INTERNATIONAL TRANSACTIONS IN OPERATIONAL RESEARCH

WILEY

INTERNATIONAL TRANSACTIONS IN OPERATIONAL RESEARCH

Intl. Trans. in Op. Res. 0 (2022) 1–21
DOI: 10.1111/itor.13143

Ranking firms based on their financial and diversity performance using multiple-stage unweighted TOPSIS

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Received 29 November 2021; received in revised form 16 March 2022; accepted 20 March 2022

Abstract

In this paper, we address the problem of the ranking of companies based on their diversity and financial performance. The addressed problem is a multiple criteria decision-making problem where a composite measure needs to be obtained to rank firms. Taking as a reference the methodological approach followed by Refinitiv in the construction of their Diversity and Inclusion Index, we propose an alternative ranking framework that overcomes some of the problems identified in the methodological approach of Refinitiv. In particular, the proposed method in this work does not require the *a priori* establishment of a weighting scheme and is able to incorporate the past behavior of the companies in terms of diversity in their workplaces.

Keywords: diversity; firms; historical performance; TOPSIS; unweighted TOPSIS

1. Introduction

Diversity can be defined as "(…) the mixture of attributes within a workforce that in significant ways affect how people think, feel, and behave at work, and their acceptance, work performance, satisfaction, or progress in the organization" (Kreitz, 2008). Inclusion goes beyond diversity, implying the integration and participation of the workforce into everyday work life (Roberson, 2006).

Diversity and inclusion strategies have the capacity to impact, among other important aspects, corporate reputation. The link between corporate reputation and financial performance has been widely studied (Luchs et al., 2009). Corporate reputation increases earnings and investors' confidence. As corporate reputation can be directly impacted by diversity and inclusion, an increasing

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number of firms try to outline their success in fomenting diverse and inclusive work environments, benchmarking themselves against companies that are leaders in that field. Several lists and indexes have appeared in recent years, ranking the most progressive companies in terms of their diversity and inclusion workplace strategies with the aim of improving their corporate reputation.

For all these reasons, diversity and inclusion in the workplace are meaningful investment considerations that are becoming increasingly important to a company's bottom line. Several authors have found not only a positive correlation between corporate reputation and financial performance but also between diversity and inclusion factors and financial corporate performance indicators (see numerous works published in recent years, e.g., Adams and Ferreira, 2009; Carter et al., 2010; Dezsö and Ross, 2012; Gong et al., 2013; Chapple and Humphrey, 2014; Sabatier, 2015; Abdullah et al., 2016; Solakoglu and Demir, 2016; Terjesen et al., 2016; Conyon and He, 2017; Li and Chen, 2018). It is not only a question of reputation and public image. The existence of flexible hours and daycare services may help in retaining talent and reducing employee turnover of talented employees with children or employees needing to take care of elderly family members. These policies can increase the satisfaction of employees, thereby increasing profitability and consumer satisfaction (Dixon-Fyle et al., 2020).

A recent report from McKinsey & Company shows how "(…) while correlation does not equal causation (greater gender and ethnic diversity in corporate leadership does not automatically translate into more profit), the correlation does indicate that when companies commit themselves to diverse leadership, they are more successful" (Dixon-Fyle et al., 2020). In their last report, they showed, based on research including data since 2014 for 15 countries and more than 1000 large companies, that the relationship between diversity on executive teams and the likelihood of financial outperformance has strengthened over time (Hunt et al., 2018; Dixon-Fyle et al., 2020). The increasing importance of corporate diversity and inclusion as potential drivers for creativity, innovation, and financial performance also seems unquestionable.

Having said this, we could then ask ourselves why the consideration of issues related to diversity and inclusion in companies is not yet decisive in investment decisions. Recently, published reports analyzing these questions have concluded that one of the main problems faced by investors is related to the quality of data: transparency, credibility, and availability are important problems directly related to the data. A second important problem is related to the available composite indicators measuring corporate diversity and inclusion. These composite indicators are used by different rating to list and rank companies based on the diversity and inclusion of their workforce. The available composite indicators suffer from several methodological problems, such as the selection of individual indicators, the aggregation procedure of those individual indicators, and the determination of the relative importance of the individual indicators in the aggregation process.

In this work, we will focus on two of the previously mentioned problems: the problem regarding the determination of weighting schemes reflecting the relative importance of the individual indicators and the incorporation of historical information into the ranking process of firms (our decision alternatives). We have addressed the problem of decision criteria weighting, proposing a method that avoids the *a priori* establishment of weights. The method allows determining the range of variation of the weights that optimizes the relative proximity of each alternative to the positive ideal solution (PIS). This overcomes an important usual problem for decision-makers, especially in those cases where subjective weights are used. This problem is even more important when we have historical decision matrices, that is, matrices with historical data. In this situation, should the weights consider the different possible relative importance of the decision criteria over time? The approach proposed in this paper provides a suitable solution to this question.

Weights can be determined objectively or subjectively. KarimiAzari et al. (2011), Peng et al. (2011), Zandi and Tavana (2011), Zhang et al. (2010), and Bilbao-Terol et al. (2021) are some examples of the use of preferential weights based on the expert knowledge of the decision-makers. Yu et al. (2011), Vahdani et al. (2012), Wu et al. (2009), and Ortega-Momtequín et al. (2021) use analytical hierarchy process-based methods, and Stefanakis and Doumpos (2020) use methods based on ELimination Et Choice Translating REality (ELECTRE), including a sensitivity analysis on the weights.

Among the objective methods, one of the most used is the establishment of equal weights (Chang et al., 2010). We can also find works using centroid weights, the entropy weight method, or the coefficient of variation weight method (Chang et al., 2010). Sometimes objective weights are also obtained from regression techniques (Olson, 2004; Wu and Olson, 2006) and from data envelopment analysis (Chen et al., 2009).

The use of subjective weighting schemes is more controversial than the use of objective ones (Jacquet-Lagrèze and Siskos, 1982; Watröbski et al., 2019), as the relative importance of the individual indicators is determined by the decision-makers based on their own experiences, knowledge, and perception of the problems (Hobbs, 1980; Mareschal, 1988; Fischer, 1995; Barron and Barrett, 1996; Ribeiro, 1996; Triantaphyllou and Sanchez, 1997; Deng et al., 2000; Eshlaghy and Radfar, 2006; Alemi-Ardakani et al., 2016; Németh et al., 2019).

