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ORIGINAL RESEARCH

Determining the underlying role of corporate sustainability criteria in a ranking problem using UW-TOPSIS

A. López-García[1] · V. Liern[1] · B. Pérez-Gladish[2]

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Abstract
ESG criteria are becoming increasingly important for institutional and retail investors with a consequent growing demand of reliable and transparent ESG data to support their decisions. Several ESG rating agencies assess companies providing ratings and rankings. However, their rating methodologies are subject to some criticisms. One of the main weaknesses is the determination of the relative importance of the ESG criteria involved in the rating process. In this work, we propose the use of a MCDM rating and ranking approach with which the decision maker can rank firms based on their ESG global performance without the elicitation of aggregation weights. The approach, UW-TOPSIS, provides three outputs: the global ESG rating of the firms, a ranking based on the ratings and, for each alternative, a vector of weights describing the discriminatory power of the ESG criteria on the alternative, thus overcoming one of the criticisms to the methodologies of ESG rating agencies. However, UW-TOPSIS has a limitation as it does not provide a global vector of weights valid for all the alternatives in the ranking, expressing the overall role or contribution of each criteria to the componsition of the ranking. The acknowledge and analysis of this situation and the proposal of a solution, is the main objective of this paper.

Keywords MCDA · UW-TOPSIS · ESG criteria · Weighting schemes

1 Introduction

Environmental, Social and Governance (ESG) factors are becoming increasingly important in investment decision making, not only due to new regulatory frameworks, but also due to the change on the priorities of both, institutional and retail investors. Firms have started to respond to the change on investors' priorities and they have started to redesign their business models. The COVID-19 pandemic has shown us that those business models which incorporate ESG

✉ B. Pérez-Gladish
bperez@uniovi.es

1 Department of Mathematics for Economics and Business, University of Valencia, Avda. Dels Tarongers, s/n, 46022 Valencia, Spain

2 Department of Quantitative Economics, University of Oviedo, Avda. Del Cristo s/n, 33006 Oviedo, Spain

factors are often better prepared for crisis management, being less exposed to the negative effects of technological or regulatory disruptions (Reteurs, 2020).

The availability of transparent and reliable ESG data allowing the assessment of the different investment alternatives is crucial. Investors, asset managers, financial institutions and other stakeholders are increasingly relying on the ESG ratings and rankings provided by ESG rating agencies.

ESG rating agencies try to measure how well a company has performed highlighting areas that need improvement. They are usually used by firms to identify opportunities in terms of weaknesses or strenghs. However, as stated by Deloitte (2022) "there is no one-fits-all methodology to analyse ESG data used by rating agencies". In order to get an overall ESG score, each pillar is evaluated individually according to several criteria grouped into several categories. ESG data from the companies is the first required input in any ESG rating process. However, it is not the only one. Other important inputs are the relative importance of the ESG criteria and the comparison method used in the aggregation process. The individual scores are aggregated into an overall or global score that represents the ESG rating of the firm. This aggregation is usually carried out by using a weighted average and by usually considering equal weights. Larker et al. (2022) point out the fact that, surprisingly, several recent studies find low correlations across ESG ratings from main rating agencies. Berg et al. (2022) go one step further, pointing out that main reasons behind these low correlations are the selection of the decision criteria, the assessment method and the weights representing the relative importance of the criteria in the aggregation process.

In this work, we focus on the problem related to the criteria weighting, using a method based on the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), a distance-based Multiple Criteria Decision Making (MCDM) method, widely used to assist decision makers in analysis, comparisons, and rankings of decision alternatives (Hwang & Yoon, 1981).

In the context of the problem addressed in this paper, TOPSIS needs only two main inputs for its evaluation: weights on criteria and the ratings of the firms on the ESG criteria. Contrary to what happens with other methods, TOPSIS relies more on the data rather than on an exhaustive analysis of the decision makers' preferences. This is probably one of the reasons why TOPSIS is such a widely used analysis, comparison and ranking method compared to other methods (Shih & Olson, 2022).

The implication on the results of different choices of weights is an issue that, within the framework of TOPSIS, has not been sufficiently discussed (Olson, 2004). As we will see in the next section, several methods have been applied in the TOPSIS framework to elicit weights objectively or subjective, depending on the context of the addressed problem. Nevertheless, in many real decision situations, the decision maker is not able or does not want to elicitate, objectively or subjectively, those weights. This is the situation addressed by UW-TOPSIS.

Un-weighted TOPSIS (UW-TOPSIS) proposed by Liern and Pérez-Gladish (2022) addresses this problem obtaining global ratings based on the best and worst possible situation of each firm without the elicitation of a vector of weights. However, UW-TOPSIS has a drawback: the decision maker does not have decisional information on the relative importance of each criterion in the determining of the obtained ranking. The contribution of this work lies in the identification and description of this problem and its managerial implications.

The rest of the paper is organized as follows. In the following section we carry out a review of the literature describing the main positive and negative features of TOPSIS, focusing on the problematic around the elicitation of weights. Next, in Sect. 3, we describe the UW-TOPSIS algorithm drawing attention to an important managerial limitation of the method: obtaining decisional weights. In this section we deepen on this limitation analizing its consequences from a managerial point of view. In Sect. 4, we propose a solution and in Sect. 5, to illustrate both, the applicability of the proposed approach and the managerial problematic around it and we present a real case study where we rate and rank a set of firms based on Environment, Social and Governance (ESG) and financial criteria. The last section presents the main conclusions of the work.

2 Literature revision

TOPSIS allows the selection of those alternatives that have the shortest distance from the positive ideal solution (PIS) and the farther distance from the negative-ideal solution (NIS). The positive ideal solution maximizes criteria of the type "the more, the better" and minimizes criteria of the type "the less, the better", whereas the negative ideal solution maximizes "the less, the better" criteria and minimizes "the more, the better" criteria. Based on this and making full use of the attribute information, TOPSIS provides a cardinal ranking of the decision alternatives without requiring independency of the attribute preferences (Chen & Hwang, 1992; Yoon & Hwang, 1995). Due to its popularity, several developments, extensions and applications of the classical TOPSIS method have been proposed in the last decades (Behzadian et al., 2012). The different new approaches depend on the type of the data in the decision matrix, the data normalization process, the type of decision criteria weighting schemes and the selection of distance functions to measure the proximity to the PIS and NIS.

Among the reasons behind the high popularity of TOPSIS, researchers highlight that it is a logic technique able to easily express the rationale of human choice (Corrente & Tasiou, 2023; Huang & Li, 2012; Okul et al., 2014; Olson, 2004; Parkan & Wu, 1997; Roszkowska, 2011). It is also a simple computation process that provides, in its classical formulation a scalar value which quickly measures the relative performance of each alternative considering the best and worst alternatives, simultaneously (Huang & Li, 2012; Kaliszewski & Podkopaev, 2016; Kim et al., 1997; Olson, 2004; Parkan & Wu, 1997; Roszkowska, 2011; Zavadskas et al., 2016).

Several authors have compared the performance of TOPSIS with other techniques such as AHP (Saaty, 1980), ELECTRE (Benayoun et al., 1966) or PROMETHEE (Brans et al., 1984),. Zanakis et al. (1998) conclude that TOPSIS presents few rank reversals compared to ELECTRE, the Multiplicative Exponential Weighting (MEW), the Simple Additive Weighting (SAW), and four versions of AHP problems. Zavadskas et al. (2016) conclude that when compared to AHP, ELECTRE and PROMETHEE the performance of TOPSIS is slightly modified by the number of alternatives and "rank discrepancies are amplified to a lesser extent for increasing values of the number of alternatives and the number of criteria" (Zavadskas et al., 2016). Table 1 summarizes some of the main advantages of classical TOPSIS and its extensions.

