Environmental Science and Policy 147 (2023) 89–102

Contents lists available at ScienceDirect

Environmental Science and Policy

journal homepage: www.elsevier.com/locate/envsci

A hybrid multi-attribute decision-making and data envelopment analysis model with heterogeneous attributes: The case of sustainable development goals

Mehdi Soltanifar[a,1], Madjid Tavana[b,c,*,2,3], Francisco J. Santos-Arteaga[d,4], Hamid Sharafi[e,5]

[a] Department of Mathematics, Semnan Branch, Islamic Azad University, Semnan, Iran
[b] Business Systems and Analytics Department, Distinguished Chair of Business Analytics, La Salle University, Philadelphia, USA
[c] Business Information Systems Department, Faculty of Business Administration and Economics, University of Paderborn, Paderborn, Germany
[d] Departamento de Análisis Económico y Economía Cuantitativa Universidad Complutense de Madrid, Madrid, Spain
[e] Department of Mathematics, Science and Research Branch, Islamic Azad University, Tehran, Iran

ARTICLE INFO

Keywords:
Multi-attribute decision-making
Decision support
Data envelopment analysis
Goal programming
Sustainable development goals
Attribute classification

ABSTRACT

This study presents an integrated multi-attribute decision-making (MADM) and data envelopment analysis (DEA) framework for solving problems with heterogeneous attributes. We classify the heterogeneous attributes into desirable and undesirable classes and provide a model for aggregating the attributes' weights and the alternatives' scores. The proposed model is initially designed as a Multiple Objective Decision Making (MODM) problem with a Data Envelopment Analysis (DEA) policy and then reformulated as a linear programming model tackled through a goal programming approach. We apply the proposed model to a set of European countries based on their fulfillment of the 17 Sustainable Development Goals (SDGs) defined by the United Nations. We show the proposed approach minimizes computational efforts and complexities and maximizes the participation and satisfaction of decision-makers. We compare the rankings derived from our model with those obtained from standard MADM techniques such as Euclid and TOPSIS. We illustrate how the different normalization methods are applied to condition the discrimination power of the models and analyze the reversals triggered by TOPSIS relative to the other techniques. We conclude by noting that our model does not rely on the weights defined by the experts to determine the ranking, which constitutes a significant advantage over the standard MADM techniques in strategic evaluation environments.

1. Introduction

Multi-Criteria Decision-Making (MCDM) methods are one of the most widely used essential techniques among the managers of organizations. This is mainly due to the inherent complexity of their decisions, which require considering multiple criteria simultaneously. Therefore, it is necessary to have a tool to improve the decisions' quality. Management effectiveness is closely related to decision-making excellence in organizations, as the effectiveness and efficiency of strategies, program quality, and overall results depend on the quality of decisions made by managers. MCDM methods are divided into two main categories: Multi-Objective Decision-Making (MODM) and Multi-Attribute Decision-Making (MADM). Generally, MODM methods are used for design purposes, while MADM techniques are applied to select the best alternative from a set. The main difference between MODM and MADM is the definition of the former within a continuous decision space, while the

* Correspondence to: Business Systems and Analytics Department, Distinguished Chair of Business Systems and Analytics, La Salle University, Philadelphia, PA 19141, USA.

E-mail addresses: soltanifar@khayam.ut.ac.ir (M. Soltanifar), tavana@lasalle.edu (M. Tavana), fransant@ucm.es (F.J. Santos-Arteaga), hamid.sharafi@srbiau.ac.ir (H. Sharafi).

[1] ORCID: 0000–0001-7386–5337
[2] ORCID: 0000–0003-2017–1723
[3] Web: http://tavana.us/
[4] ORCID: 0000–0003-2385–4781
[5] ORCID: 0000–0003-1121–6803

https://doi.org/10.1016/j.envsci.2023.06.004
Received 13 March 2023; Received in revised form 1 May 2023; Accepted 2 June 2023
1462-9011/

latter is defined in a discrete decision space. MODM methods are generally proposed to solve optimization problems with multiple objective functions. Such methods are widely used to solve problems in engineering, management, economics, medicine, and social sciences (Soltanifar, 2021a; Perosa et al., 2022; Cicciù et al., 2022; Hosouli et al., 2023).

MADM problems involve formulating alternative solutions, identifying relevant evaluation attributes, assessing their importance, measuring their performance on each alternative, and synthesizing the results into alternative rankings for implementation purposes. In most MADM problems, evaluation attributes exhibit some level of heterogeneity. They could be classified into distinct homogeneous classes: costs and benefits, desirable and undesirable, qualitative and quantitative, precise and imprecise, etc.

The available tools and methods used to solve MADM problems are generally mathematical, requiring the manipulation of numerical weights and scores before being able to select the most suitable alternative(s). MADM methods can be categorized from different points of view. From one point of view, these methods are divided into compensatory and non-compensatory approaches. In non-compensatory models, exchange between attributes is not allowed. This category includes methods such as the mastery method (method of domination), max-min, max-max, satisfactory inclusion method, specific satisfactory method, and the lexicographic method. In contrast, exchange between attributes is allowed in compensatory models, and one attribute's strength can compensate for another's weakness. Models such as the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Silva and Filho, 2020; Hajiaghaei-Keshteli et al., 2023), Analytical Hierarchy Process (AHP) (Otaya et al., 2017; Abdullah et al., 2023), VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) (Akram et al., 2021), ELimination and Choice Expressing REality (ELECTRE) (Zahid et al., 2022) and the LINear programming technique for Multidimensional Analysis of Preference (LINMAP) (Chen, 2013) are examples belonging to this latter category (Doumpos and Zopounidis, 2011; Zou et al., 2022). Many of these models have been developed to handle uncertainty using interval, fuzzy, and probabilistic measures (Mohammed, 2020; Ortiz-Barrios et al., 2021; Venkatesh et al., 2019; Gal et al., 1999; Hwang and Yoon, 1981; Köksalan and Zionts, 2001; Tzeng and Huang, 2011; Ning et al., 2022). Alinezhad and Khalili (2019) have identified a total of 27 MADM methods.

In many MADM methods, the complex process of information retrieval discourages the participation of experts. For example, in AHP, experts obtain information through pairwise comparisons. In some cases, the pairwise comparison process is time-consuming, confusing, and involves inconsistencies (Kou et al., 2016; Aguarón et al., 2021; Lin et al., 2022). There is a need to simplify and streamline the information retrieval process in MADM by developing effective and efficient hybrid methods. Some MADM methods are based on decision matrices representing alternative scores on each attribute. Attributes can be a cost or benefit variable. Most methods propose a process to convert cost attributes into benefit attributes. This process replaces the column values related to cost attributes with other values. Tavana (2002) introduced a MADM method in which there is no need to convert cost attributes into benefits and cost attribute values play a direct role in the prioritization process of the alternatives.

Data Envelopment Analysis (DEA) is a nonparametric method for estimating production frontiers (Charnes et al., 1978). This technique is used to measure the relative efficiency of Decision Making Units (DMUs). DEA is strongly related to production theory in economics and is also used for benchmarking in operations management. A substantial amount of literature has focused on establishing a relationship between MCDM and DEA. One of the main lines of research has aimed at improving the benchmarking quality of DEA with the help of interactive MODM methods (HosseinzadehLotfi et al., 2010a; Hosseinzadeh Lotfi et al., 2010b; Tavana et al., 2018). The relationship between DEA and MADM is also an intriguing topic that has always interested decision scientists and operations researchers. Conventional DEA models divide DMUs into efficient and inefficient and often require methods to distinguish among the efficient DMUs.

MADM methods can be used to perform the task of selecting alternative DMUs. Chitnis and Vaidya (2016) proposed a unified approach based on DEA and TOPSIS to overcome the difficulty of unique ranking in prevalent benchmarking and performance evaluation processes such as DEA, Super efficiency DEA models, and several others. Keshavarz and Toloo (2020) presented a hybrid DEA and a MADM approach for sustainability assessment. In their research, a hybrid approach involving DEA and MADM was proposed to calculate an index for each dimension of sustainability. Then, an overall sustainability index was calculated as the mean of the measured indexes.

Soltanifar and Sharafi (2022) ranked DMUs in DEA using a modified cross-efficiency method in the presence of negative data. They applied a fuzzy version of VIKOR to define their proposed modified method. Puri and Verma (2020) also ranked DMUs using the DEA cross-efficiency method. Their approach has the advantage that each aggressive, benevolent, and neutral cross-efficiency formula helps select the best alternative among DMUs in a MADM problem. These authors use the Ordered Weighted Averaging (OWA) technique to aggregate the final cross efficiencies and achieve a complete ranking of the DMUs. Zhou and Zhan (2020) proposed three DEA-based models to obtain more reasonable efficiency scores for DMUs. They used MADM to determine the weight of the outputs based on the preferred ratings within the outputs. Then, they multiplied the aggregated output quantities to obtain comprehensive performance scores for evaluation.

The relationship between DEA and MADM can also be presented in the context of hybrid MADM-DEA techniques, where DEA models are used to improve the performance of MADM methods. DEA is a popular performance management method that can be combined with MADM to enhance the information retrieval process. Liu and Hai (2005) proposed a DEA model to improve AHP performance and used the resulting model to rank suppliers. Such research intuition can also be seen in Soltanifar and Hosseinzadeh Lotfi (2011) and Tavana et al. (2021). Soltanifar (2021b) improved the linear assignment method using a DEA model. This method replaces the mixed-integer model with a linear programming model, prioritizes the alternatives, and determines the distance among them according to the concept of uncertainty (Baraka and Heidary Dahooei, 2018; Liu et al., 2020).

1.1. Contribution

The complexity involved in the achievement of the different Sustainable Development Goals (SDGs) and their categorization in terms of their relative importance require the application of formal models capable of simultaneously considering multiple objectives and variables and provide a consistent and unbiased evaluation of the progress achieved. We exploit the flexibility of DEA and its capacity to consider features expressed in different units of measurement to account for multiple sustainability dimensions by incorporating a large number of economic, environmental, and social indicators to the analysis. These qualities have indeed led DEA to gain importance in the construction of indicators designed to evaluate sustainable development environments (Zakari et al., 2022). However, the resulting models have generally focused on specific dimensions of the SDGs, ranging from CO2 emissions (De Castro Camioto et al., 2014) to food supply (Lucas et al., 2021).

The current study presents a group of MADM methods based on DEA for solving problems with heterogeneous evaluation attributes. The proposed method is based on the concept of preferential voting and presented using a DEA model with a linear programming formulation. The model is first designed as an MODM problem and then reformulated as a linear programming problem that is formalized through a goal programming approach. In terms of complexity, it has the advantages of linear programming in comprehension and implementation. In addition, the proposed method is structured as a decision matrix and does not need to change the nature of columns to differentiate between benefit and cost attributes. We compare the rankings derived from our method with those obtained from standard MADM techniques such as Euclid and TOPSIS. We illustrate how the different normalization methods applied to condition the discrimination power of the models and analyze the reversals triggered by TOPSIS relative to the other techniques.

Our hybrid model requires interacting with experts to define the relative importance of the groups of categories that contain the different criteria. At the same time, the optimization problem provides a consistent and neutral framework for the assignment of weights to the criteria, which can then be used in the evaluation of sustainability development policies. In other words, our hybrid model does not rely on the weights assigned by the experts to the different criteria when determining the ranking, which constitutes a significant advantage relative to standard MADM techniques in strategic evaluation environments.