Several multiple criteria decision-making (MCDM) methods are used for the construction of the composite indicators and the ranking of decision alternatives. Most of these methods require a discussion of normalization processes, weighting schemes, and aggregation methods. One of the most popular ranking methods is the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), developed by Hwang and Yoon (1981). TOPSIS is a simple mathematical method that is easily understandable by practitioners. It is rational, comprehensible, and efficient from a computational point of view. This method allows the selection of alternatives that simultaneously have the shortest distance from the PIS and the farther distance from the negative ideal solution (NIS). The PIS maximizes criteria of the type "the more, the better" and minimizes criteria of the type "the less, the better," whereas the NIS maximizes "the more, the better" criteria and minimizes "the more, the better" criteria. Based on this simultaneous minimization of distances and making full use of the attribute information, TOPSIS provides a cardinal ranking of the decision alternatives without requiring independence of the attribute preferences (Chen and Hwang, 1992; Yoon and Hwang, 1995). Other MCDM ranking methods exist, such as the best-worst multicriteria decision-making method (Rezaei, 2015) or the combined compromise solution method (Yazdani et al., 2019). However, due to its mathematical simplicity, in this work, and only for illustrative purposes, we have extended a TOPSIS-based approach. The new extension proposed in this paper will allow us to work without the *a priori* establishment of subjective weights.

Ouenniche et al. (2018) and Liern and Pérez-Gladish (2020, 2021) have recently published a classification of mainly used weighting schemes in MCDM methods. Rankings are sensitive to changes in the weights of the criteria, and therefore, subjective weighting schemes are subject to important criticisms. Liern and Pérez-Gladish (2020, 2021) have shown how the subjective methods proposed by most previous authors can be replaced by a more general method not requiring the *a priori* establishment of subjective weights, giving rise to quite similar results. In their approach, weights are handled as decision variables in a set of optimization problems where the objective is to maximize the relative proximity of a set of decision alternatives to an ideal solution.

In this work, we enrich the previous approach by incorporating historical data regarding the performance of each alternative in each decision criterion into the model. Different historical decision matrices are considered, and an extended decision matrix is proposed that includes two fictitious alternatives that will serve as references for the ranking. These fictitious alternatives directly depend on the historical data and serve as PIS and NIS obtained globally, taking into account all the historical data. The unweighted TOPSIS (UW-TOPSIS) problem is then solved in multiple phases, giving rise to a multiple-phase UW-TOPSIS (MUW-TOPSIS). This approach maintains the main advantages of the UW-TOPSIS approach, and it is able to incorporate historical data that are handled by means of intervals on the real line into the decision-making problem.

As we will see in the following sections, the main features of the MUW-TOPSIS contribute to overcome some of the weaknesses of some well-known ranking methods, like the one used by Refinitiv in their Diversity and Inclusion (D&I) Index. Most of the rating agencies publish annual rankings that only consider the performance of the companies for one year. However, questions related to the level of diversity and inclusion in firms should also take into account the historical evolution of firms. The method proposed in this work incorporates the best and worst historical performances of firms into a decision matrix in such a way that the ranking of the firms takes this information into account, enriching the available data. This feature, together with the fact that subjective weights do not have to be set beforehand, makes the proposed method a very attractive method for decision-makers.

2. D&I Index from Refinitiv: methodology

The D&I Index published by Refinitiv Knowledge Direct and available through Eikon ranks over 11,000 companies globally, identifying the top 100 publicly traded companies with the most diverse and inclusive workplaces. Refinitiv scores companies using 24 individual indicators across four key pillars: diversity, inclusion, people development, and controversies pillars. Only those companies with nonzero scores for all four pillars are assigned an overall score (the simple arithmetic mean of the pillar scores). Refinitiv equally weights each pillar in the calculation of the overall score. However, they use dynamic weights to aggregate individual indicators in each pillar according to their “availability within an industry or country.” Pillar scores for diversity, inclusion, and people development are calculated using a weighted average of their individual indicators. Scores for the controversies pillar are calculated as a simple average of its individual indicators. By “availability within an industry or country,” Refinitiv means taking into account the importance given to each attribute by the industry or the country in global terms. That is, they give more weight to those indicators reported by most companies within a country or industry. For each indicator, a benchmark is established in terms of country or industry. Refinitiv also considers in the weighting process how a company compares with industry peers in each indicator and where it falls within the minimum to maximum range of this indicator. Then, per indicator, they combine the performance times the weight to obtain a raw number. They do this for all 24 indicators to obtain the company’s global score. The steps for each pillar are as follows:

STEP 1. Determine the individual indicator weight (based on whether the measure is weighted relative to an industry group or to country). First, we perform a count for each indicator by both industry group and country. Then, we transform the raw counts to percentages when there are more than 10 companies available. If there are 10 or fewer in the industry group or country, the percentage is set to zero, and a pillar score is not calculated. Then, we use the availability percentages of the indicator within industry and country to determine into which quartile that percentage falls. Then, quartile assignments are used to determine the weighting (25%, 50%, 75%, or 100%) for that indicator within its industry group or country.

STEP 2. Obtain the appropriate min/max numeric value for the indicator within the industry group.

STEP 3. Calculate the raw score as

$$\text{Raw Score} = \frac{(\text{numericValue} - \text{minValue})}{\text{maxValue} - \text{minValue})}.$$

STEP 4. Create the normalized scores for each measure:

$$\text{Normalized Score} = \text{Raw Score} * \frac{\text{Indicator Weight}}{\text{Sum of Weights}}.$$

The sum of the normalized scores, rounded to an integer value, forms the overall score for the company for that pillar. The methodology for calculating the controversies score is considerably simpler. It is based on the company's market cap classification, and for each measure, whether any controversies were reported.

The overall rating is based on a simple average of the four individual pillar scores. A company must have nonzero scores on all four pillars to have an overall rating computed. The intent of Refinitiv is to rank only those companies that are actively tracking and reporting on all four pillars.

The key question here is why Refinitiv weights indicators within each pillar, taking into account the industry and country. In their last published methodology report (Refinitiv, 2021), they ask themselves, "Would it be fair to compare the percentage of women on the board of a company headquartered in France, where there is a quota system, versus companies from other countries where there are no quotas? Should we penalize companies because regulations in their countries do not provide quotas, and/or should this be at done using comply or explain-type regulations such as the Australian Stock Exchange? When looking at the percentage of women employees, is it fair to compare a basic materials sector company with a healthcare sector company? (…) Should we be penalizing companies simply because of the sector they are in?" (Refinitiv, 2021).

The reporting of questions regarding diversity and inclusion varies greatly within countries and industries. The decision of Refinitiv was to give more importance, that is, a greater weight, to those indicators on which more companies report. As an example, they consider the Human Rights Campaign (HRC) Corporate Equality Index, which has the country as a benchmark (see Table 3). Most companies pertaining to this index are American, and as they consider the pertain to this index of greater importance, they wanted not to exclude these companies from the index. As a result, for example, they *penalize* companies headquartered in China where "virtually no countries have HRC scores," versus companies in the United States, which are *rewarded*, where over 400 have scores." In summary, Refinitiv introduces the concept of weights depending on the level of reporting, "so that, if reporting is slow or nonexistent for an industry/country relative to others, then it is reduced in terms of weight (…). If reporting is high relative to other countries/industries, then they allocate more weights to the measure." For Refinitiv, if industries/countries report heavily on a particular indicator or measure, then that indicator is very likely to be relevant in terms of diversity and inclusion. Therefore, if weights are based on the reporting level, then the ideal situation for Refinitiv would be having all the measures or indicators in each pillar weighted 100%.