However, TOPSIS presents some disadvantages. Table 2 displays some of the main criticisms to this method and its extensions, which are mostly related to the lack of a unified normalization process, the absence of a scheme for weight elicitation and the consequences related to the use of different distance functions. It can also present rank reversal problems. Different extensions of the classical TOPSIS approach have tried to overcome some of these limitations. The choice of the normalization process can alter the results in terms of the ranking. Normalization can give rise to a narrow difference among the data making difficult to reflect the true dominance of alternatives. Liern et al. (2020) delven into this question considering both, precise and imprecise data given by intervals and provide a solution based

Table 1 Main advantages TOPSIS. *Source*: Shih and Olson (2022)

Authors	Main Advantages
Parkan and Wu (1997), Olson (2004), Roszkowska (2011), Huang and Li (2012), Okul et al. (2014), Corrente and Tasiou (2023)	A compromise can be efficiently obtained
Kim et al. (1997), Olson (2004), Roszkowska (2011), Huang and Li (2012), Zavadskas et al. (2016), Kaliszewski and Podkopaev (2016)	It uses logical thinking that represents the rationale of human choice
Kim et al. (1997), Olson (2004), Roszkowska (2011), Huang and Li (2012), Zavadskas et al. (2016)	It has a scalar value that expresses both the best and worst alternatives simultaneously
Kim et al. (1997), Parkan and Wu (1997), Olson (2004), Roszkowska (2011), Huang and Li (2012), Zavadskas et al. (2016), Kaliszewski and Podkopaev (2016)	It uses a comprehensible computation process that can be easily programmed into a spreadsheet
Zanakis et al. (1998)	Few rank reversals compared to similar methods

Table 2 Main disadvantages of TOPSIS. *Source*: Shih and Olson (2022)

Authors	Disadvantages
Huang and Li (2012), Okul et al. (2014), Kaliszewski and Podkopaev (2016), Corrente and Tasiou (2023)	It does not provide a scheme for weight elicitation
Opricovic and Tzeng (2004), Milani et al. (2005), Huang and Li (2012), Çelen (2014), Chatterjee and Chakraborty (2014), Zavadskas et al. (2016), Acuña-Soto et al. (2021), Vafaei et al. (2018), Corrente and Tasiou (2023)	There is not a unified normalization processes
Huang and Li (2012), Kuo (2017)	Few discussions around the components of an measurement of the relative closeness
Corrente and Tasiou (2023)	Very few contributions to TOPSIS deal with non-monotonic direction of preference
Opricovic and Tzeng (2004), Milani et al. (2005), Çelen (2014), Chatterjee and Chakraborty (2014), Vafaei et al. (2018), Acuña-Soto et al. (2021), Corrente and Tasiou (2023)	The use of different distance functions of each alternative from the PIS and NIS can alter the results
García-Cascales and Lamata (2012), Zavadskas et al. (2016)	Under certain conditions, possibility of rank reversal

on the use of membership functions. Discussion around judgment rules for the decision on the components of relative closeness has been addressed by Behavioral TOPSIS (see Shih & Olson, 2022 for a very good description).

Authors as Huang and Li (2012), Okul et al. (2014), Kaliszewski and Podkopaev (2016) and Corrente and Tasiou (2023) point out, as a disadvantage of TOPSIS, a lack of a framework for weights elicitation. In the classical TOPSIS approach preferential weights are usually introduced as inputs in the third step of the algorithm, after normalization of the decision matrix. The weights are generally directly given by the decision maker or the analyst in the beginning of the assessment process and, as in other compensatory MCDM models, they express the relative importance of each criterion reflecting decision maker's relative preference (Yoon & Hwang, 1995). The choice of the weights representing the relative importance of the decision criteria, is an important step in the application of TOPSIS, because different vectors of weights could provide different results (Olson, 2004). However, as pointed out by Shih and Olson (2022), "the meanings of weights involve more than just the interpretation of importance. For instance, the weight could reflect the rate of substitution among criteria, scaling factors used to convert measures into commensurate overall value, discriminating power of the criteria on the alternatives, and vote values in binary choices" (Shih & Olson, 2022, p. 38).

In this work, we are interested in finding up the discriminating power of the criteria on the alternatives for a certain ranking. That is, instead of elicitating weights for the criteria as inputs (objectively or subjectively, see Shih & Olson, 2022 for a review of usual elicitation techniques), weights become an output of the model, informing us, once a ranking is obtained, about the contribution of each criterion in the composition of the ranking.

Liern and Pérez Gladish (2022) developed Unweighted TOPSIS (UW-TOPSIS) for those situations in which the decision maker is not able or does not want to elicitate precise weights (subjective weights) or does not want to rely on objective weights based on the study of data nature. In UW-TOPSIS, similarly to what happens in some efficiency models (see Kao & Liu, 2000), decision criteria weights are the decision variables in two optimization problems where the objective is to minimize and to maximize the relative proximity of the decision alternatives to the ideal solution. These optimization problems provide for each alternative a relative proximity interval. Each of the extremes of the intervals has an associated matrix of weights reflecting the relative importance of each decision criterion for each alternative. Thus, in the UW-TOPSIS framework, the criteria weights will express, for each alternative, how much each criteria has contributed to the position of that alternative in the ranking. Let us notice that these weights would be probably different for each alternative. This can constitute a limitation of the method, as it does not allow knowing the role that each criterion has played in the ranking, in global terms. In this work, we address and discuss this limitation proposing of a method able to provide these weights, which will be called *decisional weights*. These decisional weights will be now an output of the model instead of an input and they do not have a preferential meaning.

3 Un-weighted TOPSIS

In what follows we will present the steps of the algorithm proposed by Liern and Pérez-Gladish (2022), Unweighthed TOPSIS (UW-TOPSIS). Steps 1 and 2 remain the same than in the classical TOPSIS framework (see Fig. 1). However, the PIS and NIS solutions are determined now without taking into account the relative importance of the criteria. Weights are introduced as unknowns in step 4 when separation measures from the PIS and NIS are calculated. Their values are determined in step 5 solving two groups of mathematical programing problems which maximize and minimize the separation of each alternative to the PIS and NIS respectively, taking into account different constraints referred to the values of the weights.

These constraints include the classical constraint in TOPSIS approaches which ensures all the weights are positive and sum up one and other constraints imposing lower and upper bounds on the weights. The resulting mathematical programming problems are, due to the