All in all, our MADM-DEA model generates consistent indexes applied to weight heterogeneous criteria. The model provides a simple but powerful formal framework to rank the 17 SDGs defined by the United Nations in 2015. In this regard, the model could be easily extended to incorporate the 169 targets. While plausible, this extension is outside the scope of the current paper.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on preferential voting and DEA, highlighting that undesirable outputs are widely used in DEA settings. In Section 3, these outputs will be used to present a new group voting model. Section 4 describes the MADM aspects of the proposed method, while Section 5 compares it with Euclid and TOPSIS. Section 6 presents a real-world case study to demonstrate the applicability and efficiency of the proposed method. Section 7 concludes and suggests future research directions.

2. Preferential voting

The problem of “election” using the aggregation of votes is one of the most important group decision questions for which several models have been proposed. Consider a group of people who need to make a group decision. Voting is the process of aggregating individual votes to reach a collective decision. The ballot structure is often divided into two categories. In the first category, voters may vote for one candidate, while voters may vote for more than one candidate in the second category. In other words, the second category is divided into two sub-categories. In one sub-category, the names of a few candidates are written on the ballot paper. In the second sub-category, voters could express their preferences and select several candidates.

In the non-preferential voting mechanism, m is chosen among n candidates ($m < n$). Therefore, each voter on the ballot will vote for a maximum of m candidates, and in the end, the candidates with the most votes will win. One disadvantage of this voting process is not prioritizing the polling stations. Therefore, voters cannot transfer their preferences to the community.

In preferential voting, more opinion information is used from the voters compared to other electoral systems. In this type of voting, voters are asked to choose their preferred candidate and nominate a second candidate in case their first choice does not win. They are also asked for a third-choice candidate if their first and second-choice candidates do not win. Therefore, each voter selects a subset of candidates and arranges them according to their preferences. Although no single preferential voting method is the best, some methods are preferred over others. A popular aggregation method is Borda’s count (de Borda, 1781), in which fixed weights are assigned to different preferences. Suppose y_{ij} represents the number of priority votes i ($i = 1, 2, ., m$) for candidate j ($j = 1, 2, ., n$). The evaluation index of each candidate is defined as Eq. (1).

$$E_j = \sum_{i=1}^{m} u_i y_{ij}, \quad u_1 > u_2 > \ldots > u_m \tag{1}$$

The relative weight or importance of each priority must be greater than that of the next priority. de Borda (1781) defined the weights as $u_i = m - i + 1, \quad i = 1, 2, ., m$. The winning candidate is the one displaying the highest overall evaluation index. However, the choice of predetermined weights does not necessarily maximize the overall evaluation index for each candidate, which changes when a different weight vector is considered. This drawback will undoubtedly cause the candidates to protest. Using Thompson’s assurance region (Thompson et al., 1986, 1989) and the optimistic policy of Charnes et al. (1978) in DEA, Cook and Kress (1990) provided a model for selecting the optimal weight vector for each candidate. Despite this fact, their model has two controversial problems.

The first problem is the choice of the discrimination intensity function and the corresponding weight constraints, according to which the winner can change. The second problem is using an optimistic policy model where each candidate chooses the best weight vector, which could cause a tie in the ranking. In this regard, Green et al. (1996) ranked the candidates using Sexton’s cross-efficiency evaluation (Sexton et al., 1986). They also defined a weak weight order based on accumulation. Hashimoto (1997) built on the super-efficiency method of Andersen and Petersen (1993) to propose the removal of the candidate under evaluation and introduced a constraint category in which the difference between two consecutive weights is greater than or equal to that of the two subsequent consecutive weights. Noguchi et al. (2002) introduced weight restriction through a strong order and provided a way to rank candidates with multiple attributes. Obata and Ishii (2003) designed a model to provide a fair distinction between efficient candidates, which uses weights of the same size. Foroughi et al. (2005) and Foroughi and Tamiz (2005) developed Obata’s model for efficient and inefficient candidates and algorithmically reduced its computational complexity. Llamazares (2017) showed that the winning candidate in Obata’s model would change by selecting different norms. He also developed Obata’s model with the weight restriction of Green et al. (1996) to determine the winning candidate without solving the linear programming problem. Contreras (2011) designed a two-step method for determining the group ranking of candidates. In the first step, the weight vector model determines which candidate under evaluation has the best rank. The model looks for a weight vector that minimizes the candidate rank. In the second step, a compromise solution is obtained based on the best candidate rank obtained in the first step. Hosseinzadeh Lotfi et al. (2013) improved the model presented by Contreras (2011) and derived the ranking of the candidates in the worst case. They called the model anti-ideal rank and considered it the upper limit of each candidate’s group ranking. Gong et al. (2018) proposed a DEA model for preferential voting with abstentions.

Several studies have used preferential voting as a decision support tool. Liu and Hai (2005) used preferential voting to select suppliers in the AHP. Suppliers were considered candidates and managers as voters. This method collects expert opinions without a pairwise comparison matrix and consistency verification. Soltanifar and Hosseinzadeh Lotfi (2011) used the Voting AHP to rank DMUs in DEA. Amin et al. (2012) applied preferential voting to aggregate information in the metasearch engine. Soltanifar and Shahghobadi (2013) used preferential voting to derive the best secondary goal model in cross-efficiency evaluation. Izadikhah and Farzipoor Saen (2019) applied this technique to assess suppliers’ sustainability. Zerafat Angiz et al., (2010, 2012) and Sharafi et al. (2022) studied the concept of preferential voting with fuzzy logic and developed several models.

Preferential voting models have been extended to incorporate groups with unequal power. The resulting models are known as preferential group voting (Ebrahimnejad, 2012; Ebrahimnejad and Bagherzadeh, 2016; Sharafi et al., 2019; Soltanifar, 2020).

According to the intuition provided to define Eq. (1) and to eliminate the inherent shortcomings, Cook and Kress (1990) proposed model (2).

$$E_p = \max \sum_{i=1}^{m} u_i y_{ip}, \quad p = 1, 2, ., n \tag{2}$$

Table 1
Aggregation of votes.

First category								Second category								.	k^{th} category							
Desirable				Undesirable				Desirable				Undesirable				.	Desirable				Undesirable			
1th	2^{th}	.	m^{th}	1^{th}	2^{th}	.	m^{th}	1^{th}	2^{th}	.	m^{th}	1^{th}	2^{th}	.	m^{th}	.	1^{th}	2^{th}	.	m^{th}	1^{th}	2^{th}	.	m^{th}
y^1_{11}	y^1_{21}	.	y^1_{m1}	x^1_{11}	x^1_{21}	.	x^1_{m1}	y^2_{11}	y^2_{21}	.	y^2_{m1}	x^2_{11}	x^2_{21}	.	x^2_{m1}	.	y^k_{11}	y^k_{21}	.	y^k_{m1}	x^k_{11}	x^k_{21}	.	x^k_{m1}
y^1_{12}	y^1_{22}	.	y^1_{m2}	x^1_{12}	x^1_{22}	.	x^1_{m2}	y^2_{12}	y^2_{22}	.	y^2_{m2}	x^2_{12}	x^2_{22}	.	x^2_{m2}	.	y^k_{12}	y^k_{22}	.	y^k_{m2}	x^k_{12}	x^k_{22}	.	x^k_{m2}
⋮	⋮	.	⋮	⋮	⋮	.	⋮	⋮	⋮	.	⋮	⋮	⋮	.	⋮	.	⋮	⋮	.	⋮	⋮	⋮	.	⋮
y^1_{1n}	y^1_{2n}	.	y^1_{mn}	x^1_{1n}	x^1_{2n}	.	x^1_{mn}	y^2_{1n}	y^2_{2n}	.	y^2_{mn}	x^2_{1n}	x^2_{2n}	.	x^2_{mn}	.	y^k_{1n}	y^k_{2n}	.	y^k_{mn}	x^k_{1n}	x^k_{2n}	.	x^k_{mn}

$$s.t. \quad \sum_{i=1}^{m} u_i y_{ij} \leq 1, \quad j = 1, 2, \ldots, n$$

$$u_i - u_{i+1} \geq d(i, \varepsilon), \quad i = 1, 2, \ldots, m-1$$

$$u_m \geq d(m, \varepsilon)$$

In this model, each candidate is free to choose the polling stations' weights to get the best efficiency score. Only the weights of the polling stations apply to the constraints of model (2), representing the same priority pattern between the weights as the one described in Eq. (1). $d(i, \varepsilon) : N \times R^{\geq 0} \to R^{\geq 0}$ is called the discrimination intensity function and is a monotone increasing and non-negative function. Intuitively, $d(i, \varepsilon)$ defines the minimum distance between the i-th and $(i+1)$ priority weights. ε is called the discrimination factor.

Assuming a system with n homogeneous DMUs where each unit has s inputs and m outputs, model (2′) is the constant returns to scale DEA multiplier form applied to evaluate this system.

$$E_p = \max \sum_{i=1}^{m} u_i y_{ip}, \quad p = 1, 2, ., n \tag{2′}$$

$$s.t. \quad \sum_{r=1}^{s} v_r x_{rp} = 1,$$

$$\sum_{i=1}^{m} u_i y_{ij} - \sum_{r=1}^{s} v_r x_{rj} \leq 0, \quad j = 1, 2, \ldots, n$$

$$u_i \geq 0, \quad i = 1, 2, \ldots, m$$

$$v_r \geq 0, \quad r = 1, 2, ., s$$

Model (2) is a special case of the constant returns to scale DEA model in multiplier form, in which each candidate plays the role of a DMU, and the aggregated votes received constitute the output. DMUs have a single input equal to 1 ($r = 1$ & $x_{1j}=1,\ j = 1,2,\ldots,n$). In addition, weight restrictions account for the appropriate discrimination intensity function applied to show the difference between polling stations. In model (2), candidates select the best weight vector for their polling stations. Any candidate with an optimal objective function value equal to one is efficient.

A few points must be highlighted. First, since a separate model is solved for each candidate, and model (2) selects the best weight vector for each candidate, it is sometimes not possible to rank the candidates. That is, we may obtain $E_p^*(\varepsilon) = 1$ for multiple candidates simultaneously. Second, changing the weight difference between voting priorities can modify the winning candidate. We summarized the main models proposed to address these shortcomings at the beginning of this section. The next one studies preferential voting in groups with unequal power levels. We will define a new model by introducing the concept of undesirable voters and use it to solve MADM problems.

3. Group preferential voting

Consider the process described in Section 2 and suppose voters are divided into k categories with unequal power levels, where the impact of the vote of a lower-index group is greater than that of a higher-index group. The process of aggregating votes in a group with an unequal level of voting power has already been investigated in DEA (Ebrahimnejad, 2012; Ebrahimnejad and Bagherzadeh, 2016; Soltanifar, 2020). We examine this process by dividing voters into desirable and undesirable categories and providing a model for aggregating their votes.

Assume that we choose m representatives from among n candidates and divide them into k categories. These k categories are assigned unequal power. That is, the influence of votes with a lower index is greater than those with a higher index. Moreover, some voters are considered desirable and some undesirable, but they are unaware of this grouping. This division does not affect how the voters vote.