In this work, we question the objectivity of that decision, and we try to propose a multiple criteria decision approach to score companies based on the diversity and inclusion indicators from Refinitiv without *a priori* establishment of aggregation weights. As we will see in Section 3, a new unweighted TOPSIS, MUW-TOPSIS, will be proposed, which will take into account all the available historical information and in which the relative importance of the decision criteria is given by the unknown variables in an optimization problem that aims at maximizing the relative performance of each company in terms of its diversity and inclusion level.

3. MUW-TOPSIS

3.1. Classic TOPSIS

TOPSIS ranks decision alternatives based on their simultaneous distance to a PIS and an NIS. The PIS maximizes criteria of the type "the more, the better" and minimizes criteria of the type "the less, the better," whereas the NIS minimizes "the more, the better" criteria and maximizes "the more, the better" criteria. Distance to the PIS is minimized, and distance to the NIS is maximized. The method is one of the most widely used ranking methods, as it verifies a large number of suitable properties (Chen and Hwang, 1992; Yoon and Hwang, 1995; Roy, 1996); therefore, it has been widely applied to real decision problems in several contexts (Behzadian et al., 2012; Zyoud and Fuchs-Hanusch, 2017).

As we have mentioned in the introduction, the weights of the criteria in TOPSIS-based approaches may be quantitative, qualitative or relative; precise or uncertain and objectively or subjectively determined by one or more decision-makers (Watröbski et al., 2019). In what follows, we describe the main steps in the method:

INPUT: Determine the decision matrix D, where the number of criteria is m and the number of alternatives is $n, D = [x_{ij}]_{n\times m}$.

STEP 1. Construct the normalized decision matrix. Criteria are expressed in different scales, and therefore a normalizing procedure is necessary in order to facilitate comparison. Hwang and Yoon (1981) propose a vector normalization,[1]

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n}\left(x_{ij}\right)^2}} \in [0, 1], \quad 1 \le i \le n,\ 1 \le j \le m. \tag{1}$$

[1]In addition to the vector normalization proposed in the seminal paper by Hwang and Yoon, many other normalization processes have been used (Ouenniche et al., 2018).

STEP 2. Determine the weighted normalized decision matrix. It is well known that the weights of the criteria in decision-making problems do not have the same mean, and not all of them have the same importance. The weighted normalized value v_{ij} is calculated as

$$v_{ij} = w_j \, r_{ij}, \quad 1 \le i \le n, \; 1 \le j \le m, \tag{2}$$

where w_j is the weight associated with each criterion.

STEP 3. Determine the PIS and NIS. The PIS, $A^+ = (v_1^+, \ldots, v_m^+)$, and the NIS, $A^- = (v_1^-, \ldots, v_m^-)$, are determined as follows:

$$v_j^+ = w_j r_j^+ = \begin{cases} \max\limits_{1 \le i \le n} v_{ij}, & j \in J \\ \min\limits_{1 \le i \le n} v_{ij}, & j \in J' \end{cases} \quad 1 \le j \le m, \tag{3}$$

$$v_j^- = w_j r_j^- = \begin{cases} \min\limits_{1 \le i \le n} v_{ij}, & j \in J \\ \max\limits_{1 \le i \le n} v_{ij}, & j \in J' \end{cases} \quad 1 \le j \le m, \tag{4}$$

where J is associated with the criteria that indicate profits or benefits, and J' is associated with the criteria that indicate costs or losses.

STEP 4. Calculate the separation measures. Calculation of the separation of each alternative with respect to the PIS and NIS:

$$d_i^+ = \left(\sum_{j=1}^{m} \left(v_{ij} - v_j^+ \right)^2 \right)^{1/2}, \; d_i^- = \left(\sum_{j=1}^{m} \left(v_{ij} - v_j^- \right)^2 \right)^{1/2}, \quad 1 \le i \le n. \tag{5}$$

STEP 5. Calculate the relative proximity to the ideal solution. Calculation of the relative proximity of each alternative to the PIS and NIS using the proximity index.

$$R_i = \frac{d_i^-}{d_i^+ + d_i^-}, \quad 1 \le i \le n. \tag{6}$$

Th R_i value lies between 0 and 1. If $R_i = 1$, then $A_i = A^+$, and if $R_i = 0$, then $A_i = A^-$. The closer the R_i value is to 1, the higher the priority of the ith alternative.

OUTPUT. Rank the preference order. Rank the best alternatives according to R_i in descending order.

3.2. *MUW-TOPSIS*

In what follows, we will present the steps of the new algorithm proposed in this paper, which does not require the introduction of *a priori* weights. Following Liern and Pérez-Gladish (2020, 2021), the PIS and NIS will be obtained for the initial normalized data. Weights are introduced as unknowns in Step 3 when separation measures from the PIS and NIS are calculated. Their values are determined in Step 4 by solving two groups of nonlinear optimization problems that maximize and minimize the separation of each alternative to the PIS and NIS. As we can see from Liern and Pérez-Gladish (2020, 2021), by construction, UW-TOPSIS is a generalization of the classical TOPSIS approach. In what follows, we describe the main steps of the method in detail.

INPUT: Decision matrix $[x_{ij}],\ 1 \le i \le n,\ 1 \le j \le m$, where the number of alternatives is n and the number of criteria is m.

STEP 1. Construct the normalized decision matrix

$$\left[r_{ij}\right],\ r_{ij} \in [0, 1], \quad 1 \le i \le n,\ 1 \le j \le m. \tag{7}$$

STEP 2. Determine the PIS $A^+ = (r_1^+, \ldots, r_m^+)$ and the NIS $A^- = (r_1^-, \ldots, r_m^-)$, given by

$$r_j^+ = \begin{cases} \max\limits_{1\le i\le n} r_{ij}, & j \in J \\ \min\limits_{1\le i\le n} r_{ij}, & j \in J' \end{cases} \quad r_j^- = \begin{cases} \min\limits_{1\le i\le n} r_{ij}, & j \in J \\ \max\limits_{1\le i\le n} r_{ij}, & j \in J' \end{cases} \quad 1 \le j \le m, \tag{8}$$

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

STEP 3. Let us consider $\Omega = \{w = (w_1, \ldots, w_m) \in \mathbb{R}^m,\ \ w_j \in [0, 1],\ \ \sum_{j=1}^m w_j = 1\}$. For $A^+,\ A^-$, we define two separation functions,

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

Given by

$$D_i^+\ (w) = d\left((w_1 r_{i1}, \ldots, w_m r_{im}), \left(w_1 r_1^+, \ldots, w_m r_m^+\right)\right), \quad 1 \le i \le n, \tag{9}$$

$$D_i^-\ (w) = d\left((w_1 r_{i1}, \ldots, w_m r_{im}), \left(w_1 r_1^-, \ldots, w_m r_m^-\right)\right), \quad 1 \le i \le n, \tag{10}$$

where d is a distance function in $\mathbb{R}^m$.