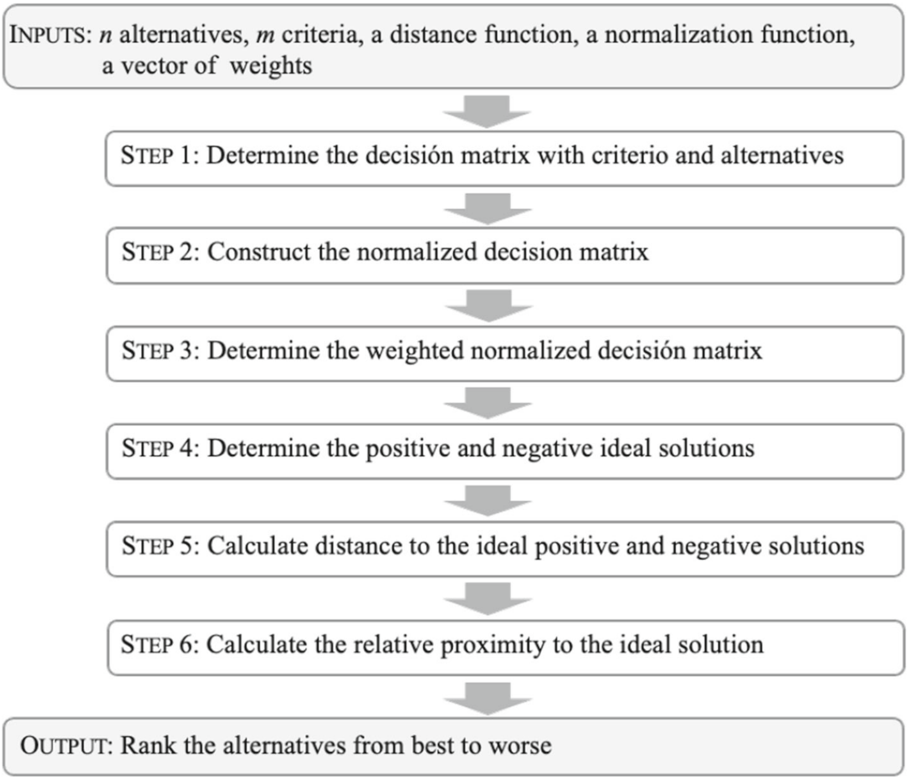

Fig. 1 TOPSIS framework. *Source*: own elaboration

nature of their objective, fractional mathematical programming problems. In what follows we describe the main steps of the UW-TOPSIS method in detail.

INPUTS. Let us consider $\{A_i, 1 \leq i \leq n\}$ alternatives, $\left\{C_j, 1 \leq j \leq m\right\}$ criteria, d a distance function in $\mathbb{R}^m$ and μ a normalization function.

STEP 1. Determine the decision matrix $\left[x_{ij}\right], 1 \leq i \leq n, 1 \leq j \leq m$.

STEP 2. Construct the normalized decision matrix $\mu\left(x_{ij}\right) = r_{ij}$,

$$\left[r_{ij}\right], r_{ij} \in [0, 1], 1 \leq i \leq n, 1 \leq j \leq m. \tag{1}$$

STEP 3. Determine the positive ideal $A^+ = (r_1^+, \ldots, r_m^+)$ and the negative ideal solutions $A^- = (r_1^-, \ldots, r_m^-)$, being

$$r_j^+ = \begin{cases} \max\limits_{1 \leq i \leq n} r_{ij}, & j \in J \\ \min\limits_{1 \leq i \leq n} r_{ij}, & j \in J\prime \end{cases} 1 \leq j \leq m, r_j^- = \begin{cases} \min\limits_{1 \leq i \leq n} r_{ij}, & j \in J \\ \max\limits_{1 \leq i \leq n} r_{ij}, & j \in J\prime \end{cases} 1 \leq j \leq m, \tag{2}$$

where J is associated with "the more, the better" criteria and J' is associated with "the less, the better" criteria.

STEP 4. Let us consider

$$\Omega = \left\{w = (w_1, \ldots, w_m) \in \mathbb{R}^m, w_j \in [0, 1], \sum\nolimits_{j=1}^{m} w_j = 1, l_j \leq w_j \leq u_j, 1 \leq j \leq m\right\} \neq \varnothing, \tag{3}$$

being $l_j, u_j \geq 0$ lower and upper bounds for each criterion's weight.

Given A^+, A^-, we define two separation functions,

$$D_i^+ : \Omega \times \mathbb{R}^m \to [0, 1], D_i^- : \Omega \times \mathbb{R}^m \to [0, 1], 1 \leq i \leq n,$$

Given by

$$D_i^+(w) = d\big((w_1 r_{i1}, \ldots, w_m r_{im}), \big(w_1 r_1^+, \ldots, w_m r_m^+\big)\big), 1 \leq i \leq n, \tag{4}$$

$$D_i^-(w) = d\big((w_1 r_{i1}, \ldots, w_m r_{im}), \big(w_1 r_1^-, \ldots, w_m r_m^-\big)\big), 1 \leq i \leq n. \tag{5}$$

Step 5. Calculate the function of relative proximity to the ideal solution, $R_i : \Omega \to [0, 1], 1 \leq i \leq n$, as

$$R_i(w) = \frac{D_i^-(w)}{D_i^+(w) + D_i^-(w)}, 1 \leq i \leq n. \tag{6}$$

Step 6. For each i, $1 \leq i \leq n$, we calculate the values $R_i^{min}(w)$, $R_i^{max}(w)$ solving the two following mathematical programming problems where decision variables are the criteria weights:

$$R_i^{\min} = \min_w\{R_i(w), w \in \Omega\}, \ \ R_i^{\max} = \max_w\{R_i(w), w \in \Omega\}, \ \ 1 \leq i \leq n. \tag{7}$$

Then, we construct n relative proximity intervals,

$$R_i^I = \big[R_i^{min}, R_i^{max}\big], 1 \leq i \leq n. \tag{8}$$

Step 7. We rank the intervals R_1^I, R_2^I, ..., R_n^I.

Output. We rank the alternatives $\{A_i, 1 \leq i \leq n\}$ considering that $A_i \geq A_j$ if and only if $R_i^I \geq R_j^I$.

To order intervals $\big\{R_i^I, 1 \leq i \leq n\big\}$ it is usual to select a real number, $R_i^*, 1 \leq i \leq n$, representing the interval and to use each R_i^* as an auxiliar score in the UW-TOPSIS method. For instance, in Liern and Pérez-Gladish (2022, 2023), the authors choose

$$R_i^* = (1 - \alpha) R_i^{\min} + \alpha R_i^{max}, 1 \leq i \leq n, \ \alpha \text{ a constant in } [0, 1], \tag{9}$$

and they consider that $R_i^I \geq R_k^I$ if and only if $R_i^* \geq R_k^*$.

As R_i^{min} and R_i^{max} represent the worst and best possible global scores for A_i, respectively, the choice of $\alpha = 0$ means that the decision maker considers the worst case scenario most likely for A_i, and $\alpha = 1$ means the decision maker considers the best scenario most likely for alternative A_i.

Proposition 1. With previous notation, if in UW-TOPSIS we consider, d, the Manhattan distance in $\mathbb{R}^m$, $d(x, y) = \sum_{j=1}^m \big|x_j - y_j\big|$, and normalization $r_{ij} = \mu\big(x_{ij}\big)$ given by

$$\mu\big(x_{ij}\big) = \begin{cases} \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}, & j \in J \\ \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}, & j \in J\prime \end{cases} \tag{10}$$

Then,

$$R_i^{min} = \text{Min}\left\{\sum_{j=1}^{m} r_{ij} w_j,\, w \in \Omega\right\},\, R_i^{max} = \text{Max}\left\{\sum_{j=1}^{m} r_{ij} w_j,\, w \in \Omega\right\},\, 1 \le i \le n. \quad (11)$$

Proof: With normalization given in (10), all the criteria are of the type “the more, the better”. Considering that $\sum_{j=1}^{m} w_j = 1$, replacing in (4) and (5) and with the Manhatann distance, we obtain

$$D_i^{+}(w) = \sum_{j=1}^{m} w_j\left(1 - r_{ij}\right) = 1 - \sum_{j=1}^{m} r_{ij} w_j,\, D_i^{-}(w) = \sum_{j=1}^{m} r_{ij} w_j,\, 1 \le i \le n.$$

Taking into account (6), $R_i(w) = \sum_{j=1}^{m} r_{ij} w_j$, $1 \le i \le n$.