Denote by y^r_{ij}, $i = 1, 2, \ldots, m$, $j = 1, 2, \ldots, n$, and $r = 1, 2, \ldots k$, the number of votes obtained by the j^{th} candidate in the i^{th} position within the r^{th} group of desirable voters and by x^r_{ij}, $i = 1,2,\ldots,m$, $j = 1,2,\ldots,n$, and $r = 1, 2, \ldots k$, the number of votes obtained by the j^{th} candidate in the i^{th} position within the r^{th} group of undesirable voters. Table 1 shows how these votes are aggregated.

Now suppose u^r_i, $i = 1, 2, \ldots m$, and $r = 1, 2, \ldots, k$, are the weights assigned to the desirable votes in the i^{th} position of the r^{th} group, and v^r_i, $i = 1,2,\ldots m$, and $r = 1, 2, \ldots, k$, are the weights assigned to the undesirable votes in the i^{th} position of the r^{th} group. Note that, just as the positive impact of the votes of desirable voters with a lower index is greater than that of the votes of desirable voters with a higher index, the negative impact of the votes of undesirable voters with a lower index is greater than that of the votes of undesirable voters with a higher index. We use this difference in impact factor to define and introduce weight restrictions and the appropriate discrimination intensity functions, as Cook and Kress (1990) suggested. Models (3) and (4) illustrate the importance of the aggregation process of desirable and undesirable votes within and across categories for candidate $p, (p = 1, 2, \ldots, n)$.

$$\max \sum_{r=1}^{k} \sum_{i=1}^{m} u^r_i y^r_{ip} \tag{3}$$

s.t.

$$\sum_{r=1}^{k} \sum_{i=1}^{m} u^r_i y^r_{ij} \leq 1, \quad j = 1, 2, \ldots, n$$

$$(a) \begin{cases} u^r_i - u^r_{i+1} \geq d^1(i, \varepsilon), & i = 1, 2, \ldots, m-1; r = 1, 2, \ldots, k \\ u^r_m \geq d^1(m, \varepsilon), & r = 1, 2, \ldots, k \end{cases}$$

$$(b) \begin{cases} u^r_i - u^{r+1}_i \geq d^2(r, \varepsilon'), & r = 1, 2, \ldots, k-1; i = 1, 2, \ldots, m \\ u^k_i \geq d^2(k, \varepsilon'), & i = 1, 2, \ldots, m \end{cases}$$

$$\min \sum_{r=1}^{k} \sum_{i=1}^{m} v^r_i x^r_{ip} \tag{4}$$

s.t.

$$\sum_{r=1}^{k}\sum_{i=1}^{m} v_i^r x_{ij}^r \geq 1, \quad j = 1,2,\ldots,n$$

$$(a')\begin{cases} v_i^r - v_{i+1}^r \geq \hat{d}^1(i,\varepsilon), & i = 1,\ldots,m-1; r = 1,2,\ldots,k \\ v_m^r \geq \hat{d}^1(m,\varepsilon), & r = 1,2,\ldots,k \end{cases}$$

$$(b')\begin{cases} v_i^r - v_i^{r+1} \geq \hat{d}^2(r,\varepsilon'), & r = 2,\ldots,k; i = 1,2,\ldots,m \\ v_i^k \geq \hat{d}^2(k,\varepsilon'), & i = 1,2,\ldots,m \end{cases}$$

$$\max \sum_{r=1}^{k}\sum_{i=1}^{m} u_i^r y_{ip}^r \tag{5}$$

$$\min \sum_{r=1}^{k}\sum_{i=1}^{m} v_i^r x_{ip}^r$$

s.t.

$$\sum_{r=1}^{k}\sum_{i=1}^{m} u_i^r y_{ij}^r \leq 1, \quad j = 1,2,\ldots,n$$

$$\sum_{r=1}^{k}\sum_{i=1}^{m} v_i^r x_{ij}^r \geq 1, \quad j = 1,2,\ldots,n$$

$$u_i^r - u_{i+1}^r \geq d^1(i,\varepsilon), \quad i = 1,2,\ldots,m-1; r = 1,2,\ldots,k$$

$$u_m^r \geq d^1(m,\varepsilon), \quad r = 1,2,\ldots,k$$

$$u_i^r - u_i^{r+1} \geq d^2(r,\varepsilon'), \quad r = 1,2,\ldots,k-1; i = 1,2,\ldots,m$$

$$u_i^k \geq d^2(k,\varepsilon'), \quad i = 1,2,\ldots,m$$

$$v_i^r - v_{i+1}^r \geq \hat{d}^1(i,\varepsilon), \quad i = 1,\ldots,m-1; r = 1,2,\ldots,k$$

$$v_m^r \geq \hat{d}^1(m,\varepsilon), \quad r = 1,2,\ldots,k$$

$$v_i^r - v_i^{r+1} \geq \hat{d}^2(r,\varepsilon'), \quad r = 2,\ldots,k; i = 1,2,\ldots,m$$

$$v_i^k \geq \hat{d}^2(k,\varepsilon'), \quad i = 1,2,\ldots,m$$

$d^1(.,\varepsilon)$, $d^2(.,\varepsilon')$, $\hat{d}^1(.,\varepsilon)$ and $\hat{d}^2(.,\varepsilon')$ are monotonically increasing and non-negative discrimination intensity functions. These functions are determined based on the Decision Makers (DMs) preferences. We reviewed some suggestions for determining these functions in Section 2. According to the DEA policy used in model (2), each candidate in model (3) is allowed to choose the weights, observing the weight restrictions (a) and (b) most optimistically. Similarly, model (4) considers the undesirable votes of each candidate. Constraints (a) and (b) in model (3) represent the difference in the positive effect of the lower and higher index votes and the positive impact of the lower and higher index categories, respectively. Constraints (a') and (b') in model (4) represent the difference in the negative effect of the lower and higher index votes and the negative impact of the lower and higher index categories, respectively.

These two models are combined in the model (5), endowed with two objective functions simultaneously considering the candidate's desirable and undesirable votes $p, (p = 1,2,\ldots,n)$. This problem can be solved as a multi-objective problem by converting the objective function into constraints, applying weighting, absolute priority, or goal programming. The objective functions for models (3) and (4) should be equal to 1 because of the respective first constraints. Using goal programming, model (5) becomes model (6) as follows:

$$\min \; d^+ + d^- \tag{6}$$

s.t.

$$\sum_{r=1}^{k}\sum_{i=1}^{m} u_i^r y_{ip}^r + d^+ = 1$$

$$\sum_{r=1}^{k}\sum_{i=1}^{m} v_i^r x_{ip}^r - d^- = 1$$

$$\sum_{r=1}^{k}\sum_{i=1}^{m} u_i^r y_{ij}^r \leq 1, \quad j = 1,2,\ldots,n$$

$$\sum_{r=1}^{k}\sum_{i=1}^{m} v_i^r x_{ij}^r \geq 1, \quad j = 1,2,\ldots,n$$

$$u_i^r - u_{i+1}^r \geq d^1(i,\varepsilon), \quad i = 1,2,\ldots,m-1; r = 1,2,\ldots,k$$

$$u_m^r \geq d^1(m,\varepsilon), \quad r = 1,2,\ldots,k$$

$$u_i^r - u_i^{r+1} \geq d^2(r,\varepsilon'), \quad r = 1,2,\ldots,k-1; i = 1,2,\ldots,m$$

$$u_i^k \geq d^2(k,\varepsilon'), \quad i = 1,2,\ldots,m$$

$$v_i^r - v_{i+1}^r \geq \hat{d}^1(i,\varepsilon), \quad i = 1,\ldots,m-1; r = 1,2,\ldots,k$$

$$v_m^r \geq \hat{d}^1(m,\varepsilon), \quad r = 1,2,\ldots,k$$

$$v_i^r - v_i^{r+1} \geq \hat{d}^2(r,\varepsilon'), \quad r = 2,\ldots,k; i = 1,2,\ldots,m$$

$$v_i^k \geq \hat{d}^2(k,\varepsilon'), \quad i = 1,2,\ldots,m$$

$$d^+, d^- \geq 0$$

where $d^+$and d^- are variables accounting for the deviation from the goals of the objective functions. The goal programming approach allows for extensions of the model focused on the satisfaction of decision makers' preferences. Furthermore, given its widespread use in goal programming environments, the pre-emptive (lexicographic) model could also be applied, allowing to prioritize the realization of the different goals. Given the optimal solution of model (6), $((u_1^{1*},\ldots,u_m^{1*},v_1^{1*},\ldots v_m^{1*}),\ldots,(u_1^{k*},\ldots,u_m^{k*},v_1^{k*},\ldots v_m^{k*}))$, the performance score of candidate p, E_p^*, can be obtained from Eq. (7):

$$E_p^* = \frac{\sum_{r=1}^{k}\sum_{i=1}^{m} u_i^{r*} y_{ip}^r}{\sum_{r=1}^{k}\sum_{i=1}^{m} v_i^{r*} x_{ip}^r} \tag{7}$$

Once all the E_p^* scores of the candidates are calculated, they are sorted in descending order, and the list is used for selecting the winning candidates.

4. Practical application

In the previous section, we described how voters were divided into desirable and undesirable categories. This classification raises several important questions. How are undesirable voters used in the voting process? What are some potential applications of the model? How can the proposed model be used to solve real-world problems? We address these questions by solving a MADM problem.

Many MADM problems include cost and benefit attributes where the goal is ranking a set of alternatives or choosing the most suitable one. Consider a car selection problem where quality is a benefit factor (a higher value is more desirable), and fuel consumption is a cost factor (a lower value is more desirable). In most MADM models, the cost attributes are converted into benefit attributes through a normalization process. The model proposed in Section 3 can solve this problem without

