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RESEARCH ARTICLE

Multicriteria and Statistical Approach to Support the Outranking Analysis of the OECD Countries

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ABSTRACT Since 2011, the Organization for Economic Co-operation and Development (OECD) has maintained the Better Life Initiative, which proposes a quality-of-life index called Better Life Index (BLI), consisting of 11 dimensions. This paper presents a multivariate analysis approach that aims to reduce the BLI dimensions. For this purpose, we applied factor extraction by main components to reorganize BLI variables into three dimensions (factors): dimension 1 - personal development and support factors; dimension 2 - financial balance; and dimension 3 - insecurity with the labor market. These three factors were used as criteria for the PROMETHEE-SAPEVO-M1 multicriteria method. We applied the methodology to data from 38 countries (35 from OECD and 3 non-OECD economies). As a result, we verified that Denmark, Iceland and Switzerland stood out as the countries with the best performances after the proposed analysis. Among the 38 countries evaluated, 19 showed positive flows, allowing the distribution into two well-defined groups. Also, adopting this hybrid methodology of multivariate analysis and multicriteria was advantageous because it reduced the evaluation criteria that the decision-maker needs to evaluate. We compared the results obtained by PROMETHEE-SAPEVO-M1 with the *ViseKriterijumska Optimizacija i Kompromisno Resenje* (VIKOR) and *Elimination Et Choix Traduisant la Realité* - Multicriteria Ordinal (ELECTRE-MOr) methods, with remarkably similar results. The main contribution of this study is to provide a hybrid methodology composed of a statistical structuring approach (factor analysis) in a problem with multiple conflicting criteria. After all, the approach proposed in this article represented a 94% reduction in the decision maker's cognitive effort.

INDEX TERMS Better life index, ELECTRE-MOr, factor analysis, PROMETHEE-SAPEVO-M1, VIKOR.

I. INTRODUCTION

The Better Life Index (BLI) is a web-based interactive tool designed to engage people in the debate about well-being and quality of life [1]. The tool allows the user to compare well-being between countries through a portal, according to the importance attributed to 11 dimensions: community, education, environment, civic participation, health, housing, income, jobs, personal satisfaction, safety and life/work (work-life balance). In this portal, the user, in addition to creating his index, can see how the average achievements of countries are compared based on their priorities, as well as the differences in well-being between men and women in each country. It is also possible to compare and share the index created with others who have also created indexes and with the Organization for Economic Co-operation and Development (OECD).

The OECD is an international organization that works to build better policies for better lives. Its goal is to shape policies that foster prosperity, equality, opportunity and well-being for all [2].

The number of user responses by country, age, gender, and which topics people consider most important for a better life are also considered. Currently, the index is calculated

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for the following countries: Australia, Austria, Belgium, Brazil, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Russia, Slovakia, Slovenia, South Africa, Spain, Sweden, Switzerland, the United States, and the United Kingdom.

According to [3], the BLI provides measures for several well-being aspects and can serve as a tool for economic diplomacy to pursue international goals for economy and sustainability.

For [4], there are two main reasons why the OECD BLI is an appropriate way for this type of analysis. First, as it contains 24 variables related to 11 different topics, it is one of the most extensive datasets on well-being worldwide [32]. Second, on the dedicated website [1], the OECD provides a survey of user weights related to the 11 topics. Therefore, the BLI is currently the most extensive research on the subjective optimal combination of well-being.

Considering well-being as a multidimensional concept, it must be measured simultaneously by more than one indicator [4].

The literature presents studies that report the difficulty of considering the dimensions and criticizing the weighting only by the user [5]–[8]. Some studies consider the dimensions of BLI using different methodologies [8], [9] but do not use the analysis in new dimensions.

Given the above, we identified a gap in the literature regarding the weighting of the dimensions of the BLI. Therefore, we propose using factor analysis with dimensions that can be aggregated, allowing a reduction in terms of the 11 dimensions originally proposed, to rank the countries considering BLI dimensions.