Definition 1. Given n alternatives, $\{A_i, 1 \le i \le n\}$, m criteria, a distance function d in $\mathbb{R}^m$ and μ a normalization function, we say a ranking of alternatives

$$A_{j_1} \ge A_{j_2} \ge \cdots \ge A_{j_n},$$

is weigthed-generated, if a vector exists $w \in \Omega$, such that with it we can obtain that ranking, that is $S = \left\{w \in \Omega,\, R_{j_1}(w) \ge R_{j_2}(w) \ge \cdots \ge R_{j_n}(w)\right\} \ne \varnothing$. This vector, $w \in \Omega$, will be called *vector of decisional weights*.

Obviously, any ranking obtained with the classical TOPSIS or with any extension considering precise weights an input in the algorithm, is weigthed-generated. However, as we will see later, it is possible to obtain rankings based on R_i^* in UW-TOPSIS which are not weigthed-generated, that is, for which it is not possible to find a vector $w \in \Omega$, which generates that ranking.

For A_i, we obtain the relative proximity values R_i^{min} and R_i^{max} with two vectors $w_i^{min} = (w_{i1}^{min}, w_{i2}^{min}, \ldots, w_{im}^{min}) \in \Omega$ and $w_i^{max} = (w_{i1}^{max}, w_{i2}^{max}, \ldots, w_{im}^{max}) \in \Omega$, $1 \le i \le n$, respectively. The UW-TOPSIS method, does not directly provide a set of weights associated to the value, R_i^* given by (9). If the amplitude of the intervals of weights is not very big, $l_j \le w_j \le u_j, 1 \le j \le m$, this will not represent an important problem, as for any intermediate relative proximity value we will have an approximte idea of the relative weights of each criterion. However, if the intervals have a big amplitude (for instance, $0 \le w_j \le 1, 1 \le j \le m$), and we are interested in $R_i^* \in (R_i^{min}, R_i^{max})$, we will have to solve a decisional problem. Figure 2 illustrates this situation. Let us observe that for R^{min} and R^{max} we obtain a matrix of weights in which each row containts the vector of the criteria weights of the decision alternative i. That is, for each decision alternative, we know the relative importance of each criterion determining the minimum and maximum relative proximity to the ideal solution. However, the relative importance of each decision criterion may be different for each alternative.

If the decision maker is looking for decisional weights (see Fig. 2), that is, for the weights which contribute to make a particular decision about the relative proximity index expressing the relative importance of each criterion globally, the previously described situation could be even worse, as he/she will be looking for a vector of weights $w = (w_1, \ldots, w_m) \in \Omega$ able to generate all the relative proximity values $R^* = \left(R_1^*, R_2^*, \ldots, R_n^*\right)$ with a common set of weights for all the alternatives. Let us illustrate this situation with an example.

Example 1 Let us consider a decision problem where we need to rank 10 firms from the pharmaceutical industry based on 5 decision criterion (see Table 1). Three of these decision

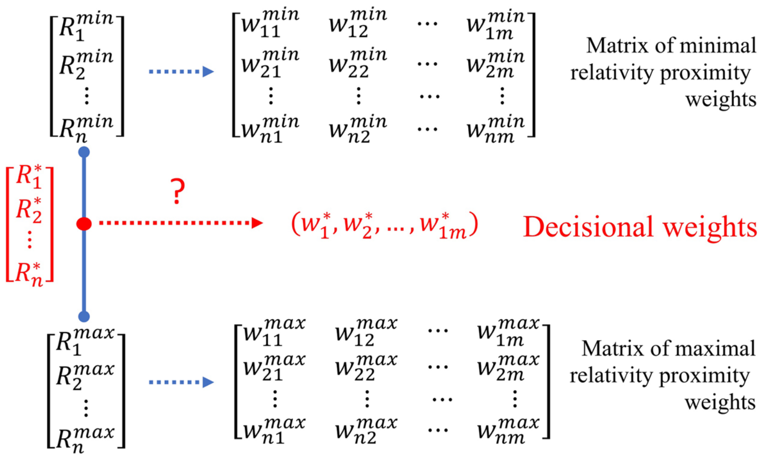

Fig. 2 Decisional weights. *Source*: own elaboration

criteria are ESG (Environment, Social, Governance) criteria and the two are financial criteria (Return, Volatility). The forth first criteria are of the type "the more, the better" and the last one is of the type "the less, the better". Data in Table 1 has been provided by Refinitiv (2021), which offers one of the most comprehensive ESG databases. Specifically, we adopt the individual environmental, social and governance ratings. These metrics range from 0 to 100, with a higher value indicating a better ESG performance of the firm. For the financial return we will use the year to data (YTD) return which is defined as the amount of profit (or loss) realized by an investment since the first trading day of the current calendar year. To calculate YTD, we subtract the starting year value from the current value and we divide the result by the starting-year value. Then we multiply by 100 to convert to a percentage. Volatility will be measure using the standard deviation.

The only information available regarding the relative weight of the decision criteria is that at least two criteria should be taken into account in the decision, that is $0.05 \leq w_j \leq 0.5$, $1 \leq j \leq 5$. In this case, the set of feasible weights (see Step 4 in the UW-TOPSIS algorithm) is

$$\Omega = \left\{ w = (w_1, \ldots, w_5) \in \mathbb{R}^5, 0.05 \leq w_j \leq 0.5, 1 \leq j \leq 5, \sum\nolimits_{j=1}^{5} w_j = 1 \right\}$$

Applying UW-TOPSIS to the decision matrix in Table 3, with the Manhatann distance and normalization given in (10) (see Proposition 1), in Table 4 we display the results for R_i^* obtained as $R_i^* = 0.6R_i^{min} + 0.4R_i^{max}$, $1 \leq i \leq 10$. The full reproducible code, developed by the authors, is available in the Appendix.

In Table 5 we have displayed the weights with which each firm reaches the worst and best relative proximity value $R_{\rm i}$.

It is clear that from the information displayed in Table 5 we cannot obtain a unique vector of weights $w \in \Omega$ with which we could obtain the results in Table 4.

$$F_1 \geq F_4 \geq F_2 \geq F_3 \geq F_5 \geq F_9 \geq F_8 \geq F_6 \geq F_7 \geq F_{10} \tag{12}$$

Taking into account Definition 1, we wonder if S is an empty set, being S

$$S = \left\{ \begin{array}{c} w \in \Omega,\ R_1(w) \geq R_4(w) \geq R_2(w) \geq R_3(w) \geq R_5(w) \geq \\ \geq R_9(w) \geq R_8(w) \geq R_6(w) \geq R_7(w) \geq R_{10} \end{array} \right\} \tag{13}$$

Table 3 Decision matrix. *Source*: own elaboration based on Refinitiv (2021)

Firms	Environment	Social	Governance	Return	Volatility
F_1	92.19207	97.01846	95.77381	0.24010	0.01728
F_2	86.39374	96.32963	95.36359	– 0.11701	0.01630
F_3	93.46930	97.52688	87.81893	– 0.16073	0.01449
F_4	82.50266	96.73020	86.95167	0.13612	0.02030
F_5	91.19674	91.39787	88.29635	– 0.00539	0.01640
F_6	91.21411	96.19961	70.53345	– 0.16689	0.02196
F_7	63.17728	93.36397	90.61404	0.35213	0.03128
F_8	86.02502	93.05279	71.52951	0.08668	0.02128
F_9	85.00002	92.34255	73.21152	0.05154	0.01128
F_{10}	76.74062	88.23728	83.80195	– 0.25737	0.01938

Table 4 Relative proximity values. *Source*: own elaboration using data from Refinitiv (2021)

Firm	R_i^*	Firm	R_i^*
F_1	0.8518690	F_6	0.4160252
F_2	0.6586368	F_7	0.3928414
F_3	0.6502236	F_8	0.4230034
F_4	0.6756216	F_9	0.5134063
F_5	0.5783486	F_{10}	0.2486541

With the distance and normalization chosen for this example, we can apply Proposition 1, and thus $R_i(w) = \sum_{j=1}^{5} r_{ij} w_j$, $1 \leq i \leq 10$. Then, the inequalities given in (19) are linear and we can easily probe that $S = \varnothing$. That is, no vector of weights exist, $w \in \Omega$, that generates que ranking of firms given in (12). In what follows we will propose a solution for this problem.

