainability practices. This research advances decision science by combining fuzzy reasoning with decision-making techniques to handle preference heterogeneity in assessments. This method helps establish standardized ESG frameworks that deliver fair and consistent results during assessments. This approach improves the trustworthiness of ESG rating agencies while building a responsible financial environment. Companies can use this framework to enhance their ESG performance while boosting their reputation and securing additional investors, which produces financial success alongside sustainability achievements".

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Author Contributions

Hussain Muhammad Irshad and Dramane Thiombiano conceived the study. Hussain Muhammad Irshad developed the methodology, with software support from Zakir Khan. Validation was performed by Hussain Muhammad Irshad, Dramane Thiombiano. Hussain Muhammad Irshad conducted the formal analysis and investigation, while Dramane Thiombiano provided resources. Zakir Khan handled data curation. The original draft was written by Hussain Muhammad Irshad, with review and editing by Dramane Thiombiano. Zakir Khan contributed to visualization, and Dramane Thiombiano supervised the project. Hussain Muhammad Irshad managed project administration. All authors reviewed and approved the final manuscript.

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The data will be available on reasonable request.

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The authors have no competing interests in this study.

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