Considering a real decision-making problem, uncertainty is intrinsic [10]; methods used as decision aids should enable an integrated algorithm, permitting the evaluation of qualitative and quantitative data, such as [11]–[13]. In other words, this feature makes it possible to structure and analyze variables where it is impossible to define a precise numerical input along with variables in a quantitative format.

In this context, aspects of subjectivity in the Multiple Criteria Decision Making (MCDM) modeling are essential [14], [15], transcribing the preferences of the decision-maker (DM) by the implemented method and being clear concerning the manipulations and attributions regarding the problem in the evaluation.

Despite the diversity of MCDM approaches, methods and techniques, the essential ingredients of MCDM are a finite or infinite set of actions (alternatives, solutions, courses of action, etc.), at least two criteria, and at least one DM. Given these basic elements, MCDM is an activity that helps in making decisions, mainly in choosing, ranking or sorting the actions [16], presenting a highly multidisciplinary approach [17]. In this sense, the PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations) family of outranking methods and their applications has attracted much attention from academics and practitioners [18].

The academic literature contains many examples of the application of MCDM in recent complex problems, as presented in [19]–[27].

This paper aims to present an algorithm composed of factor analysis and the PROMETHEE SAPEVO-M1 MCDM method [28] to rank OECD countries. Among the various MCDM methods available, we chose this variant of the family of methods PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations), because it enables the analysis of a set of alternatives considering both quantitative and qualitative criteria, structuring the weights of criteria by ordinal inputs. Besides, the method presents a computational tool [29] that implements it, greatly facilitating its application in complex case studies, such as the one proposed in this article.

This hybrid method represents integrating two methodological concepts: one intended on cardinal evaluation (PROMETHEE) and the other relative to ordinal evaluation (SAPEVO).

In the light of these considerations, we structured the following research objectives to serve as guidelines in this study:

- Reduction of BLI dimensions through factor analysis;
- Ranking of countries by applying the PROMETHEE SAPEVO-M1 MCDM method [30].

The main contribution of this study is to provide a hybrid methodology for real problems involving many criteria and alternatives, aiming to make the decision-making process more straightforward and with less cognitive effort for DM.

The paper is organized as follows. Section 2 presents the literature review. Section 3 explains the materials and methods. Section 4 presents the results and compares the ranking obtained with the *ViseKriterijumska Optimizacija i Kompromisno Resenje* (VIKOR) and *Elimination Et Choix Traduisant la Realité* - Multicriteria Ordinal (ELECTRE-MOr) methods, in order to verify the robustness and reliability of the results. Finally, Section 5 concludes this study.

II. LITERATURE REVIEW

Considering the possible forms of BLI weighting and the methodologies frequently used to evaluate the index, we made a literature review on the subject in the Scopus and Web of Science databases. The most frequent methods used were based on Data Envelopment Analysis (DEA). Besides, many publications used the Principal Component Analysis (PCA) in BLI analysis. Table 1 shows the main publications using DEA and PCA.

The academic literature also brings studies applying a multicriteria approach, such as [9], [40], [41]. Kizielewicz *et al.* [42] proposed a methodological framework to analyze individual criteria in any decision model. The authors provided a reference set of Multi-Criteria Decision Analysis (MCDA) methods (TOPSIS, VIKOR, COMET) along with their similarity coefficients.

TABLE 1. Literature review.