4 Obtaining decisional weights

Given a vector $R^* = (R_1^*, R_2^*, \ldots, R_n^*)$ with $R_i^* \in \left[R_i^{min}, R_i^{max}\right]$, $1 \leq i \leq n$, we wonder if the system of equations

$$\frac{D_i^-(w)}{D_i^+(w) + D_i^-(w)} = R_i^*, 1 \leq i \leq n, \tag{14}$$

has solution for some $w \in \Omega$.

Of course, if in (3) $l_j = u_j$, $1 \leq j \leq m$, the system in (14) has a solution w that is the vector of weights used in a classical TOPSIS approach (see Fig. 1). However, if the existence of solution in (14) is not guaranteed, we will use an approximate solution. Specifically, if we consider the function $R : \Omega \to [0, 1]^n$, given by

$$R(w) = (R_1(w), R_2(w), \ldots, R_n(w)), \tag{15}$$

Table 5 Matrices with weights associated to R^{min} and R^{max}. *Source*: own elaboration based on data from Refinitiv (2021)

	R^{min} weights					R^{max} weights				
	Environ	Social	Govern	Return	Volatility	Environ	Social	Govern	Return	Volatility
F_1	0.05	0.05	0.05	0.35	0.50	0.35	0.05	0.50	0.05	0.05
F_2	0.05	0.05	0.05	0.50	0.35	0.05	0.35	0.50	0.05	0.05
F_3	0.05	0.05	0.35	0.50	0.05	0.50	0.35	0.05	0.05	0.05
F_4	0.35	0.05	0.05	0.05	0.50	0.05	0.50	0.35	0.05	0.05
F_5	0.05	0.50	0.05	0.35	0.05	0.50	0.05	0.05	0.05	0.35
F_6	0.05	0.50	0.05	0.35	0.05	0.50	0.35	0.05	0.05	0.05
F_7	0.50	0.05	0.05	0.05	0.35	0.05	0.05	0.35	0.50	0.05
F_8	0.05	0.05	0.50	0.05	0.35	0.50	0.05	0.05	0.35	0.05
F_9	0.05	0.35	0.50	0.05	0.05	0.35	0.05	0.05	0.05	0.50
F_{10}	0.05	0.05	0.05	0.35	0.50	0.05	0.05	0.35	0.05	0.50

we need to find a vector $w^* \in \Omega$ such that $R(w)$ is approximately equal to R^*. To find vector w^*, we can solve an optimization problem

$$\text{Min}\left\{d\left(R(w), R^*\right), w \in \Omega\right\}. \tag{16}$$

The properties of Ω facilitate the existence of solution in (16) (see (3)). For example, (16) can be easyly solved as follows

$$\text{Min}\left\{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{D_i^-(w)}{D_i^+(w)+D_i^-(w)} - R_i^*\right)^2, w \in \Omega\right\}. \tag{17}$$

That is, if we suppose that R^* is the vector with the true values, in (17) we obtain the vector $w^* \in \Omega$ which minimizes the mean-squared error (MSE), assuming $R(w^*)$ as an estimation of R^*.

The purpose of (17) is to be as close as possible to a set of given scores, R_i^*. Nevertheless, this does not guaraantee that the rankings given by $\left\{R_i^*, 1 \le j \le m\right\}$ and $\left\{R_i(w^*), 1 \le j \le m\right\}$ are the same. If, in addition to the proximity among the scores, we want to maintain the ranking $R_{j_1} \ge R_{j_2} \ge \cdots \ge R_{j_n}$ given by $\left\{R_i^*, 1 \le j \le m\right\}$, as in Definition 1, we should optimize in $S = \left\{w \in \Omega, R_{j_1}(w) \ge R_{j_2}(w) \ge \cdots \ge R_{j_n}(w)\right\}$, that is

$$\text{Min}\left\{d\left(R(w), R^*\right), w \in \text{S}\right\}. \tag{18}$$

Solving (18) means finding a vector of weights that reconciles two uses of TOPSIS: a rating and a ranking generator. Nevertheless, as we will see in what follows, feasibility in (18) is not guaranteed (19) and this is one of the questions addressed in this work.

In what follows, we will summarize the previous reasoning as a subrutine that we will use in the overall scheme displayed in Fig. 3.

4.1 Subroutine ApW

Using previously notation, we can express the previous reasoning in algorithmic form.

INPUTS. Let us consider a vector $R^* = (R_1^*, R_2^*, \ldots, R_n^*)$ with $R_i^* \in \left[R_i^{min}, R_i^{max}\right], 1 \le i \le n$, and an associated ranking of alternatives$A_{j_1} \ge A_{j_2} \ge \cdots \ge A_{j_n}$.

STEP 1. We construct the set $S = \left\{w \in \Omega, R_{j_1}(w) \ge R_{j_2}(w) \ge \cdots \ge R_{j_n}(w)\right\}$

STEP 2. We calculate

$$EMC_S = \text{Min}\left\{\frac{1}{n}\sum_{i=1}^{n}\left(R_i(w) - R_i^*\right)^2, w \in \text{S}\right\}. \tag{19}$$

- If EMC_S is feasible, being its solution $w^* = \left(w_1^*, w_2^*, \ldots, w_m^*\right)$, go to STEP 4.
- If EMCS is infeasible, go to STEP 3.

STEP 3. We calculate

$$EMC_\Omega = \text{Min}\left\{\frac{1}{n}\sum_{i=1}^{n}\left(R_i(w) - R_i^*\right)^2, w \in \Omega\right\}. \tag{20}$$

and we obtain the optimum solution $w^* = \left(w_1^*, w_2^*, \ldots, w_m^*\right)$.

STEP 4. Using vector $w^* = \left(w_1^*, w_2^*, \ldots, w_m^*\right)$ obtained in (19) or (20), we apply the classic TOPSIS approach to the original decision matrix $\left[x_{ij}\right], 1 \le i \le n, 1 \le j \le m$, obtaining the relative proximities $R_1(w^*), R_2(w^*), \ldots, R_n(w^*)$.