STEP 4. Calculate the function of relative proximity to the ideal solution, $R_i : \Omega \to [0, 1],\ 1 \le i \le n$, as

$$R_i\,(w) = \frac{D_i^-\,(w)}{D_i^+\,(w) + D_i^-\,(w)}, \quad 1 \le i \le n. \tag{11}$$

STEP 5. For each i, $1 \le i \le n$, we calculate the values $R_i^L(w)$, $R_i^U(w)$ solving the two following mathematical programming problems where decision variables are the criteria weights:

$$R_i^L = \text{Min}\left\{R_i\,(w),\ \sum_{j=1}^{m} w_j = 1,\ l_j \le w_j \le u_j,\ 1 \le j \le m\right\}, \quad 1 \le i \le n, \tag{12}$$

$$R_i^U = \text{Max}\left\{R_i\,(w),\ \sum_{j=1}^{m} w_j = 1,\ l_j \le w_j \le u_j,\ 1 \le j \le m\right\}, \quad 1 \le i \le n, \tag{13}$$

where $l_j, u_j \geq 0$ are the lower and upper bounds for each criterion's weight. Then, we obtain n relative proximity intervals,

$$R_i^I = \left[R_i^L,\ R_i^U\right], \quad 1 \leq i \leq n. \tag{14}$$

STEP 6. We rank the intervals $R_1^I, R_2^I, \ldots, R_n^I$ (see Remark 1).
OUTPUT. Ranking of the alternatives according to the ordering ofR_i^I, $1 \leq i \leq n$.

Remark 1. Given the intervals $A = [a_1, a_2]$ and $B = [b_1, b_2]$ contained in $\mathbb{R}$, we will say that A is larger than B if and only if

$$A \succ B \Leftrightarrow \begin{cases} k_1a_1 + k_2a_2 > k_1b_1 + k_2b_2, & k_1a_1 + k_2a_2 \neq k_1b_1 + k_2b_2 \\ a_1 > b_1, & k_1a_1 + k_2\,a_2 = k_1\,b_1 + k_2b_2 \end{cases}$$

where k_1 and k_2 are two preestablished positive constants (see Canós and Liern, 2008). Values k_1 and k_2 inform represent the degree of confidence of the decision-maker that the alternatives are in their best position or on the contrary (Canós and Liern, 2008). When ordering the intervals $[R_i^L,\ R_i^U],\ 1 \leq i \leq n$, the relation $k_2\ /\ k_1$ informs us about the importance (or truthfulness) given to the best situation of the alternatives R_i^U regarding the worst situation R_i^L.

In this work, we aim to order n alternatives that have been assessed on m criteria during t periods, giving place to t decision matrices:

$$\left[x_{ij}^1\right],\ \left[x_{ij}^2\right],\ \ldots,\ \left[x_{ij}^T\right], \quad 1 \leq i \leq n,\ 1 \leq j \leq m, \tag{15}$$

In order to apply the method, we first determine the global PIS and NIS, taking into account all the t periods, as follows:

$$I_j^+ = \begin{cases} \max\limits_{\substack{1\leq i\leq n \\ 1\leq t\leq T}} x_{ij}^t, & j \in J \\ \min\limits_{\substack{1\leq i\leq n \\ 1\leq t\leq T}} x_{ij}^t, & j \in J' \end{cases} \qquad I_j = \begin{cases} \min\limits_{\substack{1\leq i\leq n \\ 1\leq t\leq T}} x_{ij}^t, & j \in J \\ \max\limits_{\substack{1\leq i\leq n \\ 1\leq t\leq T}} x_{ij}^t, & j \in J' \end{cases} \quad 1 \leq j \leq m. \tag{16}$$

Using vectorial notation:

$$I^+ = \left(I_1^+, I_2^+, \ldots, I_m^+\right), \quad I^- = \left(I_1^-, I_2^-, \ldots, I_m^-\right). \tag{17}$$

Taking into account (17), we construct and extended decision matrix for period t, D^t, including in the last two rows two fictitious alternatives I^+ and I^-:

$$D^t = \begin{bmatrix} x_{11}^t & x_{12}^t & \cdots & x_{1m}^t \\ \vdots & & \vdots & \\ x_{n1}^t & x_{n2}^t & \cdots & x_{nm}^t \\ I_1^+ & I_2^+ & \cdots & I_m^+ \\ I_1^- & I_2^- & \cdots & I_m^- \end{bmatrix}. \tag{18}$$

In what follows, we describe the steps to be followed in the application of UW-TOPSIS to a problem with data for t periods (MUW-TOPSIS):

INPUT: Decision matrix $[x_{ij}^t]$, $1 \le i \le n$, $1 \le j \le m$, and the I^+ global PIS and I^- global NIS.

STEP 1. Calculate the extended decision matrix, D^t for each period t.

STEP 2. Apply Steps 1–5 from UW-TOPSIS to D^t and obtain $n+2$ intervals of relative proximity for each period t:

$$\left\{ R_i^t = \left[R_i^{tL},\ R_i^{tU}\ \right]\ ,\ 1 \le i \le n\right\}_{t\,=\,1}^{T}.$$

STEP 3. Calculate the aggregated intervals of relative proximity:

$$R_i^* = \left[R_i^{L*},\ R_i^{U*}\right] = \left[\min_{1\le t\le T}\ R_i^{tL},\ \ \max_{1\le t\le T}\ R_i^{tU}\right],\quad 1 \le i \le n. \tag{19}$$

STEP 4. We rank the intervals $R_1^*, R_2^*, \ldots, R_n^*$.

OUTPUT: Ranking of alternatives according to the ordering given byR_i^*, $1 \le i \le n$.

One of the main inconveniences of the classical TOPSIS is the dependency on the data (rank reversal problem). García-Cascales and Lamata (2012) analyze how to avoid the rank reversal problem, and they propose to consider the PIS and NIS, respectively, PIS, $A^+ = (1,1, \ldots, 1)$ and NIS $A^- = (0,0, \ldots,0)$. This is useful in situations in which new data are incorporated into the initial decision matrix (new alternatives or new criteria). However, this is not our case. In the proposed approach, we evaluate the same criteria and the same alternatives over several periods of time. Using $A^+ = (1,1, \ldots, 1)$ and $A^- = (0,0, \ldots,0)$ as external to the data, PIS and NIS, in all the periods could avoid the use of the extended matrices given in (18). Nevertheless, as we will see in what follows, the obtained rankings need not be the same.