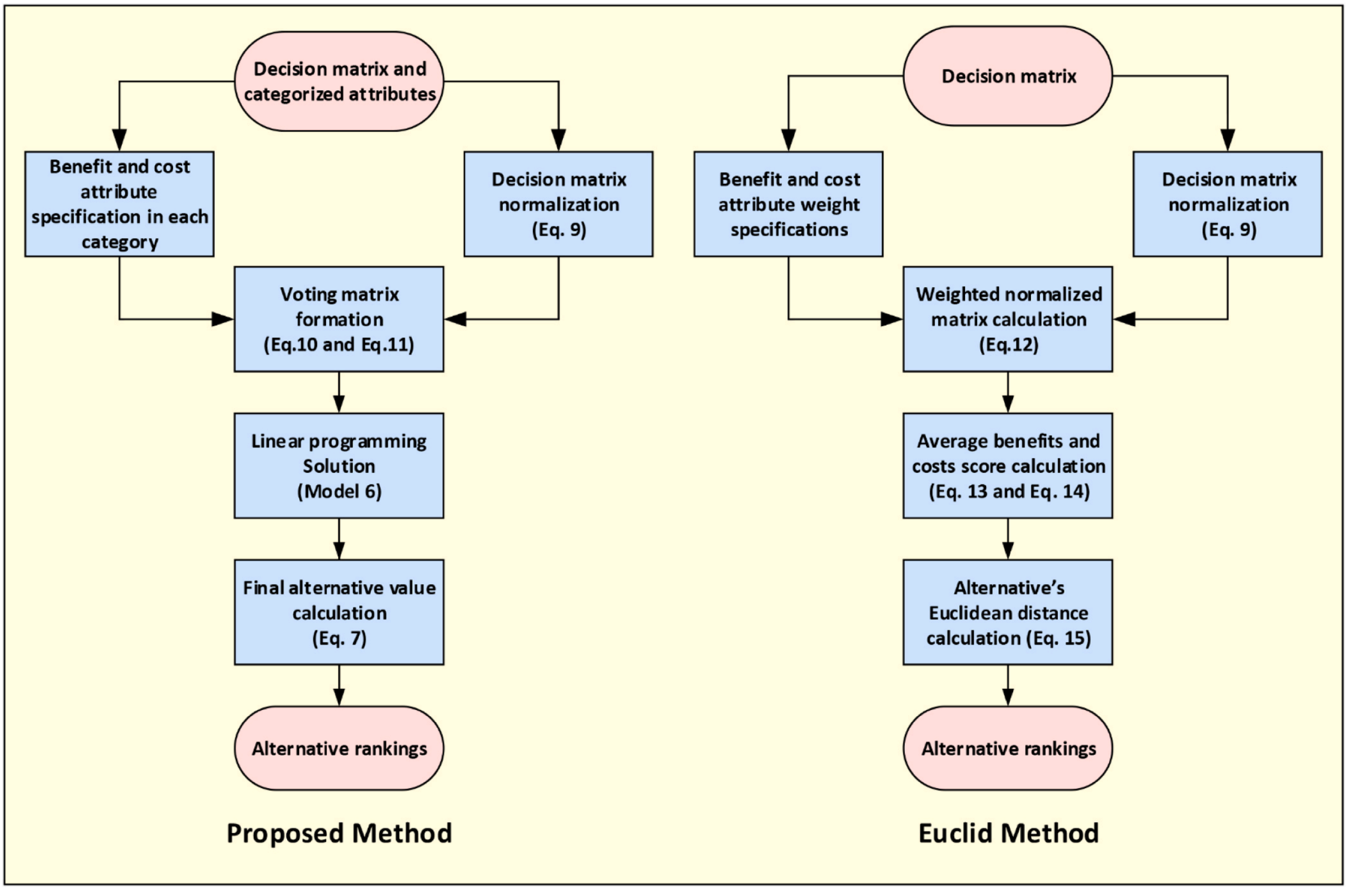

Fig. 1. Flowchart of the proposed method and Euclid.

attribute conversion by considering the benefit attributes as desirable voters with positive impact and the cost attributes as undesirable voters with negative impact. The proposed approach reduces computational efforts and promotes interaction with the DMs. Also, since in most methods the effects of different attributes on the final prioritization tend to vary, the weights of the attributes are determined first with the help of experts. The proposed method organizes attributes into different categories and introduces alternative attribute priorities in the discrimination intensity functions to determine the effect of the attributes. As a result, fewer judgments are sought from the experts.

The proposed method collects limited judgment data from the DMs. However, the accuracy of decision-making often outweighs its speed. In such cases, the decision matrix presented in Table 1 cannot accurately rank the alternatives since some of the impacts of the alternatives and the attributes are not captured. It is sufficient to consider the aggregate score of the $p(p = 1, 2, \ldots, n)$ different alternatives in the desirable and undesirable categories to eliminate this drawback from model (6). In fact, y^r_{ip} and x^r_{ij} are no longer the votes obtained by candidate p from the point of view of the desirable and undesirable voters; instead, these are now the sums of the scores obtained from the benefit and cost attributes. Consequently, a more informative decision matrix is used in the ranking process.

Let us describe the proposed method. Assume we want to evaluate n similar alternatives $(A_1, A_2, \ldots, A_n)$ by considering s multiple attributes $(C_1, C_2, \ldots, C_s)$. Eq. (8) presents the overall decision matrix for this problem:

$$D = \begin{bmatrix} t_{11} & \cdots & t_{1s} \\ \vdots & \ddots & \vdots \\ t_{n1} & \cdots & t_{ns} \end{bmatrix} \tag{8}$$

Step 1: Normalize the decision matrix (8) using Eq. (9).

$$\widehat{t}_{pq} = \frac{t_{pq} - t^-_q}{t^+_q - t^-_q}\ ; \quad p = 1, 2, \ldots, n; \quad q = 1, 2, \ldots, s. \tag{9}$$

where $t^-_q = \min_{1 \le p \le n} t_{pq}$ and $t^+_q = \max_{1 \le p \le n} t_{pq}$, $q = 1, 2, ., s$. This method is one of the many approaches suggested in the literature for normalizing decision matrices in MADM. It should be noted that normalization is used to standardize the unit of measurement regardless of the attribute type.

Step 2: Categorize the attributes using the judgments of the experts. This categorization describes the importance of attributes. Suppose the experts divide the attributes into k categories so that the importance of the characteristics embedded in category a is higher than that of the characteristics embedded in category b whenever $a < b$. Each attribute category can be divided into benefit and cost categories.

Step 3: Form the voting matrix shown in Table 1 using Eqs. (10) and (11). The number of alternatives and selected attributes will be equal in the resulting Table 1 $(m = n)$ since we need to identify and allocate the priority of each alternative among all the alternatives in each category.

$$y^r_{ij} = \sum_{\substack{q \in\ r^{th}\text{category of profit attributes} \\ \hat{t}_{jq}\text{ is the } i^{th}\text{priority in the column}}} \widehat{t}_{jq} \tag{10}$$

$$x^r_{ij} = \sum_{\substack{q \in\ r^{th}\text{category of cost attributes} \\ \hat{t}_{jq}\text{ is the } i^{th}\text{ priority in the column}}} \widehat{t}_{jq} \tag{11}$$

Step 4: Solve model (6) and calculate the score of the alternatives using Eq. (7). The flowchart of the proposed method is presented in Fig. 1.

Table 2
Decision matrix for choosing the best car.

Decision Matrix	First Category		Second Category	
	Comfort	Price	Prestige	MPG
Attribute type	**Benefit**	**Cost**	**Benefit**	**Cost**
Acura TL	0.705	0.937	0.707	0.818
Toyota Camry	0.211	0.806	0.07	0.5
Honda Civic	0.084	0.257	0.223	0.75

Table 3
Normalized decision matrix for choosing the best car.

Normalized Decision Matrix	First Category		Second Category	
	Comfort	Price	Prestige	MPG
Attribute type	**Benefit**	**Cost**	**Benefit**	**Cost**
Acura TL	1.000	1.000	1.000	1.000
Toyota Camry	0.205	0.807	0.000	0.000
Honda Civic	0.000	0.000	0.240	0.786

5. Comparative assessment

This section compares the proposed technique with the Euclid method defined by Tavana (2002). We discuss the similarities and differences between the two methods and highlight their strengths and weaknesses. We have chosen Euclid as a comparison benchmark due to its similarity with the method being proposed. In both cases – and unlike most MADM techniques –, cost attributes are evaluated without being turned into profit attributes in the normalization process. We will also compare the results derived from the proposed method with those obtained from one of the most widely applied MADM models, namely, TOPSIS. This latter technique will allow us to evaluate and compare the effect that different normalization methods have on the rankings obtained.

5.1. Methodological comparison

Tavana (2002) introduced a method for solving MADM problems based on the strategic alternative evaluation matrix. Consider our earlier problem with n alternatives,$(A_1, A_2, \dots, A_n)$, s attributes $(C_1, C_2, \dots, C_s)$, and the decision matrix in the form of Eq. (8). Euclid requires five steps as follows:

Step 1: Normalize the decision matrix (8) by applying Eq. (9).

Step 2: Assign an importance weight to each attribute. We have $\sum_{q=1}^{s} w_q = 1$, if the weight specified for attribute q is equal to w_q.

Step 3: Calculate the weighted normalized matrix using Eq. (12).

$$\overline{D} = \begin{bmatrix} \bar{t}_{11} & \cdots & \bar{t}_{1s} \\ \vdots & \ddots & \vdots \\ \bar{t}_{n1} & \cdots & \bar{t}_{ns} \end{bmatrix} = \begin{bmatrix} \hat{t}_{11} & \cdots & \hat{t}_{1s} \\ \vdots & \ddots & \vdots \\ \hat{t}_{n1} & \cdots & \hat{t}_{ns} \end{bmatrix} \times \begin{bmatrix} w_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_s \end{bmatrix} \tag{12}$$

Step 4: Calculate an average benefit and average cost score for each alternative using Eqs. (13) and (14), respectively.

$$PA_j = \frac{\sum_{q \in \text{ benefit attributes}} \bar{t}_{jq}}{\text{number of profit attributes}} \tag{13}$$

$$CA_j = \frac{\sum_{q \in \text{ cost attributes}} \bar{t}_{jq}}{\text{number of cost attributes}} \tag{14}$$

Step 5: Calculate the Euclidean distance of each alternative from the ideal point using Eq. (15) and rank the alternatives based on their Euclidean distances. An alternative with a lower Euclidean distance is preferred over an alternative with a higher one.

$$ED_j = \sqrt{(PA_j - 1)^2 + (CA_j - 0)^2} \tag{15}$$

The flowchart of the Euclid method is also presented in Fig. 1. As mentioned before, the proposed method and Euclid do not need to convert cost attributes into benefits in the normalization process. Both methods are designed to maintain the benefit and cost nature of the attributes. The proposed method considers the benefit and cost attributes as desirable and undesirable voters, and Euclid considers them as benefit and cost scores. The Euclid method requires the alternative scores of each attribute plus the attribute weights – if needed – to build a decision matrix. After the decision matrix is constructed, there are no other interactions with the experts. The proposed method is less demanding on the experts, who only provide information on attribute

Table 6
Weighted Normalized decision matrix for choosing the best car.

Weighted Normalized Decision Matrix	Comfort	Price	Prestige	MPG
Attribute type	**Benefit**	**Cost**	**Benefit**	**Cost**
Acura TL	0.400	0.400	0.100	0.100
Toyota Camry	0.082	0.323	0.000	0.000
Honda Civic	0.000	0.000	0.024	0.079

Table 7
Results of the Euclid Method.

The results of the Euclid method	*PA*	*CA*	*ED*	Rank
Acura TL	0.250	0.250	0.791	1
Toyota Camry	0.041	0.161	0.973	2
Honda Civic	0.012	0.039	0.989	3

Table 4
Voting matrix for choosing the best car.

Voting Matrix	First category, desirable (Comfort)			First category, undesirable (Price)			Second category, desirable (Prestige)			Second category, undesirable (MPG)		
Polling Position	1	2	3	1	2	3	1	2	3	1	2	3
Acura TL	1.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000	1.000	0.000	0.000
Toyota Camry	0.000	0.205	0.000	0.000	0.807	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Honda Civic	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.240	0.000	0.000	0.786	0.000

Table 5
Results of the model (6) and Eq. (7) for different ε values.