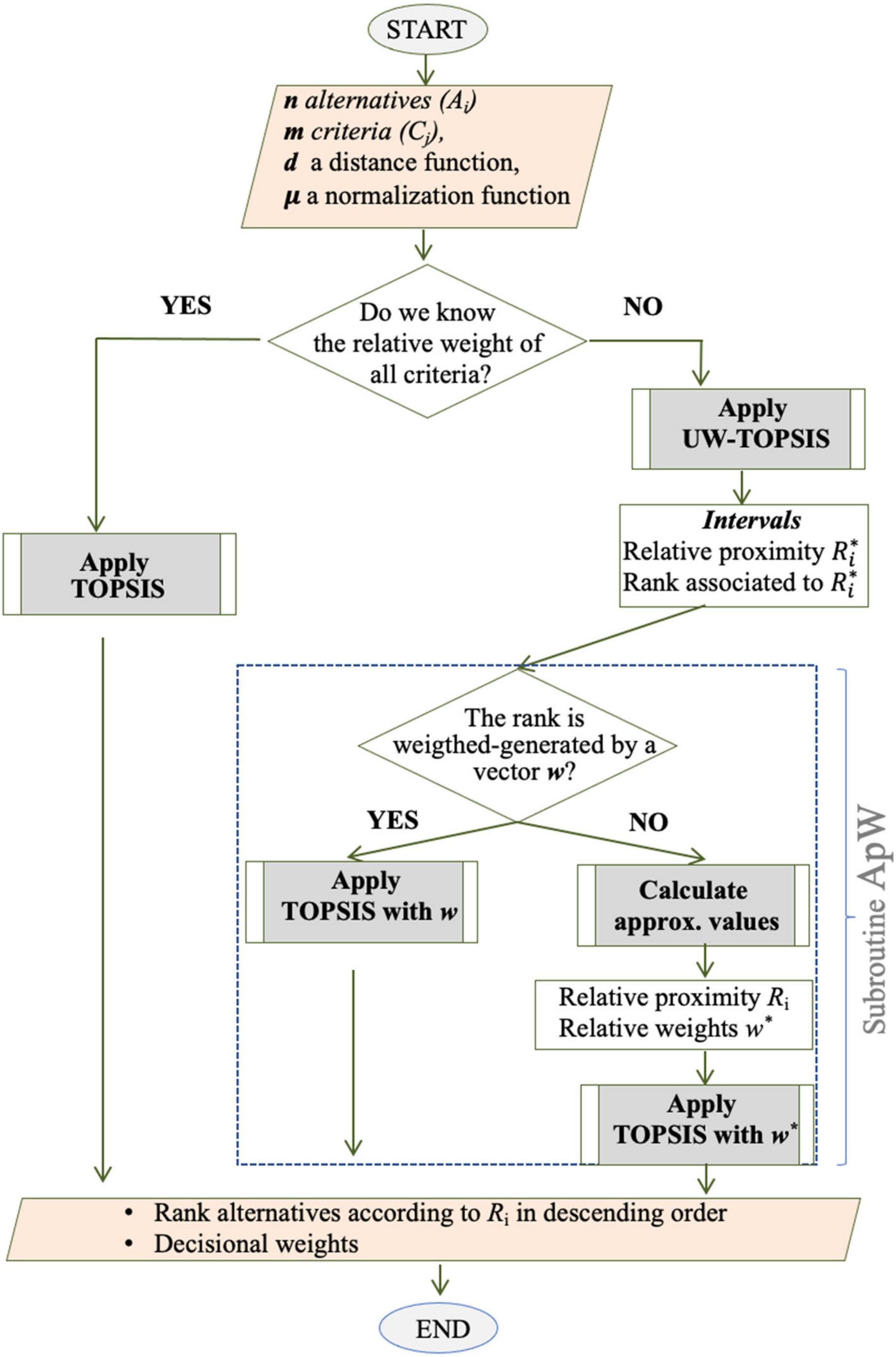

Fig. 3 Flowchart with the different options to obtain a ranking of the alternatives and to know the relative weights of the criteria. *Source*: own elaboration

OUTPUT. We rank the alternatives $\{A_i, 1 \leq i \leq n\}$ considering $A_i \geq A_j$ if and only if $R_i(w^*) \geq R_j(w^*)$.

As we can observe in Fig. 3, the decision maker will only need to know, at the beginning of the process, the decision alternatives, the decision criteria and to decide about the normalization and distance functions (this decision will be determined by the type of decisional problem). If the criteria weights for the aggregating process can be elicitated by the decision maker (objectively or subjectively), we will apply the classical TOPSIS approach to rank the alternatives. However, in those situations in which the decision maker does not want or is not able to elicitate the criteria weights, we will apply UW-TOPSIS. UW-TOPSIS will consider the weights as unknowns in the optimization problems that search for the minimum and maximum relative proximity of each alternative to the ideal solution. Therefore, after the optimization process we will have, for each alternative, instead of a scalar representing the relative proximity, an interval. The extremes of the intervals will represent the worst and best situation for each alternatives in terms of the value of R_i and will have an associate vector of weights, expressing, for each alternative, the contribution of each criterion in its possition in the ranking. If the decision maker wants to rank the alternatives based on the obtained global scores or rates, R_i, he/she only needs to choose any of the multiple available methods to rank intervals on the real line. As commented before, in this work, we have chosen to work with the convex linear combination of the extremes of the intervals, letting the decision maker decide his/her risk aversion regarding the ranking scenario: if he/she feels pessimistic, he/she will choose the lower extreme of the interval and rank the alternatives accordingly. If he/she feels totally optimistic he/she will choose the upper extreme of the interval. For any other intermediate situation, he/she will choose an intermediate value for the coefficient in the linear combination, obtaining the associate ranking.

At this point of the process, is where the procedure propossed in this work starts. If the ranking is weighted-generated then we will have the decisional weights. If this is not the case, then we will need to find a vector of weights that better aproximate the value of R_i. Once these approximate decisional weights have been obtained they are included in a classical TOPSIS as inputs and the corresponding ranking is obtained.

To show the usefulness of the proposed solution, let us go back to the previous example (Example 1). If in this example, we apply the Subroutine ApW, we obtain the vector of decisional weights

$$w^* = (0.1046952, 0.1943971, 0.1768560, 0.2532284, 0.2708232)$$

The results applying the classical TOPSIS with this vector of weights w^* are shown in Table 6.

Figure 4 displays the relative proximity values R_i^* (Table 2) and $R_i(w^*)$ (Table 6) facilitating comparison and the goodness of fit.

Table 6 Relative proximity values using classical TOPSIS with decisional weights w^*. *Source*: own elaboration based on Refinitiv (2021)

Firm	$R_i(w^*)$	Firm	$R_i(w^*)$
F_1	0.8571948	F_6	0.4272853
F_2	0.6847303	F_7	0.5012133
F_3	0.6877042	F_8	0.4650904
F_4	0.6717830	F_9	0.5792635
F_5	0.5935877	F_{10}	0.3010469

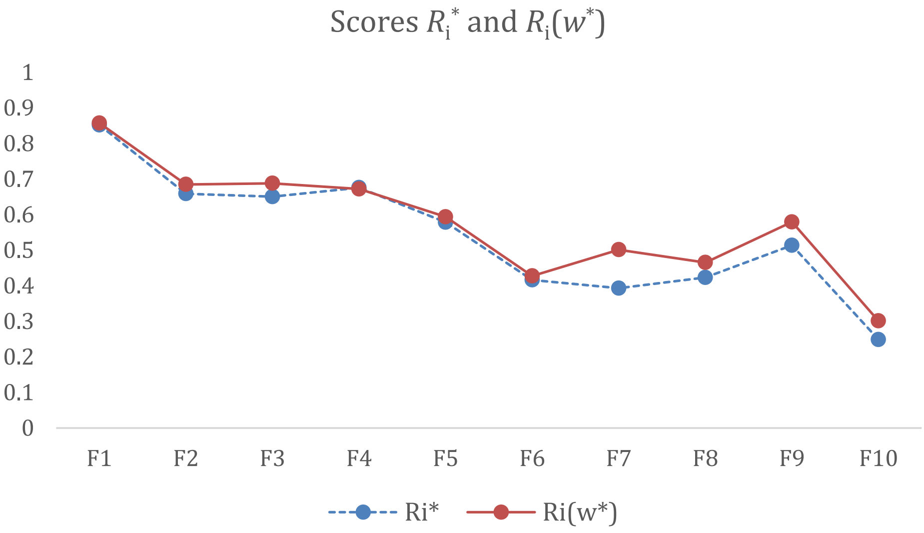

Fig. 4 Comparison of relative proximity values. *Source*: own elaboration

In the next section we illustrate the proposed model with a real case study extending Example 1.