Remark 2. In this work, we have only taken into account the case in which the decision matrix $[x_i]$ is expressed in terms of precise values. The generalization to the case in which the matrix is composed of uncertain data and expressed by intervals will depend on the selected departure model for the UW-TOPSIS approach.

1. If the relative proximity of each alternative is expressed using a real number R_i (Jahanshahloo et al., 2006), values R_i^L and R_i^U will be obtained following (12) and (13).
2. If the relative proximity of each alternative is expressed using an interval $[R_i^1,\ R_i^2\ ]$ (León et al., 2019), values R_i^L and R_i^U are calculated following (12) and (13), but in this case, for R_i^1 and R_i^2, that is,

$$R_i^L = \ \mathrm{Min}\left\{\min_{w\in\Omega^*} R_i^1(w),\ \ \min_{w\in\Omega^*} R_i^2(w)\ \right\}, \tag{20}$$

$$R_i^U = \ \mathrm{Max}\left\{\max_{w\in\Omega^*} R_i^1(w),\ \ \max_{w\in\Omega^*} R_i^2(w)\ \right\}, \tag{21}$$

where $\Omega^* = \{w \in \Omega,\ \ l_j \le w_j \le u_j,\ 1 \le j \le m\}$.

Table 1
Decision alternatives

	ISIN	Firm	Industry group	Country
F_1	IE00B4BNMY34	Accenture PLC	Software and IT services	Ireland
F_2	DE0008404005	Allianz SE	Insurance	Germany
F_3	CA0641491075	Bank of Nova Scotia	Banking services	Canada
F_4	CH0198251305	Coca Cola HBC AG	Beverages	Switzerland
F_5	GB0002374006	Diageo PLC	Beverages	GB
F_6	DE000EVNK013	Evonik Industries AG	Chemicals	Germany
F_7	US4781601046	Johnson & Johnson	Pharmaceuticals	Uses
F_8	FR0000121485	Kering SA	Specialty retailers	France
F_9	IE00BTN1Y115	Medtronic PLC	Healthcare equipment and supplies	Ireland
F_{10}	IT0004965148	Moncler SpA	Textiles and apparel	Italy
F_{11}	CH0038863350	Nestle SA	Food and tobacco	Switzerland
F_{12}	CH0012005267	Novartis AG	Pharmaceuticals	Switzerland
F_{13}	AU000000RIO1	Rio Tinto Ltd	Metals and mining	Australia
F_{14}	DE0007236101	Siemens AG	Consumer goods conglomerates	Germany
F_{15}	SG1T75931496	Singapore Telec. Ltd	Telecommunications services	Singapore
F_{16}	IT0003153415	Snam SpA	Oil and gas related equipment and services	Italy
F_{17}	FR0000130809	Societe Generale SA	Banking services	France
F_{18}	NL00150001Q9	Stellantis NV	Automobiles and auto parts	The Netherlands
F_{19}	IT0003497168	Telecom Italia SpA	Telecommunications services	Italy
F_{20}	CA8849037095	Thomson Reuters Corp	Professional and commercial services	Canada

Source: Refinitiv (2021).

4. Ranking of firms based on their diversity and inclusion with MUW-TOPSIS

In this section, we will try to illustrate the main advantages of multiple-stage unweighted TOPSIS. We will consider an example where 20 firms will be ranked based on diversity and financial criteria. The sample of firms has been randomly obtained from the list of current constituents of the D&I Index published by Refinitiv.

4.1. Data description

In this work, we will use annual data from Refinitiv Datastream (formerly Thomson Reuters Datastream) to rank 20 firms from the D&I Index based on two financial decision criteria and six decision criteria from one of the four pillars of this index, diversity. We will work with annual data over the period 2017–2020. Our sample of firms is composed of the constituents of the 2020 D&I Index, which has complete published data not only in 2020 but also in the three previous years. Table 1 displays the firms (decision alternatives) with their activity sector.

Tables 2 and 3 include, respectively, a description of financial and diversity decision criteria. Traditionally, financial performance is measured by accounting or by market-based indicators. They represent different perspectives on the value of financial performance. Accounting measures capture historical aspects of financial performance and are therefore backward-looking (Cavaco and Crifo, 2014). Although several accounting-based measures are used to measure the financial performance

Table 2
Financial decision criteria

	Criteria	Description
C_1	ROA	Return on assets, measured as (net income/total assets) × 100
C_2	Tobin´s Q	Tobin´s Q, measured as total market value of firm/total assets value

Table 3
Diversity decision criteria

Criteria	Eikon item code	Description	Benchmark group
C_3	TR.AnalyticBoardCultural Diversity	Percentage of board members that have a cultural background different from the location of the corporate headquarters	Country
C_4	TR.WomenEmployees	Percentage of women employees	Industry
C_5	TR.NewWomenEmployees	Percentage of new women employees	Industry
C_6	TR.WomenManagers	Percentage of women managers	Industry
C_7	TR.AnalyticBoardFemale	Percentage of females on the board	Country
C_8	TR.AnalyticExecutive MembersGenderDiversity	Percentage of female executive members	Country

Source: Refinitiv (2021).

of firms, return on assets (ROA) has been demonstrated by numerous authors to be a better indicator of operating profit when examining the relation between financial performance and corporate social responsible dimensions (Aupperle et al., 1985; McGuire et al., 1988; Blackburn et al., 1994; Waddock and Graves, 1997; Muth and Donaldson, 1998; Berman et al., 1999; McWilliams and Siegel, 2000; Orlitzky et al., 2003; Core et al. 2006; Brown and Caylor, 2009; Kyere and Ausloos, 2021).

Tobin’s Q is a financial market-based measure that captures the existing assets and future growth potentials of a company. It is an interesting measure because it captures investors’ expectations of future events, including the evaluation of current business strategies (Rose-Ackerman, 1973; Demsetz and Villalonga, 2001; Ehikioya, 2009; Christensen et al., 2010; Rodríguez-Fernández, 2016; Kyere and Ausloos, 2021). It has also been used by several authors in the discussion of the relation between corporate social performance and financial performance (Dowell et al., 2000; Hillman and Keim, 2001; Akpinar et al., 2008; Surroca et al., 2010; Cavaco and Crifo, 2014). The Tobin’s Q represents the investors’ evaluation of the ability of a firm to generate future economic earnings; it is, therefore, forward-looking and can be considered a proxy for growth opportunities. Data on ROA and Tobin’s Q have been taken from Refinitiv.