Method/Authors	Objective
DEA/[9]	The authors provided a composite indicator of well-being for the 35 OECD countries, as well as South Africa, Russia and Brazil for the period of 2013–2016, considering data on 10 different well-being domains from the OECD BLI. They combined DEA with the Benefit-of-the-Doubt (BOD) principle and MCDM techniques.
DEA/[31]	BLI was used to evaluate more comprehensive socioeconomic characteristics. The employed Life Satisfaction Approach (LSA) to estimate the happiness functions of Japanese survey respondents by incorporating extensive socioeconomic characteristics as explanatory variables. The results indicated that the respondents value small changes in their socioeconomic circumstances more highly than other factors.
DEA/[32]	To aggregate 11 individual well-being indicators into a composite indicator using the World Bank's estimates of each country's productive base. The composite indicator based on BOD was distributed similarly and highly correlated with the existing Human Development Indicator (HDI). It was also positively correlated with Gross Domestic Product (GDP) per capita. On the other hand, the author showed that the composite indicator based on DEA was negatively correlated with HDI and GDP per capita.
DEA/[33]	The author estimated a happiness function and specified the sensitivity score for each country in a sample. A comprehensive set of well-being indicators released by the BLI were drawn, along with measures of income inequality.
DEA/[34]	To measure the performance of railway companies that produce passenger and freight services worldwide.
DEA and PCA/[35]	Methodology to build a measure of well-being in the form of a single index, as for GDP, which considered: (1) the social and environmental costs not considered in the GDP, and (2) the use of conventional resources (capital and labor).
PCA/[36]	To review the BLI and discuss methodological issues in the definition of the criteria used to rank the countries and their aggregation method. According to the authors, the BLI establishes a hierarchy among the evaluated countries, independent of the chosen set of weights.
PCA/[37]	Study to quantify and analyze the quality of life in the Gauteng City-Region of South Africa. The authors employed categorical PCA suitable for analyzing categorical data typically used in quality-of-life research.
PCA/[38]	Novel quality of life approach: the elements of the good life as sketched out by [36]. This approach focused on life results in seven domains: health, security, friendship, respect, leisure, personality, and harmony with nature. The authors refined the original concept and suggested a way to measure the well-being of individuals with the help of the Good Life Index.
PCA/[39]	Study to measure the Physical Quality of Life Index (PQLI) between the states in Malaysia. Results showed that the more developed states with high GDP also experienced high PQLI. However, some states experienced high GDP with low PQLI, and vice versa.

Stoilova [43] proposed a methodology based on the combination of multicriteria methods to examine the development of railway passenger transport in the European Union countries by using criteria related to the transportation process and the countries' economic development level. Stoilova [44] analyzed the development of railway transport in twelve different railway transport markets in the Balkan region.

According to [45], the problem of selecting the proper methods and parameters for the decision problems is raised in many studies. The authors identified a set of feasible MCDA methods and planned a simulation experiment based on reference literature guidelines. The research allowed the generation of a set of models differentiated by the number of attributes and decision variants and similarity research for the obtained rankings sets.

Shekhovtsov *et al.* [46] calculated the relevance of criteria using four different approaches and evaluated their effectiveness using a reference ranking and some MCDA methods.

Shekhovtsov and Kołodziejczyk [47] confirmed that each normalization method returns a different ranking order. So, when it comes to the accuracy of the results, it is essential to compare the extent to which the ranking pairs are similar.

According to [48], the rankings obtained with different MCDA methods are often different. The authors examined how different rankings can be obtained using TOPSIS and VIKOR methods.

In this article, we performed a comparative analysis of the results obtained by applying the PROMETHEE-SAPEVO-M1 with the VIKOR and ELECTRE-MOr methods to verify the reliability of the obtained ordering.

After the literature review, we verified that no previous studies are implementing a reduction in the pre-processing of variables in MCDA problems. Therefore, the approach proposed in this work is innovative, filling this gap in the literature.

According to [49], problems related to multicriteria applications can be classified into three categories:

1. A large number of criteria;
2. A large number of alternatives;
3. A large number of criteria and alternatives.

Our research falls into Category 3, because the original problem presents 38 alternatives and 11 criteria, which would require a high cognitive effort for decision-makers since, to obtain the weights of the criteria, the PROMETHEE-SAPEVO-M1 method performs pairwise comparations between the criteria.

Considering the most used MCDA method in the world - Analytic Hierarchy Process (AHP), proposed by [50] - the number of pairwise comparisons needed to evaluate the criteria would be 55. In the approach proposed in this article, the number of pairwise evaluations required is only 3, representing a 94% reduction in the decision maker's cognitive effort.