Remark 2. If we repeat the reasoning with a degree of optimism $\alpha = 0.6$, that is $R_i^* = 0.4R_i^{min} + 0.6R_i^{max}$, $1 \leq i \leq 10$, the obtained ranking would be

$$\begin{aligned} R_1^* = 0.887 \geq R_3^* = 0.745 \geq R_2^* = 0.734 \geq R_4^* = 0.709 \geq R_5^* = 0.651 \geq \\ \geq R_9^* = 0.611 \geq R_6^* = 0.542 \geq R_7^* = 0.531 \geq R_8^* = 0.491 \geq R_{10}^* = 0.334 \end{aligned} \tag{21}$$

The vector of weights obtained with our method is

$$w^* = (0.22923, 0.2184641, 0.1745323, 0.2011543, 0.1766192)$$

with error EMC $= 0.0011255381$ (see (19)). Vector w^* does not generates the ranking associated to (21), as it permutes firms F_8 and F_7, that is,

$$F_1 \geq F_3 \geq F_2 \geq F_4 \geq F_5 \geq F_9 \geq F_6 \geq F_8 \geq F_7 \geq F_{10}.$$

Nevertheless, with vector

$$w^* = (0.1988455, 0.2320587, 0.1923732, 0.1978837, 0.1788389)$$

we can obtain the ranking associated to (21) with an error EMC $= 0.001248$, slightly higher than the one obtained with our method.

5 Real case study: ranking firms based on their environmental, social and governance performance

Refinitiv measures a company's relative Environmental, Social and Governance (ESG) performance, commitment and effectiveness across 10 main themes, based on publicly available and auditable data (see Fig. 5). To illustrate the proposed methodology with a real case, let

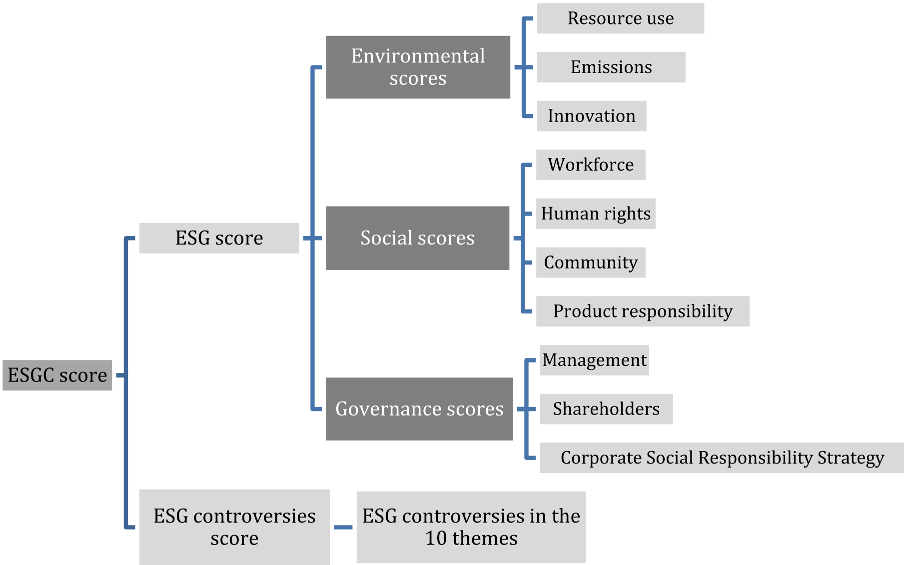

Fig. 5 Refinitiv dimensions and main themes. *Source*: own elaboration based on Refinitiv

us rank the firms included by Refinitiv in the Top 100 EMEA companies in terms of their Environmental, Social and Governance (ESG) Performance using data from august 2022.

The firms relative ESG performance is expressed by means of ESG scores ranging from 0 to 100, reflecting the commitment and effectiveness of the firms in each dimension, based on company-reported data. Refinitive also provides an overall ESG combined (ESGC) score, which takes into account significant ESG controversies affecting the firms. As the importance of ESG factors is different across industries and countries, Refinitiv takes into account the sector of the firms in the case of the environmental and social dimensions and the country in the case of the governance dimension.

In this work we will use the Environmental, Social and Governance scores. In addition, we will consider two financial criteria: return and risk. For the financial return we will use the year to data (YTD) return which is defined as the amount of profit (or loss) realized by an investment since the first trading day of the current calendar year. To calculate YTD, we subtract the starting year value from the current value and we divide the result by the starting-year value. Then we multiply by 100 to convert to a percentage. Volatility will be measure using the standard deviation. All the data, ESG scores and financial data were provided by Refinitiv on august 2022. Table 7 displays the main statistics of the dataset.

Table 7 Descriptive statistics

Dimension	# Obs	Mean	St. Dev	Median	Min	Max	Skewness	Kurtosis
Environment	100	83.67	9.87798	85.47	62.34	99.05	– 0.54918	– 0.5391
Social	100	87.34	7.34199	89.17	65.10	97.59	– 0.72982	– 0.2597
Governance	100	77.04	11.7311	78.80	41.08	95.77	– 0.86415	0.8614

We have considered 5 different scenarios for the weights. In all scenarios the upper bound is set at 0.5. With this we force the solution to take into account all the decision criteria. For the lower bounds we have consider different situations ranging from 0 to 0.1 (see Table 8). The obtained decisional weights are displayed in Table 8. Results are displayed by sectors. We have used the Global Industry Classification Standard (GICS) which is a common global classification standard used by Refinitiv. Last column shows the root-mean-squared errors (RMSE). As mentioned in the previous section, the full reproducible code, developed by the authors, is available in the Appendix.

Let us observe scenario 2. In this scenario the weights have, in the optimization problem, a minimum bound equal to 0.025 and a maximum bound equal to 0.5. Figure 6 displays the optimum decisional criteria weights by sectors. As we can observe, the financial return has the same relative importance regardless the sector.

There is a small discrepancy among sectors in the relative importance of the social criterion and the governance criterion. However, we can observe some important differences in the relative importance of the environmental decision criterion. The sector with the hightest environment relative importance is *Communication Services* with more than 40% of relative importance. On the other hand, for the *Information* sector, the relative importance of the environment criteria is less than 15%. The remaining sectors give this decision criteria a similar importance.

It is interesting to observe, how the Information sector is the one giving more importance to financial volatility and Communication Services sector is the sector for which financial volatility has less importance.

The obtained results provide information to the decision maker regarding those criteria which are not influencing the ranking of the firms given their sectors. In the previously commented example, the financial return of the firms is not determining their position in the ranking. The same is applicable to the social criterion. The focus in this case, would be on the environmental and governance criteria and on the financial volatility.

6 Conclusions

Investors, consumers and goverments are increasingly demanding reliable ESG rating and ranking of firms. These ratings can identified the weaknesses and strenghs in terms of ESG performance of the companies, therefore representing an opportunity to improve. Several rating agencies provide all around the world ESG global ratings. However, the methodology behind the rating and ranking processes followed by these agencies has been widely critizied. Among its main weaknesses we can find problems related to the reliability of the ESG data provided by the companies but also related to the decision criteria selection and to the determination of their relative importance in the aggregation process giving rise to the global ESG rating.

TOPSIS is a well-known and widely applied MCDM distance-based method which has a double possible use: the rating and ranking of a set of decision alternatives based on different decision criteria. Classical TOPSIS approaches usually require two main inputs: the individual scores of the alternatives with respect to the criteria and criteria weights. If the decision maker is able to elicitate, objectively or subjective, the criteria weights then, the classical TOPSIS approaches are useful. Otherwise, for those situations in which this is not possible we propose the use of UW-TOPSIS.