Diversity and inclusion criteria are also taken from Refinitiv. The ratings are available through Eikon. A complete description of the methodology behind the calculations of the ratings provided by Eikon has been included in Section 2. As we have seen, the diversity pillar includes board gender diversity (%), board member cultural diversity (%), women employees (%), new women employees (%), women executive employees (%), women managers (%), diversity process (Y/N), and diversity objectives (T/N). All the considered firms in our selected sample have and have had diversity processes and diversity objectives in the period 2017–2020. Therefore, these two metrics are not

Table 4
Decision matrix for $t = 2017$

2017	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
F_1	41.6667	41.0000	45.0000	29.0000	33.3333	13.3333	41.6667	41.0000
F_2	41.6667	51.8000	52.7000	37.6000	33.3333	20.0000	41.6667	51.8000
F_3	40.0000	57.7630	54.0000	39.0000	33.3333	26.0870	40.0000	57.7630
F_4	83.3333	26.0000	37.0000	35.0000	25.0000	22.2222	83.3333	26.0000
F_5	50.0000	31.4360	39.3090	30.0000	40.0000	37.5000	50.0000	31.4360
F_6	5.0000	24.9000	30.0000	23.2000	35.0000	25.0000	5.0000	24.9000
F_7	10.0000	46.5000	51.2900	44.7000	20.0000	12.5000	10.0000	46.5000
F_8	18.1818	58.0800	57.5000	50.7000	63.6364	33.3333	18.1818	58.0800
F_9	8.3333	49.2860	47.8420	34.4000	25.0000	20.0000	8.3333	49.2860
F_{10}	18.1818	70.4000	69.1970	53.7000	27.2727	0.0000	18.1818	70.4000
F_{11}	53.3333	35.1000	41.6950	37.5000	33.3333	7.6923	53.3333	35.1000
F_{12}	61.5385	48.8410	53.0000	41.0000	23.0769	7.1429	61.5385	48.8410
F_{13}	72.7273	18.0000	17.0000	22.4000	18.1818	23.0769	72.7273	18.0000
F_{14}	10.0000	24.0000	26.0000	16.2000	30.0000	25.0000	10.0000	24.0000
F_{15}	10.0000	35.0000	35.4970	27.0000	30.0000	25.0000	10.0000	35.0000
F_{16}	11.1111	13.5000	35.8110	16.4000	44.4444	33.3333	11.1111	13.5000
F_{17}	33.3333	58.7000	60.9200	44.0000	46.6667	19.6429	33.3333	58.7000
F_{18}	100.0000	20.0000	24.7730	16.1000	27.2727	8.3333	100.0000	20.0000
F_{19}	40.0000	35.7640	46.3330	27.0000	40.0000	4.0000	40.0000	35.7640
F_{20}	33.3333	44.0000	47.0000	39.0000	16.6667	26.6667	33.3333	44.0000

Source: Refinitiv (2021).

considered decision criteria in our illustrative example. The final diversity decision criteria are displayed in Table 3.

In Tables 4–7, we show the decision matrices, including data for each year and each firm and decision criteria. In (22) and (23), we calculate the PIS and NIS, respectively. These are the required inputs in our MUW-TOPSIS model.

According to (16), we calculate the global PIS and NIS by taking into account all the periods:

$$I^+ = (100.00,\ 72.30,\ 72.32,\ 59.10,\ 64.29,\ 38.46,\ 2722.75,\ 3200.50) \tag{22}$$

$$I^- - = (5.00,\ 13.50,\ 17.00,\ 16.10,\ 11.11,\ 0.00,\ -2.95,\ 0.38) \tag{23}$$

Remark 3. In order to check the effects produced by changes on the PIS and NIS, we consider data from 2020 for the 20 firms and the first six criteria (see Table 7). Let us suppose that for all criteria, the weights verify $w_j \in [0.1,\ 0.3],\ 1 \leq j \leq 6$. If we apply the method UW-TOPSIS with I^+, I^- given by (22), (23) and with $A^+ = (1,\ldots 1)$, $A^- = (0,\ldots,0)$, in Table 8 it can be observed that the rankings are different.

In Table 9 the relative proximity intervals for each period t are displayed (see Step 2 in MUW-TOPSIS).

In Table 10, we show the aggregated relative proximity intervals for all the periods (Columns 2 and 3). Column 4 displays the middle point of each interval. Using these middle points, we have applied Step 4 from the MUW-TOPSIS method.

Table 5
Decision matrix for $t = 2018$

2018	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
F_1	41.6667	51.2000	51.6000	37.8000	33.3333	20.0000	8.5465	141.0100
F_2	33.3333	41.0000	47.0000	28.0000	27.7778	11.1111	0.7928	175.1400
F_3	37.5000	56.0000	54.0000	44.0000	37.5000	21.4286	6.2702	68.0500
F_4	50.0000	31.8050	41.2610	34.0000	50.0000	37.5000	9.2551	2452.0000
F_5	9.5238	24.9000	28.0000	24.3000	33.3333	25.0000	4.4041	2795.0000
F_6	16.6667	47.1740	44.4430	38.0000	25.0000	14.2857	11.3084	21.8000
F_7	8.3333	49.2530	50.7050	37.0000	25.0000	20.0000	14.8724	129.0500
F_8	7.6923	35.4000	44.7600	30.3000	30.7692	22.2222	22.1241	411.6001
F_9	18.1818	70.5000	69.3820	57.3000	27.2727	0.0000	3.0148	90.9600
F_{10}	64.2857	37.0000	45.7280	43.2000	35.7143	8.3333	1.8036	28.9300
F_{11}	9.0909	25.0000	31.2570	28.1750	27.2727	14.2857	9.1874	79.8000
F_{12}	8.3333	18.4200	20.2550	23.7900	25.0000	30.0000	10.5680	74.2900
F_{13}	70.0000	17.7000	17.0000	22.6000	30.0000	20.0000	13.9568	78.4700
F_{14}	10.0000	24.0000	27.0000	16.4000	35.0000	25.0000	0.3726	87.8540
F_{15}	35.7143	58.1000	58.3030	45.8000	42.8571	21.4286	4.3245	2.9300
F_{16}	11.1111	13.9000	21.5380	18.8000	44.4444	29.4118	11.2450	3.8190
F_{17}	8.3333	34.0000	31.8010	26.0000	25.0000	23.8095	3.5202	27.8200
F_{18}	100.0000	20.2000	24.1400	16.7000	25.0000	9.5238	0.8104	10.0070
F_{19}	13.3333	36.0000	47.7560	26.5730	40.0000	11.5385	1.9495	0.4833
F_{20}	27.2727	47.0000	46.0000	40.0000	18.1818	27.2727	5.6689	65.9300

Source: Refinitiv (2021).