The results of model (6) andEq. (7)	ε_{max}= 0.143	ε = 0.071	ε = 0.048	ε = 0.010	ε = 0.007	ε = 0.004
Acura TL	0.336	0.362	0.372	0.389	0.390	0.391
Toyota Camry	0.077	0.135	0.155	0.190	0.192	0.196
Honda Civic	0.069	0.094	0.103	0.117	0.118	0.119

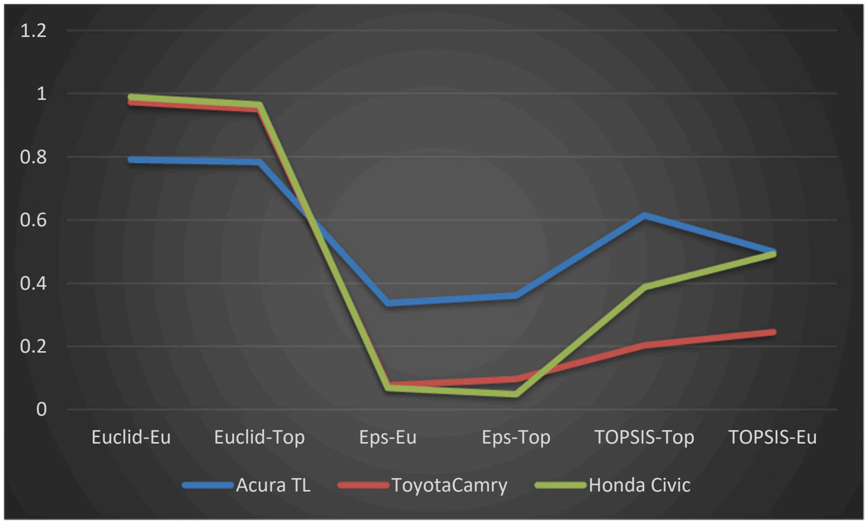

Fig. 2. Scores derived from all the techniques analyzed.

Table 8
Differences and similarities between Euclid and the proposed method.

Similarities	Differences
• Using a decision matrix structure to rank alternatives • Normalization through Eq. (9) • No change in the nature of cost attributes during the normalization process.	• Computation of the impact of different attributes on the final result • Interaction with experts during the solution process • The process of determining the final score of the alternatives

Table 9
Advantages and disadvantages of Euclid and the proposed method.

Method	Advantages	Disadvantages
Proposed Method	• No change in terms of cost attributes during the normalization process • Low computational efforts in the solution process • The impact of attributes is determined through the prioritization of their respective categories. • Ability to interact with the experts to define the discrimination intensity functions determining the final score of the alternatives • Applying the benefits of linear programming features using DEA-based policies in the solution process	
Euclid Method	• No change in terms of cost attributes during the normalization process • Low computational efforts in the solution process	• Possibility of invalidating the results in case of inaccuracy when determining the weight of the attributes • Impossibility of interacting with the experts when determining the Euclidean distance

categorization. However, the interactions with the experts are not necessarily limited to their initial data. The development of the discrimination intensity functions may involve additional interactions. A familiar example introduced by Saaty (2013) in the decision sciences literature is used next to demonstrate the applicability of the two methods.

5.2. Comparative Results

Saaty (2013) introduced this numerical example to choose the best car among three alternatives (Acura TL, Toyota Camry, and Honda Civic) by considering different priorities for the following four attributes: Prestige, Comfort, Price, and Miles per Gallon (MPG). This example is usually presented in the MADM literature in a hierarchical structure or a decision matrix. Table 2 shows the decision matrix for this problem. It is clear that the Comfort and Prestige attributes are of the benefit type, while the Price and MPG attributes are of the cost type. Experts have judged that Comfort and Price are more important than Prestige and MPG. After normalizing the decision matrix using Eq. (9), we obtain the (normalized) matrix presented in Table 3. We then form the voting matrix described in Table 4 using Eqs. (10) and (11).

Intuition regarding the method being implemented can be obtained from the distribution of values within Table 4. Note, for instance, that the Honda Civic is ranked second within the Prestige and MPG criteria in Table 3. As a result, it is assigned the second position within the corresponding categories in Table 4, increasing the importance score received relative to its third position within the Comfort and Price criteria. The transition between Tables 3 and 4 illustrates how the proposed model behaves when applied to a MADM setting.

The results in Table 5 are obtained after solving model (6) for different discrimination intensity functions and calculating Eq. (7). Note that we can interact with the DM to select the most appropriate discrimination intensity functions leading to a satisfactory solution. In this example, we have assumed $d^1(.,\varepsilon) = d^2(.,\varepsilon') = \varepsilon$, and solved model (6) for different epsilon values. ε_{max} is the maximum value of epsilon for which model (6) remains feasible. The results show that AcuraTL $\succ$ ToyotaCamry $\succ$ HondaCivic.

To implement the Euclid method, we need to obtain the weights of the attributes from the experts. Suppose that the weights of Comfort, Price, Prestige, and MPG are 0.4, 0.4, 0.1, and 0.1, respectively. Table 6 presents the resulting weighted normalized decision matrix. In contrast, Table 7 shows the average benefit and cost scores, the Euclidean distances of each alternative from the ideal point, and the corresponding rankings. The ranking results are identical for both methods.

Finally, we have incorporated TOPSIS into the analysis motivated by its different normalization method, which leads to a different ranking of the alternatives. The decision matrix in TOPSIS is normalized using the following formula:

Table 10
A description of the decision attributes.

Attribute	Type	Description*
C1	Cost	**People at risk of income poverty after social transfers**: People at risk of poverty, i.e., persons with an equalized disposable income below the risk-of-poverty threshold, which is set at 60% of the national median equalized disposable income (after social transfers).
C2	Benefit	**Government support of agricultural research and development**: Government Budget Appropriations or Outlays on R&D (GBAORD). GBAORD data measures government support of research and development (R&D) activities, or, in other words, how much priority Governments place on the public funding of R&D.
C3	Cost	**Self-reported unmet need for medical examination and care**: Share of the population aged 16 and over-reporting unmet needs for medical care due to one of the following reasons: 'Financial reasons,' 'Waiting list' and 'Too far to travel' (all three categories are cumulated). The attribute is derived from self-reported data, so it is, to a certain extent, affected by the subjective perception of the respondents as well as by their social and cultural background.
C4	Benefit	**Tertiary educational attainment**: Share of the population aged 30–34 who have successfully completed tertiary studies (e.g., university, higher technical institution, etc.).
C5	Benefit	**Share of women in senior management positions**: Share of female board members in the largest publicly listed companies. Publicly listed means that the shares of the company are traded on the stock exchange.
C6	Cost	Share of the total population having neither a bath nor shower nor indoor flushing toilet in their household.
C7	Cost	**Greenhouse gas (GHG) emissions energy consumption intensity**: Ratio between energy-related GHG emissions and gross inland energy consumption. It expresses how many tonnes of CO2 equivalents of energy-related GHGs are being emitted in a certain economy per unit of energy that is being consumed.
C8	Benefit	**Real GDP per capita**: Ratio of real GDP to the average population of a specific year. GDP measures the value of the total final output of goods and services produced by an economy within a certain period of time.
C9	Benefit	**Gross domestic expenditure on R&D:** Gross domestic expenditure on R&D (GERD) as a percentage of the gross domestic product (GDP).
C10	Benefit	**Purchasing power adjusted GDP per Capita**: GDP per capita is calculated as the ratio of GDP to the average population in a specific year. Basic figures are expressed in purchasing power standards (PPS), representing a common currency that eliminates the differences in price levels between countries to allow for meaningful volume comparisons of GDP.
C11	Benefit	**The recycling rate of municipal waste**: The tonnage recycled from municipal waste is divided by the total municipal waste. Recycling includes material recycling, composting, and anaerobic digestion. The municipal waste consists primarily of waste generated by households but may also include similar wastes generated by small businesses and public institutions and collected by the municipality.
C12	Cost	**Generation of waste excluding major mineral wastes**: Waste generated in a country. Major mineral wastes, dredging spoils, and soils are excluded.
C13	Cost	**Greenhouse gas emissions**: Total national emissions, including international aviation of the so-called 'Kyoto basket' of greenhouse gases.
C14	Benefit	Number and proportion of coastal and inland bathing sites with excellent water quality.
C15	Benefit	**The surface of terrestrial sites designated under Natura 2000**. The Natura 2000 network comprises marine and terrestrial protected areas designated under the EU Habitats and Birds Directives to maintain or restore a favorable conservation status for habitat types and species of EU interest.
C16	Cost	**Population reporting on crime, violence, or vandalism**: Share of people who reported that they have a problem with crime, violence, and destruction in their district.
C17	Benefit	**Official development assistance as a share of gross national income**: Official development assistance (ODA) consists of grants or loans undertaken by the official sector to promote economic development and welfare in recipient countries.

*Source: Eurostat (2021)

$$\widehat{t}_{pq} = \frac{t_{pq}}{\sqrt{\sum_{k=1}^{n} t_{kq}^2}}, p = 1, ., n, q = 1, ., s; \qquad (9')$$

which differs from the one defined in Eq. (9). In particular, the normalization process described in Eq. (9') does not assign a value of zero to any of the normalized entries of the matrix – unless the original entry consisted of a zero –. This is an important difference that modifies the evaluation of the alternatives and the subsequent ranking. Indeed, TOPSIS reverses the order of the ranking for the second and third alternatives when compared to Euclid and the proposed method.

TOPSIS ranks the cars as follows: AcuraTL ≻ HondaCivic ≻ ToyotaCamry. The intuition for this reversal is simple. Note that the distance between the second and third alternative ranking scores is relatively small under both Euclid and the proposed model. As a result, a different ranking is obtained when modifying the weighting method, allowing the Honda Civic to account for its Comfort benefits while also considering the MPG costs of the Toyota Camry.

The scores derived from all the techniques are presented in Fig. 2, where the evaluation differences can be explicitly observed. The scores obtained for $\varepsilon_{\max}$ using the normalization formula of Euclid and TOPSIS in the proposed model are denoted by Eps-Eu and Eps-Top, respectively. Fig. 2 also shows the rankings derived from Euclid and TOPSIS with each other normalization methods, denoted by Euclid-Top and TOPSIS-Eu, respectively. Note that higher values represent better performances in TOPSIS and the proposed method, while the opposite is true for Euclid.

The results obtained show that the normalization method applied in TOPSIS exhibits more discrimination power than the Euclidean one. Therefore, by changing the normalization method of the proposed model to that of TOPSIS, we can expect results to display more marked differences across alternatives. This is indeed the case within the proposed model, where shifting to the TOPSIS normalization method leads to a ranking that clearly separates the evaluation of the last two alternatives.

Finally, we observe that all models remain consistent in terms of the ranking provided independently of the normalization formula being implemented – with TOPSIS reversing the ranking of the last two alternatives relative to the other models –. The normalization and reversal effects described through this section constitute interesting outcomes from the analysis that should be investigated further in future research.

In the next section, we describe some practical implications from comparing the Euclid method and the one proposed in this study.

5.3. Practical implications and further discussion

We have explored two methods for solving MADM problems: Euclid and the method proposed in this study. The similarities and differences between both methods are summarized in Table 8, while Table 9 describes the advantages and disadvantages of the two methods.

As shown in Tables 8 and 9, the proposed MADM method applies a linear programming model designed according to the theoretical foundations of DEA. These tables highlight that the proposed method faces limited computational requirements and enhances the interaction with the DMs through the discrimination intensity functions. In addition, our method preserves the consistency of the ranking when the normalization process applied to the decision matrix is modified. In the next section, we present a real-world study to demonstrate the applicability and efficacy of the method proposed in this study.

Table 11
Decision matrix[**].