Table 8 Results in different scenarios. *Source*: own elaboration

Sector	Environment	Social	Governance	Return	Volatility	MSE
Scenario 1 $w_i \in [0,\ 0.5]$						
Communication Services	0.46848	0.32565	0.17103	0.03272	0.00211	0.00067
Consumer Staples	0.30296	0.34352	0.21542	0.03027	0.10783	0.00041
Health	0.32213	0.31106	0.27396	0.03415	0.05869	0.00153
Industrials	0.28737	0.31564	0.25857	0.03461	0.10380	0.00148
Information	0.12917	0.38181	0.27592	0.02101	0.19209	0.00035
Scenario 2 $w_i \in [0.025, 0.5]$						
Communication Services	0.42792	0.26583	0.19535	0.04731	0.06359	0.00025
Consumer Staples	0.25976	0.29053	0.24280	0.05207	0.15483	0.00051
Health	0.30442	0.26875	0.25862	0.05688	0.11132	0.00051
Industrials	0.25386	0.26794	0.29381	0.05368	0.13071	0.00092
Information	0.14075	0.32256	0.27536	0.03987	0.22146	0.00022
Scenario 3 $w_i \in [0.05,\ 0.5]$						
Communication Services	0.40271	0.19713	0.22343	0.07109	0.10564	0.00022
Consumer Staples	0.22140	0.23978	0.24562	0.07988	0.21332	0.00025
Health	0.26631	0.24695	0.24448	0.07904	0.16323	0.00024
Industrials	0.22239	0.20008	0.31442	0.08229	0.18082	0.00046
Information	0.15731	0.27630	0.26190	0.06116	0.24333	0.00010
Scenario 4 $w_i \in [0.075,\ 0.5]$						
Communication Services	0.40099	0.10612	0.24942	0.09789	0.14558	0.00017
Consumer Staples	0.23259	0.18833	0.22228	0.10529	0.25151	0.00016
Health	0.27654	0.09803	0.26257	0.12287	0.23998	0.00027
Industrials	0.17039	0.20175	0.30080	0.10747	0.21958	0.00027
Information	0.16787	0.24091	0.25381	0.08172	0.25569	0.00007
Scenario 5 $w_i \in [0.1,\ 0.5]$						
Communication Services	0.37028	0.10000	0.24712	0.11467	0.16792	0.00013
Consumer Staples	0.25604	0.18585	0.17524	0.12260	0.26027	0.00012
Health	0.22903	0.10252	0.23230	0.15541	0.28074	0.00027
Industrials	0.13963	0.22108	0.27203	0.12888	0.23838	0.00021
Information	0.17552	0.21131	0.25187	0.10288	0.25842	0.00003

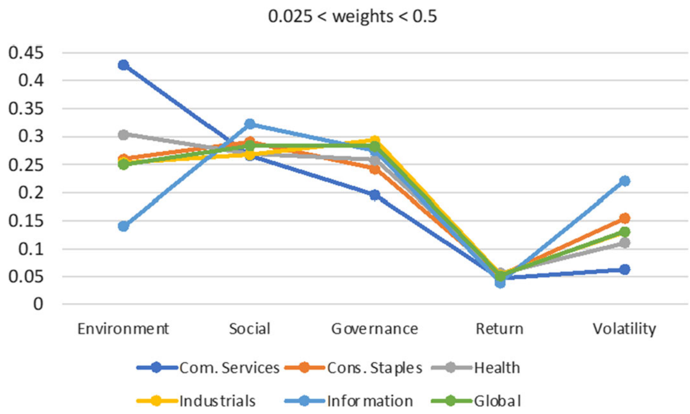

Fig. 6 Decisional weights by sectors in scenario 2. *Source*: own elaboration based on Refinitiv

In UW-TOPSIS the decision criteria weights are considered variables in two optimization problems which determine and interval with the minimum and maximum relative proximity to the positive ideal solution. In this method, two matrices of weights are obtained associated to the extremes of the relative proximity intervals. However, if the decision maker looks for a unique vector of weights with the relative importance of the criteria (decisional weights), as in the classic TOPSIS, the UW-TOPSIS method is not always able to direcly provide it. In this paper, we discuss this situation and its managerial consequences proposing an approximate method that solves the problem of the determination of those decision weights.

The proposed approach has been applied to the ranking of a set of firms based on ESG and financial criteria. Using different lower and upper bounds we have generated several scenarios which have provided us with decisional vectors of weights expressing the relative importance of the decision criteria globally, that is, taking into account all the alternatives. Following the spirit of Refinitiv, we have calculated the vectors of weights taking into account the sector classification of the firms. The vectors with weights can be easily obtained taking also into account the country of the firms. The obtained results inform us about the real relevance of each decision criteria.

The full reproducible code, developed by the authors, available for all the readers, is displayed in the Appendix.

Author contributions All authors contributed equally to this research paper. All authors have read and agreed to the published version of the manuscript.

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Declarations

Conflict of interest The authors declare no conflict of interest.

Appendix: Code

Lower and upper bounds for the weights have been taken from example 1.

```
# Library import
library(xlsx)
library(readxl)
library(nloptr)
library(uwTOPSIS)

# Function definition
least_square_TOPSIS <- function(w, x, directions, R0){
  # Function that fits the TOPSIS score
  # to a certain vector R0 by means of
  # the least squares method
  LST <- TOPSIS(w, x, directions) - R0
  return( sum( LST^2 ) )
}
weight_constraint <- function(w, x, directions, R0) {
  # Constraint function to set the sum of weights equal to 1
  constraint <- c(sum(w) - 1, 1 - sum(w))
  return(constraint)
}
# Data preparation
df <- read_excel("path_to_data.xlsx")
w0 <- rep(1 / (ncol(df) - 1), ncol(df) - 1)
L <- rep(0.05, ncol(df) - 1)
U <- rep(0.5, ncol(df) - 1)
directions <- c('max', 'max', 'max', 'max', 'min')
norm.method <- 'minmax'

# uwTOPSIS algorithm
X <- uwTOPSIS(x = df,
              directions,
              norm.method,
              L,
              U,
              p=1,
              alpha=0.4,
              makefigure = FALSE)
# Save results in a xlsx file
for (idx in seq_along(X)) {
  if(idx == 1){
    write.xlsx(X[[idx]],
               file='ESG_uwTOPSIS.xlsx',
               sheetName = names(X)[idx],
               row.names = FALSE)
  }
  else{
    write.xlsx(X[[idx]],
               file='ESG_uwTOPSIS.xlsx',
               sheetName = names(X)[idx],
               append = TRUE)
```

```
    }
  }
  # Least squares method for fitting TOPSIS to the score sequence R0
  alpha <- 0.5
  R0 <- alpha*X$scores$Min + (1-alpha)*X$scores$Max
  sols <- nloptr(x0 = w0,
                 eval_f = least_square_TOPSIS,
                 eval_g_ineq = weight_constraint,
                 lb = L,
                 ub = U,
                 opts = list(algorithm = "NLOPT_LN_COBYLA",
                             xtol_rel = 1e-8,
                             xtol_abs = 1e-8,
                             maxeval = 2000),
                 x = df,
                 directions = directions,
                 R0 = R0)
  # Save solution of least squares problem
  solution <- data.frame(weights = sols$solution,
                         optimal = c(sols$objective,
                                     rep(0, length(sols$solution)-1)),
                         optimal_normalized = c(sols$objective/nrow(df),
                                                rep(0, length(sols$solution)-1)),
                         )
  # Append the dataframe to the output xlsx file
  write.xlsx(t(df_solution),
             file='ESG_uwTOPSIS.xlsx',
             sheetName = 'least_square_TOPSIS',
             append=TRUE)
```

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