Thus, the present work intends to mitigate one of the problems concerning the reduction of criteria using factor analysis.

Factor analysis was introduced by [51]. Another relevant contribution was made by [52] in developing the idea of the multi-factor analysis.

Regarding the PCA, the factor analysis aims to describe the original variability of random variables that make up the set of problem variables in a smaller number of random variables called common factors related to the original vector through a linear model [53].

According to [54], factor analysis is the linear combination of the original variables. Once the factors are identified, their numerical values, punctuation can be obtained for each sample element. These scores can be used in different analyses involving additional techniques.

According to [30], the PROMETHEE-SAPEVO-M1 hybrid modeling aims to "unite" two methods—the PROMETHEE [55] and the SAPEVO-M method [56], an evolution of the SAPEVO method [57]. In this paper, we applied the methodology with a single DM.

III. MATERIALS AND METHODS

This section aims to present methodological steps as they are being applied to the problem. Such an approach aims to function as a workflow that can be replicated in other instances. Fig. 1 shows the methodological steps addressed.

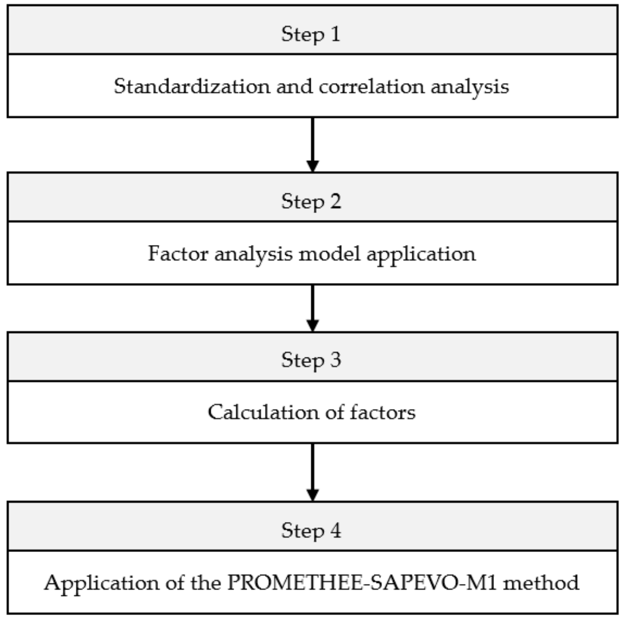

FIGURE 1. Steps of the methodology.

A. STANDARDIZATION AND EXPLORATORY ANALYSIS

To access the data and variables, we used the OECD.STATS portal [58]. The data available on the portal comprise the period from 2013 to 2017, compiled for all countries. Therefore, this article based its analysis on the latest consolidated edition of the BLI [59]. The database is divided into 11 dimensions that are compiled by 24 variables, a large number to be applied in an ordinal MCDM analysis.

In order to allow the evaluation of alternatives in the light of the criteria, the data were normalized using two types of standardization. The first, based on the z-score method, which produces standard variables with mean 0 and variance 1, was used for all 24 variables that make up BLI (1).

$$Z_i = \frac{X_i - \mu}{\sigma} \tag{1}$$

where Z_i = The i-th standardized score; X_i = The i-th observation of the variable; μ = The mean of the observations of the variable; and σ = The standard deviation of the variable.

The second one consisted of the standardization of variables between 0 and 1. This technique was used to present the results of the calculation of the synthetic index and the factors found in (2).

$$Y_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{2}$$

where: Y_i = The transformed value of the i-th observation of the variable in question; X_{min} = The minimum value of the variable in question; and X_{max} = The maximum value of the variable in question. Table 2 shows, in detail, the definitions of variables.