Country	C1 Cost	C2 Benefit	C3 Cost	C4 Benefit	C5 Benefit	C6 Cost	C7 Cost	C8 Benefit	C9 Benefit	C10 Benefit	C11 Benefit	C12 Cost	C13 Cost	C14 Benefit	C15 Benefit	C16 Cost	C17 Benefit
Belgium	14.8	5.0	1.8	47.5	35.9	0.1	86.8	35950	2.89	36700	54.7	3504	82.7	97.62	13	13.3	0.42
Bulgaria	22.6	4.0	1.4	32.5	18.5	7.5	99.1	6840	0.84	16500	31.5	3097	57.2	67.03	35	20.2	0.10
Czechia	10.1	5.6	0.5	35.1	18.2	0.2	75.0	18330	1.94	28900	33.3	1542	64.8	0	14	7.8	0.13
Denmark	12.5	17.5	1.8	49.4	30.0	0.3	68.5	49720	2.91	40500	51.5	1774	70.7	87.62	8	7.5	0.71
Germany	14.8	10.8	0.3	35.5	35.6	0	90.0	35840	3.18	37500	66.7	1872	70.4	86.65	15	13.1	0.60
Estonia	21.7	5.2	15.5	46.2	9.4	3.5	90.8	15760	1.61	26100	30.8	9711	50.0	51.85	18	7.4	0.13
Ireland	13.1	19.7	2.0	55.4	26.	0.1	82.8	60170	0.78	60200	37.6	1611	113.6	71.74	13	8.8	0.31
Greece	17.9	5.0	8.1	43.1	10.3	0.2	81.4	17750	1.27	20700	21.0	1478	90.8	95.77	27	16.9	0.14
Spain	20.7	9.6	0.2	44.7	26.4	0.3	83.0	25200	1.25	28400	34.7	1540	119.7	93.24	27	11.6	0.21
France	13.6	4.7	1.2	47.5	45.2	0.2	79.6	33270	2.19	33100	46.3	1501	83.1	81.95	13	14.7	0.44
Croatia	18.3	2.8	1.4	33.1	27.0	0.8	88.0	12450	1.11	20300	30.2	922	75.2	98.43	37	2.7	0.13
Italy	20.1	5.1	1.8	27.6	36.1	0.5	83.7	26910	1.45	29800	51.3	1850	84.4	88.20	19	9.4	0.24
Cyprus	14.7	7.1	1.0	58.8	9.4	0.5	93.5	24530	0.63	27900	15.0	930	153.8	99.12	29	12.7	0.21
Latvia	22.9	6.1	4.3	45.7	31.7	7.7	84.1	12510	0.64	21500	41.0	701	46.0	84.85	12	6.1	0.10
Lithuania	20.6	3.2	1.4	57.8	12.0	8.7	102.3	14010	1.00	26000	49.4	1403	42.6	100.00	13	3.2	0.11
Luxembourg	17.5	0.3	0.2	56.2	13.1	0.1	91.4	83640	1.19	81000	48.9	2278	94.2	0	27	11.2	1.05
Hungary	12.3	4.0	1.0	33.4	12.9	2.7	78.7	13270	1.48	22800	35.9	1099	67.8	0	21	5.3	0.22
Malta	17.1	2.6	0	38.1	10.0	0	57.4	21960	0.59	31100	8.90	1090	96.1	97.7	13	13.6	0.29
Netherlands	13.2	8.2	0.2	51.4	34.2	0.0	94.0	41870	2.16	39900	56.9	2612	88.6	76.67	15	16.3	0.59
Austria	13.3	4.1	0.3	42.4	31.3	0.1	85.0	38170	3.19	39400	58.2	1884	102.7	0	15	8.4	0.27
Poland	15.4	2.6	4.2	46.6	23.5	1.6	88.6	13020	1.32	22700	34.1	2112	87.4	29.45	20	4.4	0.12
Portugal	17.2	1.7	1.7	36.2	24.6	0.5	85.4	18630	1.40	24700	28.9	1316	118.9	95.63	21	6.7	0.16
Romania	23.8	1.1	4.9	25.8	12.6	22.4	84.3	9110	0.48	21700	11.5	1115	46.8	77.55	23	9.6	0.10
Slovenia	12.0	5.0	2.9	44.9	24.6	0.1	88.8	20700	2.04	27700	59.2	1479	94.4	95.24	38	8.0	0.16
Slovakia	11.9	2.9	2.7	40.1	29.1	1.3	83.6	15860	0.83	21900	38.5	1579	59.2	0	30	5.6	0.12
Finland	11.6	10.3	4.7	47.3	34.2	0.2	73.6	37230	2.79	34700	43.5	2569	81.4	63.64	13	6.4	0.42
Sweden	17.1	4.5	1.4	52.5	37.5	0	69.2	43920	3.40	37000	46.6	2135	75.3	72.54	12	13.0	0.99
United Kingdom	18.6	6.0	4.5	50.0	32.6	0	82.9	32910	1.76	32600	44.1	1877	61.6	66.08	9	24.2	0.70

[**] Source: Eurostat (2021)

Table 12
Normalized decision matrix.

Country	C1 Cost	C2 Benefit	C3 Cost	C4 Benefit	C5 Benefit	C6 Cost	C7 Cost	C8 Benefit	C9 Benefit	C10 Benefit	C11 Benefit	C12 Cost	C13 Cost	C14 Benefit	C15 Benefit	C16 Cost	C17 Benefit
Belgium	0.3431	0.2423	0.1161	0.6576	0.7402	0.0045	0.6548	0.3790	0.8253	0.3132	0.7924	0.3111	0.3606	0.9762	0.1667	0.4930	0.3368
Bulgaria	0.9124	0.1907	0.0903	0.2030	0.2542	0.3348	0.9287	0.0000	0.1233	0.0000	0.3910	0.2659	0.1313	0.6703	0.9000	0.8140	0.0000
Czechia	0.0000	0.2732	0.0323	0.2818	0.2458	0.0089	0.3920	0.1496	0.5000	0.1922	0.4221	0.0933	0.1996	0.0000	0.2000	0.2372	0.0316
Denmark	0.1752	0.8866	0.1161	0.7152	0.5754	0.0134	0.2472	0.5583	0.8322	0.3721	0.7370	0.1191	0.2527	0.8762	0.0000	0.2233	0.6421
Germany	0.3431	0.5412	0.0194	0.2939	0.7318	0.0000	0.7261	0.3776	0.9247	0.3256	1.0000	0.1300	0.2500	0.8665	0.2333	0.4837	0.5263
Estonia	0.8467	0.2526	1.0000	0.6182	0.0000	0.1563	0.7439	0.1161	0.3870	0.1488	0.3789	1.0000	0.0665	0.5185	0.3333	0.2186	0.0316
Ireland	0.2190	1.0000	0.1290	0.8970	0.4637	0.0045	0.5657	0.6944	0.1027	0.6775	0.4965	0.1010	0.6385	0.7174	0.1667	0.2837	0.2211
Greece	0.5693	0.2423	0.5226	0.5242	0.0251	0.0089	0.5345	0.1421	0.2705	0.0651	0.2093	0.0862	0.4335	0.9577	0.6333	0.6605	0.0421
Spain	0.7737	0.4794	0.0129	0.5727	0.4749	0.0134	0.5702	0.2391	0.2637	0.1845	0.4464	0.0931	0.6933	0.9324	0.6333	0.4140	0.1158
France	0.2555	0.2268	0.0774	0.6576	1.0000	0.0089	0.4944	0.3441	0.5856	0.2574	0.6471	0.0888	0.3642	0.8195	0.1667	0.5581	0.3579
Croatia	0.5985	0.1289	0.0903	0.2212	0.4916	0.0357	0.6815	0.0730	0.2158	0.0589	0.3685	0.0245	0.2932	0.9843	0.9667	0.0000	0.0316
Italy	0.7299	0.2474	0.1161	0.0545	0.7458	0.0223	0.5857	0.2613	0.3322	0.2062	0.7336	0.1275	0.3759	0.8820	0.3667	0.3116	0.1474
Cyprus	0.3358	0.3505	0.0645	1.0000	0.0000	0.0223	0.8040	0.2303	0.0514	0.1767	0.1055	0.0254	1.0000	0.9912	0.7000	0.4651	0.1158
Latvia	0.9343	0.2990	0.2774	0.6030	0.6229	0.3438	0.5947	0.0738	0.0548	0.0775	0.5554	0.0000	0.0306	0.8485	0.1333	0.1581	0.0000
Lithuania	0.7664	0.1495	0.0903	0.9697	0.0726	0.3884	1.0000	0.0934	0.1781	0.1473	0.7007	0.0779	0.0000	1.0000	0.1667	0.0233	0.0105
Luxembourg	0.5401	0.0000	0.0129	0.9212	0.1034	0.0045	0.7572	1.0000	0.2432	1.0000	0.6920	0.1750	0.4640	0.0000	0.6333	0.3953	1.0000
Hungary	0.1606	0.1907	0.0645	0.2303	0.0978	0.1205	0.4744	0.0837	0.3425	0.0977	0.4671	0.0442	0.2266	0.0000	0.4333	0.1209	0.1263
Malta	0.5109	0.1186	0.0000	0.3727	0.0168	0.0000	0.0000	0.1969	0.0377	0.2264	0.0000	0.0432	0.4811	0.9770	0.1667	0.5070	0.2000
Netherlands	0.2263	0.4072	0.0129	0.7758	0.6927	0.0000	0.8151	0.4561	0.5753	0.3628	0.8304	0.2121	0.4137	0.7667	0.2333	0.6326	0.5158
Austria	0.2336	0.1959	0.0194	0.5030	0.6117	0.0045	0.6147	0.4079	0.9281	0.3550	0.8529	0.1313	0.5405	0.0000	0.2333	0.2651	0.1789
Poland	0.3869	0.1186	0.2710	0.6303	0.3939	0.0714	0.6949	0.0805	0.2877	0.0961	0.4360	0.1566	0.4029	0.2945	0.4000	0.0791	0.0211
Portugal	0.5182	0.0722	0.1097	0.3152	0.4246	0.0223	0.6236	0.1535	0.3151	0.1271	0.3460	0.0683	0.6862	0.9563	0.4333	0.1860	0.0632
Romania	1.0000	0.0412	0.3161	0.0000	0.0894	1.0000	0.5991	0.0296	0.0000	0.0806	0.0450	0.0459	0.0378	0.7755	0.5000	0.3209	0.0000
Slovenia	0.1387	0.2423	0.1871	0.5788	0.4246	0.0045	0.6993	0.1805	0.5342	0.1736	0.8702	0.0863	0.4658	0.9524	1.0000	0.2465	0.0632
Slovakia	0.1314	0.1340	0.1742	0.4333	0.5503	0.0580	0.5835	0.1174	0.1199	0.0837	0.5121	0.0974	0.1493	0.0000	0.7333	0.1349	0.0211
Finland	0.1095	0.5155	0.3032	0.6515	0.6927	0.0089	0.3608	0.3957	0.7911	0.2822	0.5986	0.2073	0.3489	0.6364	0.1667	0.1721	0.3368
Sweden	0.5109	0.2165	0.0903	0.8091	0.7849	0.0000	0.2628	0.4828	1.0000	0.3178	0.6522	0.1592	0.2941	0.7254	0.1333	0.4791	0.9368
United Kingdom	0.6204	0.2938	0.2903	0.7333	0.6480	0.0000	0.5679	0.3395	0.4384	0.2496	0.6090	0.1305	0.1709	0.6608	0.0333	1.0000	0.6316

Table 13
Attributes categorization.