Table 6
Decision matrix for $t = 2019$

2019	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
F_1	45.4545	44.0000	49.0000	30.0000	36.3636	18.7500	7.6424	210.5700
F_2	41.6667	51.0000	50.3000	37.9000	33.3333	20.0000	0.7085	218.4000
F_3	30.7692	56.0000	53.4500	46.0000	38.4615	25.0000	5.8375	73.3500
F_4	84.6154	28.8000	33.0000	38.0000	23.0769	20.0000	9.1291	2565.0000
F_5	50.0000	32.7590	42.6000	36.0000	50.0000	38.4615	4.1897	3200.5000
F_6	10.0000	25.7000	30.0000	25.2000	35.0000	25.0000	8.3598	27.2100
F_7	7.1429	47.8000	51.4000	45.8000	28.5714	27.2727	11.2914	145.8700
F_8	27.2727	62.9000	63.4000	55.1000	63.6364	35.7143	17.1171	585.2000
F_9	9.0909	49.5780	52.5850	38.0000	27.2727	18.1818	3.2095	113.4500
F_{10}	23.0769	71.2000	70.4510	58.1000	30.7692	0.0000	−0.7067	40.0700
F_{11}	71.4286	38.0000	46.1530	42.0000	28.5714	15.3846	5.4158	104.7800
F_{12}	58.3333	49.9190	53.0000	44.0000	25.0000	25.0000	9.1268	91.9000
F_{13}	66.6667	19.0000	23.0000	22.6000	11.1111	14.2857	17.4595	100.4000
F_{14}	10.0000	24.0000	25.0000	17.2000	35.0000	25.0000	0.2961	105.1400
F_{15}	15.3846	34.0000	33.5280	28.0000	30.7692	23.8095	4.6733	3.3700
F_{16}	11.1111	14.6000	22.0930	17.6000	33.3333	31.2500	6.3055	4.6860
F_{17}	35.7143	56.9000	57.0210	43.7000	42.8571	23.3333	2.7704	31.0150
F_{18}	100.0000	20.4000	21.5980	16.6000	18.1818	5.0000	0.7631	11.5326
F_{19}	6.6667	37.0000	45.4580	27.7680	40.0000	5.0000	0.8446	0.5564
F_{20}	25.0000	45.0000	45.0000	43.0000	25.0000	20.0000	5.6655	92.8900

Source: Refinitiv (2021).

Table 7
Decision matrix for $t = 2020$

2020	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
F_1	45.4545	45.0000	49.0000	30.0000	36.3636	28.5714	1.2031	261.2100
F_2	41.6667	51.3000	50.4000	38.2000	33.3333	20.0000	5.3816	200.7000
F_3	30.7692	55.0000	50.4000	45.0000	46.1538	25.8065	6.8586	68.8000
F_4	84.6154	29.0000	31.0000	38.0000	23.0769	20.0000	0.3075	2377.0000
F_5	44.4444	33.6490	41.1000	39.0000	44.4444	33.3333	4.9748	2878.0000
F_6	10.0000	26.0000	30.0000	26.1000	35.0000	25.0000	−1.8323	26.6800
F_7	7.1429	48.1000	52.5000	46.4000	35.7143	27.2727	14.4175	157.3800
F_8	35.7143	63.1000	64.6000	55.4000	64.2857	38.4615	11.7235	594.3999
F_9	8.3333	50.5490	51.2950	39.0000	25.0000	21.4286	11.2876	117.1400
F_{10}	25.0000	72.3000	72.3180	59.1000	33.3333	0.0000	4.6562	50.1400
F_{11}	71.4286	38.0000	43.9450	43.2000	35.7143	15.3846	4.8832	104.2600
F_{12}	64.2857	50.4250	52.0000	45.0000	28.5714	28.5714	−1.2681	83.6500
F_{13}	58.3333	20.0000	29.5000	26.1000	33.3333	21.4286	1.9948	113.8300
F_{14}	10.5263	26.0000	30.0000	18.4000	36.8421	0.0000	8.9012	117.5200
F_{15}	10.0000	34.0000	32.8260	28.0000	30.0000	22.2222	0.0139	2.3100
F_{16}	11.1111	15.6000	18.3510	19.9000	33.3333	31.2500	4.4269	4.6010
F_{17}	42.8571	56.4000	56.9430	43.3000	42.8571	28.8136	2.1502	17.0220
F_{18}	100.0000	20.6000	32.5270	16.9000	18.1818	0.0000	0.6874	12.8140
F_{19}	13.3333	38.0000	38.1980	28.7150	40.0000	6.2500	−2.9472	0.3774
F_{20}	21.4286	46.0000	47.0000	43.0000	21.4286	23.0769	9.6259	104.1800

Source: Refinitiv (2021).

Table 8
Comparison of rankings with different positive ideal solution (PIS) and negative ideal solution (NIS) options

PIS $A^+ = (1,\ldots1)$, NIS $A^- = (0,\ldots,0)$		*PIS I^+ (f), NIS I^- (g)*	
Firms	Average	Firms	Average
F_8	0.2125298	F_8	0.5303811
F_{17}	0.2098621	F_{17}	0.4975602
F_{12}	0.2264346	F_{12}	0.5238011
F_{10}	0.2186812	F_5	0.5059856
F_3	0.2258468	F_{11}	0.5557406
F_5	0.1548949	F_1	0.3425030
F_{11}	0.2003367	F_3	0.4511928
F_4	0.2946412	F_4	0.6711453
F_1	0.1783593	F_2	0.3798856
F_2	0.2271029	F_{10}	0.4845213
F_{18}	0.2204811	F_7	0.5420693
F_7	0.2367606	F_{18}	0.5860071
F_9	0.1750910	F_{13}	0.4017182
F_{20}	0.1164154	F_{20}	0.2189131
F_{13}	0.1484915	F_9	0.3210749
F_{16}	0.1552671	F_{16}	0.3547521
F_6	0.2415765	F_6	0.5910897
F_{15}	0.2043530	F_{15}	0.4362203
F_{19}	0.1438402	F_{19}	0.3007104
F_{14}	0.1768294	F_{14}	0.3960911

Source: Own elaboration.

Table 9
Relative proximity intervals for each period t

Firms	2017		2018		2019		2020	
	R_i^{1L}	R_i^{1U}	R_i^{2L}	R_i^{2U}	R_i^{3L}	R_i^{3U}	R_i^{4L}	R_i^{4U}
F_1	0.3514	0.4551	0.4163	0.5799	0.4175	0.5180	0.4317	0.6291
F_2	0.4203	0.5921	0.3061	0.4479	0.4180	0.5738	0.4180	0.5771
F_3	0.4239	0.6549	0.4214	0.6287	0.4012	0.6315	0.4079	0.6397
F_4	0.3414	0.6581	0.4429	0.7382	0.3407	0.6649	0.3453	0.6666
F_5	0.4055	0.6824	0.1757	0.4777	0.4655	0.7499	0.4297	0.6818
F_6	0.1780	0.4930	0.2231	0.4677	0.1922	0.4945	0.1916	0.4934
F_7	0.1941	0.5189	0.2128	0.5136	0.2595	0.6022	0.2921	0.6103
F_8	0.4082	0.7747	0.2069	0.4820	0.4643	0.8079	0.5101	0.8322
F_9	0.2206	0.4994	0.2350	0.6666	0.2359	0.5317	0.2255	0.5343
F_{10}	0.2344	0.6609	0.3556	0.5889	0.2579	0.6850	0.2710	0.6980
F_{11}	0.3110	0.4806	0.1447	0.3148	0.4077	0.6288	0.4427	0.6414
F_{12}	0.2876	0.5675	0.1607	0.4953	0.4459	0.6196	0.4924	0.6796
F_{13}	0.2438	0.5928	0.2468	0.5714	0.1966	0.4961	0.2752	0.5283
F_{14}	0.1595	0.4637	0.1572	0.4831	0.1656	0.4878	0.1028	0.3351
F_{15}	0.2088	0.4938	0.4306	0.6664	0.2218	0.4769	0.1949	0.4473
F_{16}	0.2079	0.6193	0.1797	0.5728	0.1794	0.5338	0.1773	0.5322
F_{17}	0.4253	0.6828	0.1762	0.4547	0.4386	0.6607	0.4870	0.6952
F_{18}	0.2774	0.6238	0.2956	0.6432	0.2613	0.6107	0.2464	0.6260
F_{19}	0.2355	0.4789	0.1974	0.4700	0.1552	0.4516	0.1740	0.4274
F_{20}	0.2942	0.5767	0.2692	0.5786	0.2772	0.5106	0.2500	0.5422