Fig. 2 graphically shows the hypothesis tests that assess the significance of the correlation with pairs of variables at a level of 5%. According to [54], this correlation level is indicative of using factor analysis. The figure shows that, if the correlation is significant, it is painted, and the color indicates whether the correlation between the variables is positive (blue) or negative (red). When we observe the figure, it is possible to note that most pairs are statistically correlated, which, in the entry as criteria of an MCDM method, could be an indication of a redundant criterion.

TABLE 2. Definition of the variables.

Dimension	Variables	Units	Index
Housing	Dwellings without basic facilities Housing expenditure Rooms per person	Percentage Percentage Ratio	V_1 V_2 V_3
Income	Household net adjusted disposable income Household net financial wealth	U.S. Dollar U.S. Dollar	V_4 V_5
Jobs	Labor market insecurity Employment rate Long-term unemployment rate Personal earnings	Percentage Percentage Percentage U.S. Dollar	V_6 V_7 V_8 V_9
Community	Quality of support network	Percentage	V_{10}
Education	Educational attainment Student skills Years in education	Percentage Average score Years	V_{11} V_{12} V_{13}
Environment	Air pollution Water quality	Micrograms per cubic meter Percentage	V_{14} V_{15}
Civic engagement	Stakeholder engagement for developing regulations Voter turnout	Average score Percentage	V_{16} V_{17}
Health	Life expectancy Self-reported health	Years Percentage	V_{18} V_{19}
Life Satisfaction	Life satisfaction	Average score	V_{20}
Safety	Feeling safe walking alone at night Homicide rate	Percentage Ratio	V_{21} V_{22}
Work-Life Balance	Employees working very long hours Time devoted to leisure and personal care	Percentage Hours	V_{23} V_{24}

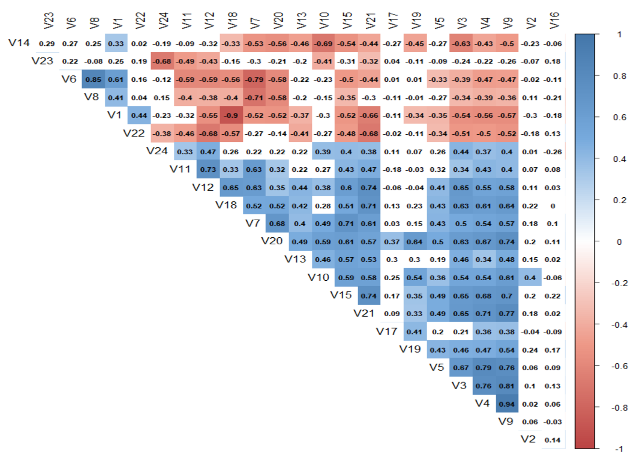

FIGURE 2. Correlation analysis.

B. APPLICATION OF FACTOR ANALYSIS MODEL

According to [54], a factor analysis extracts the maximum common variance of all variables and places them in a common score. In terms of assumptions of the factor analysis, we found that all variables are continuous. According to the correlation analysis performed in the previous section, it was also verified that most variables correlate with a coefficient greater than 0.3. According to Table 3, Kaiser–Meyer–Olkin (KMO) statistic was verified, which, according to [60], is an indicator that compares the magnitude of the correlation coefficients observed with the magnitudes of partial correlation coefficients and ranges from 0 to 1. A KMO index greater than 0.5 shows adequacy for factor analysis [54]. Finally, Bartlett's test of sphericity (BTS) should be statistically significant ($p < 0.05$), although this is not appropriate when not all data are normal. Therefore, interpretation in the KMO test prevails.

TABLE 3. Bartlett's test of sphericity and the Kaiser–Meyer–Olkin test.

	Test	Measure
	KMO	0.729
BTS	Chi-square Approx.	1232.438
	Df	276
	Sig.	0.000

TABLE 4. Extraction of factors.

	Initial Auto Value		
Component	Total	% Variance Explained	% Cumulative of Explained Variance
1	12.280	51.165	51.165
2	3.690	15.375	66.541
3	1.614	6.725	73.266

C. CALCULATION OF FACTORS

There are some possible methods for factor extraction, such as maximum likelihood, least squares, and PCA. Among these methodologies, we opted for the PCA, because, according to [54], normality is not necessary for this extraction to be used.