First category (Society)		Second category (Environment)		Third category (Economy)	
Desirable	Undesirable	Desirable	Undesirable	Desirable	Undesirable
C2; C4; C5; C11; C17	C1; C3; C6; C16	C14; C15	C12; C13	C8; C9; C10	C7

6. Case study

The case study evaluates 27 European Union (EU) countries and the United Kingdom according to 17 SDGs attributes adopted by the Agenda 2030 for 2019. Stanujkic et al. (2020) used CoCoSo and the Shannon Entropy method to build a similar example for 27 EU countries in 2015–2018. We illustrate how the ranking obtained follows from applying the weighting framework defined through our hybrid MADM-DEA model to the different attributes considered. The attributes have all been retrieved from the Eurostat database (Eurostat, 2021). Table 10 presents these attributes along with a brief technical description. The attributes have also been categorized in this table.

The scores retrieved from each of the 28 EU countries per attribute are presented in Table 11. This table constitutes the decision matrix of the case study. We use Eq. (9) to normalize the decision matrix presented in Table 12.

We then divide the 17 attributes into three categories: Social, Environmental, and Economic. We asked several colleagues from our Economics, Sociology, and Environmental Sciences departments to prioritize the criteria across important categories. The Delphi method has been used to aggregate the opinions of our expert colleagues and determine the priority assigned to each category in Table 13. This table shows how, based on the goals outlined in Agenda 2030, experts prioritized the attributes of the social category over those of the environmental one and the latter's attributes over those of the economic category. In each category, benefit attributes are considered desirable voters, while cost attributes are considered undesirable voters.

Given the data presented in the normalized decision matrix and the categorization of the attributes provided in Table 13, we form a voting matrix similar to Table 1 and use model (6) to aggregate the votes and determine the score of each country applying Eq. (7). Finally, after interacting with the experts, the discrimination intensity functions were set to ε, and model (6) was solved for different ε values. The sensitivity of the results to the choice of ε value can be easily inferred from the

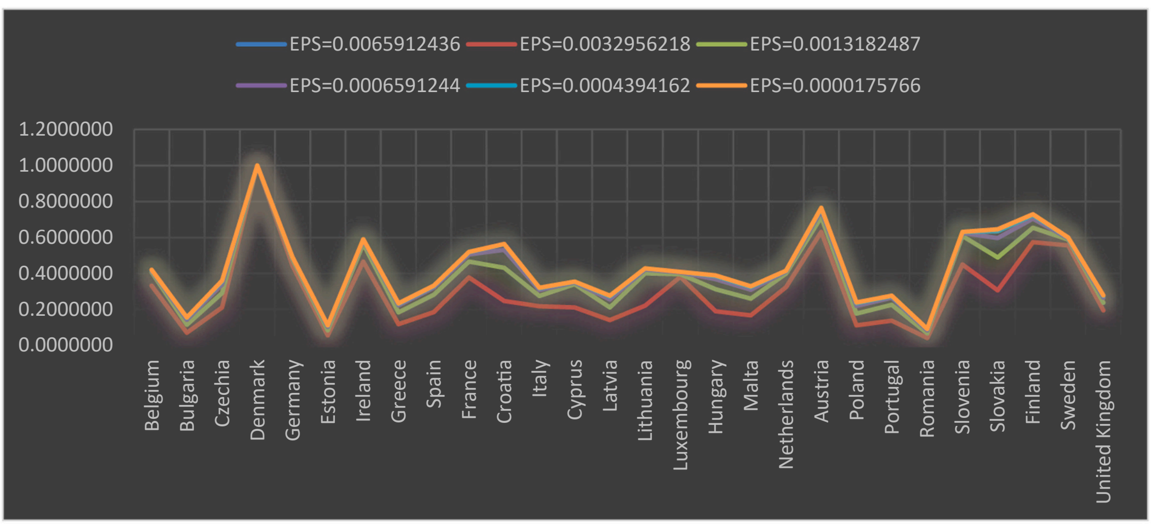

Fig. 3. Final score of the countries for different ε values.

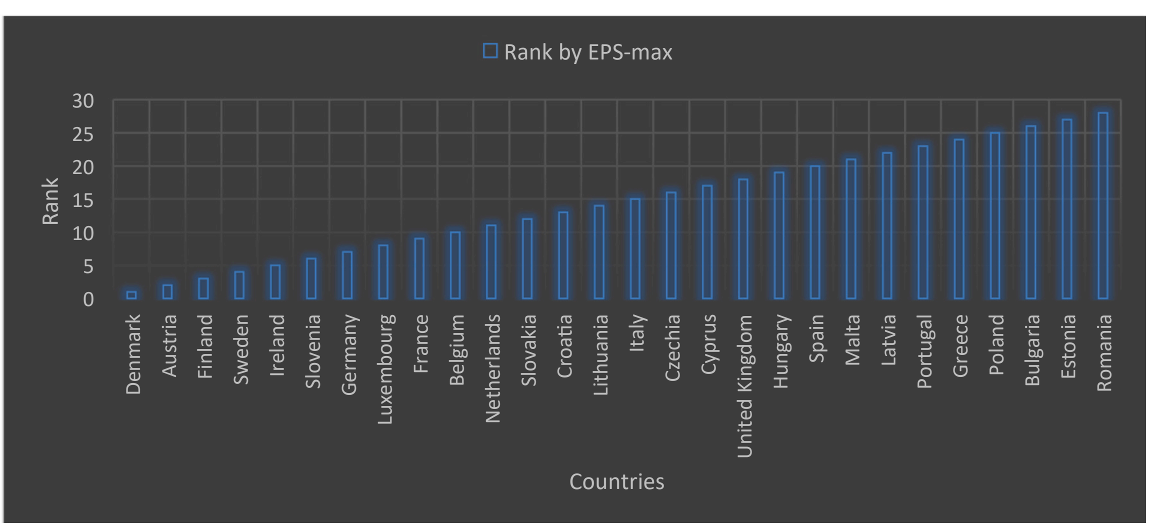

Fig. 4. Final country rank for $\varepsilon_{\max}$.

evaluations presented in Fig. 3. The final ranking of the countries presented in Fig. 4 was determined based on $\varepsilon_{\max}$. Low-rank countries can consider high-rank (benchmark) countries to adjust their policies as a roadmap for progress. Moreover, the categories defined by the experts can be used as a priority guide on which to focus the implementation of the subsequent adjustments. As can be seen, the proposed MADM method, which has been designed based on a DEA model, was able to rank a problem with 28 units without delivering a tie. Since DEA evaluates units applying an optimistic policy, usually more than one unit reaches the ceiling of efficiency. This is particularly the case if the number of units is large. Therefore, achieving a complete ranking would require the specific use of ranking models. However, in this real-world problem, a full ranking was obtained by directly applying the proposed method, which constitutes one of its most immediate advantages.

7. Conclusion

The selection of alternatives and their ranking are the primary goals of MADM. Most practicing managers prefer effective and efficient MADM methods that are simple and inclusive when considering expert opinions. Real-world MADM problems usually include both benefit and cost attributes. As a result, many MADM methods convert the cost attributes into benefits through the normalization process performed before ranking the alternatives.

We have presented a group voting method with unequal power levels among members that incorporates "undesirable voters." The proposed method is straightforward to use. The benefit attributes are categorized as desirable voters, while the cost attributes are categorized as undesirable voters. We have demonstrated the applicability and efficacy of the proposed method with a numerical example and a case study where we have applied our hybrid MADM-DEA model to rank a set of European countries based on their fulfillment of the 17 SDGs defined by the United Nations in 2015.

From a strategic perspective, one of the proposed method's main advantages is that DMs do not rely on the weights defined by the experts. The latter may have incentives to report strategically, and lower dependence on their subjective judgments significantly improves the standard MADM techniques. Finally, uncertainty considerations – common to the DEA literature – can be easily incorporated into the model, allowing for potential extensions of the current approach in fuzzy environments.

Declaration of Competing Interest

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

Data Availability

Data will be made available on request.

Acknowledgment

Dr. Francisco J. Santos-Arteaga is grateful for the support received from the María Zambrano contract from the Universidad Complutense de Madrid financed by the Ministerio de Universidades with funding from the European Union Next Generation program.