Source: Own elaboration.

Table 10
Aggregated Relative Proximity Indexes for all the periods

Firms	R_i^{L*}	R_i^{U*}	$0.5\ R_i^{L*} + 0.5\ R_i^{U*}$
F_1	0.351393	0.629087	0.462470
F_2	0.306072	0.592133	0.420496
F_3	0.401158	0.654894	0.502653
F_4	0.340725	0.738192	0.499712
F_5	0.175713	0.749925	0.405398
F_6	0.178007	0.494538	0.304619
F_7	0.194097	0.610281	0.360570
F_8	0.206904	0.832204	0.457024
F_9	0.220571	0.666605	0.398984
F_{10}	0.234394	0.698014	0.419842
F_{11}	0.144654	0.641400	0.343352
F_{12}	0.160698	0.679641	0.368275
F_{13}	0.196613	0.592752	0.355068
F_{14}	0.102768	0.487768	0.256768
F_{15}	0.194877	0.666378	0.383478
F_{16}	0.177342	0.619258	0.354108
F_{17}	0.176247	0.695199	0.383828
F_{18}	0.246440	0.643245	0.405162
F_{19}	0.155208	0.478948	0.284704
F_{20}	0.249978	0.578565	0.381413

Source: Own elaboration.

Table 11
Obtained ranking taking into account the middle point of the aggregated relative proximity intervals

Rank	Firm	Sector
F_3	Bank of Nova Scotia	Banking services
F_4	Coca Cola HBC AG	Beverages
F_1	Accenture PLC	Software and IT services
F_8	Medtronic PLC	Healthcare equipment and supplies
F_2	Allianz SE	Insurance
F_{10}	Nestle SA	Food and tobacco
F_5	Diageo PLC	Beverages
F_{18}	Stellantis NV	Automobiles and auto parts
F_9	Moncler SpA	Textiles and apparel
F_{15}	Societe Generale SA	Banking services
F_{17}	Singapore Telecommunications Ltd	Telecommunications services
F_{20}	Thomson Reuters Corp	Professional and commercial services
F_{12}	Kering SA	Specialty retailers
F_7	Johnson & Johnson	Pharmaceuticals
F_{13}	Rio Tinto Ltd	Metals and mining
F_{16}	Snam SpA	Oil and gas related equipment and services
F_{11}	Novartis AG	Pharmaceuticals
F_6	Evonik Industries AG	Chemicals
F_{19}	Telecom Italia SpA	Telecommunications services
F_{14}	Siemens AG	Consumer goods conglomerates

Source: Own elaboration.

Table 11 displays the ranking of the firms according to the middle point of the aggregated proximity intervals (Table 10).

The lower extreme of the aggregate relative proximity intervals, R_i^{L*}, shows the worst possible situation of the company in the rank. The upper extreme of these intervals, R_i^{R*}, shows the best possible situation in the rank. The smaller the amplitude of the interval, the greater the stability of the company in a position in the rank. Information provided in Table 10 could be used, therefore, to obtain the ranking of the companies in two possible scenarios: a pessimistic scenario (ranking based on R_i^{L*}) and an optimistic scenario (ranking based on R_i^{R*}).

Behind each aggregated relative proximity interval, there are set weights obtained from the optimization problems in (12) and (15), Step 5 in the UW-TOPSIS algorithm. These optimal weights inform the decision-maker about which indicators or criteria benefit or harm the companies in the global ranking.

5. Conclusion

In this work, an extension of UW-TOPSIS has been proposed that is able to incorporate into the model historical information determining the final ranking of the alternatives. The approach takes into account several decision criteria but does not require the *a priori* establishment of weights for the criteria describing their relative importance. The proposed method can be easily extrapolated to any decision situation in which all the criteria are of the type "the more the better" or "the less the better." In previous works, the relative proximity index was considered a synthetic indicator for one period. However, with our proposal, the relative proximity index becomes a synthetic indicator that can be used to assess diversity and inclusion in general, considering the historical performance of the firms. This is possible since the relative proximity index obtained with this approach does not depend directly on the data, although it considers the historical information.

The characteristics and main advantages of the method are illustrated with a real example in which a sample of firms is ranked based on financial and diversity criteria. Based on the indicators, data and methodology used by Refinitiv in the construction of their D&I Index, we propose an alternative ranking of the companies that does not require the *a priori* establishment of the relative importance of the indicators in the diversity pillar. Refinitiv introduces weights describing that relative importance depending on the country of the headquarters of the firms and/or its sector group penalizing those indicators with low or poor reporting practices in the country and/or sector. This practice could be controversial, as one could question whether a company with good reporting in an indicator in a country or sector with poor reporting should be penalized or rewarded. In an attempt to avoid this discussion, our method proposes a ranking in which the weights are unknown variables helping to determine the maximum possible relative proximities to an ideal situation in terms of diversity and financial performance.

Moreover, Refinitiv does not take into account past performance in terms of diversity, which, from our point of view, is as important as in the case of the financial performance of the firm. The proposed method in this paper gives the decision-maker the opportunity of taking into account this past information, enriching the decision-making process.

In future works, we will take into account the amplitude of the aggregated relative proximity intervals in order to control for ambiguity and fuzziness of the intervals. Another future line of research requires taking into account countries and sectors of activity. Our proposal is to rank companies within their countries and sectors. This will allow homogeneous comparison and will solve the problem acknowledged by Refinitiv regarding comparisons among firms in different contexts.

Acknowledgments

Vicente Liern and Blanca Pérez-Gladish would like to thank financial support to the Spanish Ministerio de Ciencia, Innovación y Universidades, project reference number: RTI2018-093541-B-I00. [Correction added on May 04, after first online publication: The acknowledgements has been corrected in this version.]

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