There should be a reduction in the original p-variables to facilitate the interpretation of the principal components. Thus, the information in the original p-variables is replaced by the information of the main uncorrelated components k ($k < p$). However, the quality of this approach depends on the number of components.

To determine the number of factors, we analyzed the proportion of the total variance related to each estimated eigenvalue ω_i, given by $\omega_i = \omega_i/p, i = 1, 2, \ldots, p$. The eigenvalues that represent the highest proportions of total variance remain and, therefore, the value of m will be equal to the number of retained eigenvalues [53].

Table 4 shows the percentage of variation for the first three components and the cumulative variation as components are added. Hair *et al.* [54] suggest the 60% variance as an acceptable limit. Thus, factor extraction should continue until this level is reached. In the present case, it is observed that this level is already reached with two components, but to have a robust data set analysis, we chose to use three factors, presenting 73.266% of the variance.

According to [54], interpreting the original factors F_1, $F_2, \ldots, F_m$ may not be straightforward. In this situation, an orthogonal transformation of the original factors can be used to obtain a simpler structure to be analyzed. There are two main types of rotation: orthogonal and oblique [61]. In addition, the two forms of rotation produce very similar results, especially when there is a clear pattern of correlation between the variables used [54]. The type of varimax orthogonal rotation is the most used because this method aims to minimize the number of variables that present high loads in each factor) [62]. Therefore, this work used this rotation to analyze the data better.

For identifying and naming the factors, we considered a factorial load of at least 0.7 in the variable module concerning the factor, which is ideal [54]. We observed the recommendations proposed by [54], suggesting that one of the assumptions of factor analysis is the simple structure of its components.

For each factor, we presented its name and the variables that presented a factor load greater than 0.7. In parentheses, we report the factorial load of the variable within the factor. After this analysis, the factorial scores for each factor were obtained as follows:

1) FACTOR 1 (PERSONAL DEVELOPMENT AND SUPPORT FACTORS)

According to the criterion adopted, the following variables have significant weight: V_{12}—Student skills (0.969); V_{24}—Time devoted to leisure and personal care (0.952); V_{18}—Life expectancy (0.95); V_{10}—Quality of support network (0.949); V_{13}—Years in education (0.921); V_7—Employment rate (0.883); V_{15}—Water quality (0.859); V_{20}—Life satisfaction (0.845); V_2—Housing expenditure (0.839); V_{11}—Educational attainment (0.772); and V_{21}—Feeling safe alone at night (0.762).

These variables relate to issues of the individual's development regarding educational variables. The factor also presents the variable of the amount of free time for reading and personal care (V_{24}) with the second-highest factor load, indicating a preponderance of the variable in the factor. Finally, some variables deal with the conditions of support to the individual, such as the quality of the support network (V_{10}), feeling of safety when going out alone at night (V_{21}) and water quality (V_{15}).

2) FACTOR 2 (FINANCIAL EQUILIBRIUM)

For the second factor, the following variables have significant weight: V_9—Personal earnings (0.774); V_5—Household net financial wealth (0.724); and V_4—Household net adjusted disposable income (0.72). In this factor, it is possible to perceive that it deals with the individual's revenue (V_9) and how the family balances revenues and expenses (V_5, V_4).

3) FACTOR 3 (JOB MARKET INSECURITY)

For the third factor, the following variables present significant weights: V_6—Labor market insecurity (0.936); and V_8—Long term unemployment rate (0.915). In this factor, only these two variables were relevant, which gave a well-defined meaning to the factor; that is, the first variable (V_6) is associated with the expected loss of income due to unemployment, and the second one (V_8) is associated with the time that the person becomes unemployed. These two variables show the feeling and fragility of people losing their job and eventually not getting it back.