References

Abdullah, A.G., Shafii, M.A., Pramuditya, S., Setiadipura, T., Anzhar, K., 2023. Multi-criteria decision making for nuclear power plant selection using fuzzy AHP: evidence from Indonesia. Energy AI 14, 100263.
Aguarón, J., Escobar, M.T., Moreno-Jiménez, J.M., 2021. Reducing inconsistency measured by the geometric consistency index in the analytic hierarchy process. Eur. J. Oper. Res. 288 (2), 576–583.
Akram, M., Kahraman, C., Zahid, K., 2021. Group decision-making based on complex spherical fuzzy VIKOR approach. Knowl. -Based Syst. 216, 106793.
Alinezhad, A., Khalili, J., 2019. New methods and applications in multiple attribute decision making (MADM). Int. Ser. Oper. Res. Manag. Sci. 277, 205–215.
Amin, G.R., Emrouznejad, A., Sadeghi, H., 2012. Metasearch information fusion using linear programming. RAIRO-Oper. Res. 46 (4), 289–303.
Andersen, P., Petersen, N.C., 1993. A procedure for ranking efficient units in data envelopment analysis. Manag. Sci. 39 (10), 1261–1264.
Baraka, S., Heidary Dahooei, J., 2018. A novel hybrid fuzzy DEA-Fuzzy MADM method for airlines safety evaluation. J. Air Transp. Manag. 73, 134–149.
de Borda, J.C., 1781. Mémoire sur les élections au scrutin, Mémoire de l'Académie Royale. Hist. De. l'Académie Des. Sci., Paris 657–665.
Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2 (6), 429–444.
Chen, T.Y., 2013. An interval-valued intuitionistic fuzzy LINMAP method with inclusion comparison possibilities and hybrid averaging operations for multiple criteria group decision making. Knowl. -Based Syst. 45, 134–146.
Chitnis, A., Vaidya, O.S., 2016. Efficiency ranking method using DEA and TOPSIS (ERM-DT): case of an Indian bank. Benchmark.: Int. J. 23 (1), 165–182.
Cicciù, B., Schramm, F., Schramm, V.B., 2022. Multi-criteria decision making/aid methods for assessing agricultural sustainability: a literature review. Environ. Sci. Policy 138, 85–96.
Contreras, I., 2011. A DEA-inspired procedure for the aggregation of preferences. Expert Syst. Appl. 38, 564–570.
Cook, W.D., Kress, M., 1990. A data envelopment model for aggregating preference rankings. Manag. Sci. 36 (11), 1302–1310.
De Castro Camioto, F., Barberio Mariano, E., do Nascimento Rebelatto, D.A., 2014. Efficiency in Brazil's industrial sectors in terms of energy and sustainable development. Environ. Sci. Policy 37, 50–60.
Doumpos, M., Zopounidis, C., 2011. Preference disaggregation and statistical learning for multi attributes decision support: a review. Eur. J. Oper. Res. 209 (3), 203–214.
Ebrahimnejad, A., 2012. A new approach for ranking of candidates in voting systems. OPSEARCH 49, 103–115.
Ebrahimnejad, A., Bagherzadeh, M.R., 2016. Data envelopment analysis approach for discriminating efficient candidates in voting systems by considering the priority of voters. Hacet. J. Math. Stat. 45 (1), 165–180.
Eurostat. Available online: https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=ilc_di04 (Accessed on 5 July 2021).
Foroughi, A.A., Tamiz, M., 2005. An effective total ranking model for a ranked voting system. Omega 33, 491–496.
Foroughi, A.A., Jones, D.F., Tamiz, M., 2005. A selection method for a preferential election. Appl. Math. Comput. 163, 107–116.
Gal, T., Stewart, T., Hanne, T., 1999. Multi attributes Decision Making Advances in MCDM Models: Algorithms, Theory, and Applications. Springer.
Gong, Z., Zhang, N., Li, K.W., Martínez, L., Zhao, W., 2018. Consensus decision models for preferential voting with abstentions. Comput. Ind. Eng. 115, 670–682.
Green, R.H., Doyle, J.R., Cook, W.D., 1996. Preference voting and project ranking using DEA and cross-evaluation. Eur. J. Oper. Res. 90, 461–472.
Hajiaghaei-Keshteli, M., Cenk, Z., Erdebilli, B., Selim Özdemir, Y., Gholian-Jouybari, F., 2023. Pythagorean fuzzy TOPSIS method for green supplier selection in the food industry. Expert Syst. Appl. 224, 120036.
Hashimoto, A., 1997. A ranked voting system using a DEA/AR exclusion model: a note. Eur. J. Oper. Res. 97, 600–604.
Hosouli, S., Elvins, J., Searle, J., Boudjabeur, S., Bowyer, J., Jewell, E., 2023. A Multi-Criteria decision making (MCDM) methodology for high temperature thermochemical storage material selection using graph theory and matrix approach. Mater. Des. 227, 111685.
Hosseinzadeh Lotfi, F., Jahanshahloo, G.R., Ebrahimnejad, A., Soltanifar, M., Mansourzadeh, S.M., 2010b. Target setting in the general combined-oriented CCR model using an interactive MOLP method. J. Comput. Appl. Math. 234 (1), 1–9.
Hosseinzadeh Lotfi, F., Rostamy-Malkhalifeh, M., Aghayi, N., Ghelej Beigi, Z., Gholami, K., 2013. An improved method for ranking alternatives in multiple attributes decision analysis. Appl. Math. Model. 37, 25–33.
HosseinzadehLotfi, F., Jahanshahloo, G.R., Soltanifar, M., Ebrahimnejad, A., Mansourzadeh, S.M., 2010a. Relationship between MOLP and DEA based on output-orientated CCR dual model. Expert Syst. Appl. 37 (6), 4331–4336.
Hwang, C.L., Yoon, K., 1981. Multiple Attribute Decision Making. Springer, Berlin.
Izadikhah, M., Farzipoor Saen, R., 2019. Solving voting system by data envelopment analysis for assessing sustainability of suppliers. Group Decis. Negot. 28, 641.
Keshavarz, E., Toloo, M., 2020. A hybrid data envelopment analysis and multi-attribute decision making approach to sustainability assessment. Expert Syst. 37 (4), e12347.
Köksalan, M., Zionts, S., 2001. Multiple Attributes Decision Making in the New Millennium. Springer.
Kou, G., Ergu, D., Lin, C., Chen, Y., 2016. Pairwise comparison matrix in multiple attributes decision making. Technol. Econ. Dev. Econ. 22 (5), 738–765.
Lin, C., Kou, G., Peng, Y., Alsaadi, F.E., 2022. Aggregation of the nearest consistency matrices with the acceptable consensus in AHP-GDM. Ann. Oper. Res. 316, 179–195.
Liu, F., H., F., Hai, H., 2005. The voting analytic hierarchy process method for selecting supplier. Int. J. Prod. Econ. 97 (3), 308–317.
Liu, J., Fang, M., Jin, F., Wu, C., Chen, H., 2020. Multi-attribute decision making based on stochastic DEA cross-eciency with ordinal variable and its application to evaluation of banks' sustainable development. Sustainability 12 (6), 2375.
Llamazares, B., 2017. Aggregating preference rankings using an optimistic-pessimistic approach: closed-form expressions. Comput. Ind. Eng. 110, 109–113.
Lucas, E., Galán-Martín, A., Pozo, C., Guo, M., Guillén-Gosálbez, G., 2021. Sci. Total Environ. 755 (Part 1), 142826.

Mohammed, A., 2020. Towards a sustainable assessment of suppliers: an integrated fuzzy TOPSIS-possibilistic multi-objective approach. Ann. Oper. Res. 293, 639–668.
Ning, B., Wei, G., Lin, R., Guo, Y., 2022. A novel MADM technique based on extended power generalized Maclaurin symmetric mean operators under probabilistic dual hesitant fuzzy setting and its application to sustainable suppliers selection. Expert Syst. Appl. 204, 117419.
Noguchi, H., Ogawa, M., Ishii, H., 2002. The appropriate total ranking method using DEA for multiple categorized purposes. J. Comput. Appl. Math. 146, 155–166.
Obata, T., Ishii, H., 2003. A method for discriminating efficient candidates with ranked voting data. Eur. J. Oper. Res. 151, 233–237.
Ortiz-Barrios, M., Cabarcas-Reyes, J., Ishizaka, A., Barbati, M., Jaramillo-Rueda, N., Carrascal-Zambrano, G.J., 2021. A hybrid fuzzy multi-attributes decision making model for selecting a sustainable supplier of forklift filters: a case study from the mining industry. Ann. Oper. Res. 307, 443–481.
Otaya, İ., Oztaysi, B., Onar, S.C., Kahraman, C., 2017. Multi-expert performance evaluation of healthcare institutions using an integrated intuitionistic fuzzy AHP&DEA methodology. Knowl. -Based Syst. 133, 90–106.
Perosa, F., Seitz, L.F., Zingraff-Hamed, A., Disse, M., 2022. Flood risk management along German rivers – a review of multi-criteria analysis methods and decision-support systems. Environ. Sci. Policy 135, 191–206.
Puri, J., Verma, M., 2020. Integrated data envelopment analysis and multi attributes decision-making ranking approach based on peer-evaluations and subjective preferences: case study in banking sector. Data Technol. Appl. 54 (4), 551–582.
Saaty, T.L., 2013. The modern science of multi attributes decision making and its practical applications: the AHP/ANP approach. Oper. Res. 61 (5), 1101–1118.
Sexton, T.R., Silkman, R.H., Hogan, A.J. (1986). Data envelopment analysis: Critique and extensions. In R.H. Silk (Ed.), *Measuring efficiency: An assessment of data envelopment analysis*, 32, 73–105.
Sharafi, H., Hosseinzadeh Lotfi, F., Jahanshahloo, Gh, Rostamy-malkhalifeh, M., Soltanifar, M., Razipour-GhalehJough, S., 2019. Ranking of petrochemical companies using preferential voting at unequal levels of voting power through data envelopment analysis. Math. Sci. 13 (3), 287–297.
Sharafi, H., Soltanifar, M., Hosseinzadeh Lotfi, F., 2022. Selecting a green supplier utilizing the new fuzzy voting model and the fuzzy combinative distance-based assessment method. Eur. J. Decis. Process. 10, 100010.
Silva, D.F.D.L., Filho, A.T.D.A., 2020. Sorting with TOPSIS through boundary and characteristic profiles. Comput. Ind. Eng. 141, 106328.
Soltanifar, M., 2020. A new voting model for groups with members of unequal power and proficiency. Int. J. Ind. Math. 12 (2), 121–134.
Soltanifar, M., 2021a. An investigation of the most common multi-objective optimization methods with propositions for improvement. Decis. Anal. J. 1, 100005.
Soltanifar, M., 2021b. The voting linear assignment method for determining priority and weights in solving MADM problems. J. Appl. Res. Ind. Eng. 8, 1–17.
Soltanifar, M., Hosseinzadeh Lotfi, F., 2011. The voting analytic hierarchy process method for discriminating among efficient decision making units in data envelopment analysis. Comput. Ind. Eng. 60 (4), 585–592.
Soltanifar, M., Shahghobadi, S., 2013. Selecting a benevolent secondary goal model in data envelopment analysis cross-efficiency evaluation by a voting model. Socio-Econ. Plan. Sci. 47 (1), 65–74.
Soltanifar, M., Sharafi, H., 2022. A modified DEA cross efficiency method with negative data and its application in supplier selection. J. Comb. Optim. 43 (1), 265–296.
Stanujkic, D., Popovic, G., Zavadskas, E.K., Karabasevic, D., Binkyte-Veliene, A., 2020. Assessment of progress towards achieving sustainable development goals of the "agenda 2030″ by using the CoCoSo and the shannon entropy methods: the case of the EU countries. Sustainability 12 (14), 5717.
Tavana, M., 2002. Euclid: strategic alternative assessment matrix. J. Multi-Attrib. Decis. Anal. 11, 75–96.
Tavana, M., Ebrahimnejad, A., Santos-Arteaga, F.J., Mansourzadeh, S.M., Kazemi Matin, R., 2018. A hybrid DEA-MOLP model for public school assessment and closure decision in the City of Philadelphia. Socio-Econ. Plan. Sci. 61, 70–89.
Tavana, M., Soltanifar, M., Santos-Arteaga, F.J., 2021. Analytical hierarchy process: revolution and evolution. Ann. Oper. Res. https://doi.org/10.1007/s10479-021-04432-2.
Thampson, R.G., Langemeiar, L.N., Lee, C.T., Thrall, R.M., 1989. The Measurement of Productive Efficiency with an Application to Kansas Royl and Wheat Farming, Jesse H. Jones Graduate School of Administration. Work. Pap. 65.
Thompson, R.G., Singeleton, F.D., Thrall, R.M., Smith, B.A., 1986. Comparative site evaluations for locating a high energy lab in Texas. Intetfaces 1380–1395.
Tzeng, G.H., Huang, J.J., 2011. Multiple Attribute Decision Making: Methods and Applications, 1 ed. Chapman and Hall/CRC. June 22, 2011.
Venkatesh, V.G., Zhang, A., Deakins, E., Luthra, S., Mangla, S., 2019. A fuzzy AHP-TOPSIS approach to supply partner selection in continuous aid humanitarian supply chains. Ann. Oper. Res. 283, 1517–1550.
Zahid, K., Akram, M., Kahraman, C., 2022. A new ELECTRE-based method for group decision-making with complex spherical fuzzy information. Knowl. -Based Syst. 243, 108525.
Zakari, A., Khan, I., Tan, D., Alvarado, R., Dagar, V., 2022. Energy efficiency and sustainable development goals (SDGs). Energy 239, 122365.
Zerafat Angiz, M., Emrouznejad, A., Mustafa, M., Al-Eraqi, A.S., 2010. Aggregating preference ranking with fuzzy Data Envelopment Analysis. Knowl. -Based Syst. 23 (6), 512–519.
Zerafat Angiz, M., Tajaddini, A., Mustafa, A., Kamali, J., 2012. Ranking alternatives in a preferential voting system using fuzzy concepts and data envelopment analysis. Comput. Ind. Eng. 63 (4), 784–790.
Zhou, S., Zhan, Y., 2020. A new method for performance evaluation of decision-making units with application to service industry. J. Manag. Anal. 8 (1), 84–100.
Zou, W.C., Wan, S.P., Chen, S.M., 2022. A fairness-concern-based LINMAP method for heterogeneous multi-criteria group decision making with hesitant fuzzy linguistic truth degrees. Inf. Sci. 612, 1206–1225.