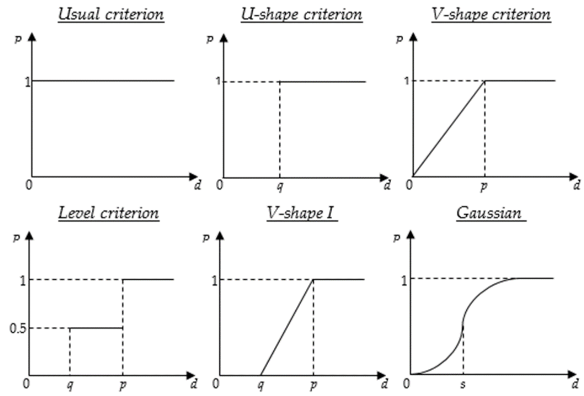

FIGURE 3. Six types of preferences functions. Adapted from [65].

D. CALCULATION OF FACTORS

The PROMETHEE-SAPEVO-M1 method represents the integration of two MCDM methods—PROMETHEE and SAPEVO-M. According to [30], the method allows a mono decision evaluation through a non-compensatory algorithm for ranking problems, considering quantitative and qualitative variables through cardinal and ordinal inputs. The process structure of the proposal is designed in Fig. 1, representing the steps that compose the method. In Section 3, the axiomatic structure detail is presented.

To perform the alternatives under criteria J, where $g_j \in J$, $j = 1, \ldots k$, it is sustained as the same PROMETHEE procedure. In each criterion, it is necessary to define if it is a relation of cost (minimization) or benefit (maximization). The method keeps suggesting the six types of preference functions (Fig. 3) as presented in [63], where the preference function selected lies with the property of attribute [64].

According to each type of preference function selected to each criterion, it may be necessary to set some parameters where three types of thresholds are usually used. The parameter q indicates a value of indifference preference, where $P(d) = 0$ if $d \leq q$; the parameter p indicates a strict preference, where $P(d) = 1$ if $d \geq p$; the parameter s, as the previous thresholds, indicates a superior relationship, but the normalization is nonlinear with the attribute value difference P(d), as presented in the Gaussian function (Fig. 3) [30].

According to [66], the linear preference function V-shape I is the most valuable, and it is present in most theoretical and practical studies regarding the PROMETHEE methods.

E. VIKOR METHOD

The VIKOR method was developed as a method of commitment programming to determine a ranking with weights of a set of alternatives [67] for selecting the appropriate options [68]. To observe this weight that measures the ranking, a few steps must be followed [69], [70], such as:

1) STEP 1

Determine the highest values f_i^* and the lowest values f_i^- of all the alternatives in each criterion, i = 1, 2, . . . , n.

$$f_i^* = max_i f_{ij}$$
$$f_i^- = min_i f_{ij}$$

where f_i^* is the highest value presented by the alternatives in each criterion; f_i^- is the lowest value presented by the alternatives in each criterion; and f_{ij} is the alternative value in each criterion.

2) STEP 2

Calculate the values S (maximum utility group) (3) and R (minimum individual weight) (4), with j = 1, 2, . . . , j, in the relationships where W_i is the weight of the criterion.

$$S_j = \frac{\sum_{i=1}^{n} W_i \left(f_i^* - f_i^-\right)}{\left(f_i^* - f_i^-\right)} \tag{3}$$

$$R_j = max_j \left(\frac{\sum_{i=1}^{n} W_i \left(f_i^* - f_i^-\right)}{\left(f_i^* - f_i^-\right)}\right) \tag{4}$$

S_j is the maximum utility group of the alternative j; W_i is the weights of the criteria obtained by calculating entropy; and R_j is the minimum individual weight of alternative j.

3) STEP 3

Calculate the values of Q_j (5), with j = 1, 2, . . . , j, by the ratio in which $S^* = min_j S_j$; $S^- = max_j S_j$ and $R^* = min_j R_j$; $R^- = max_j R_j$. Parameter v is entered as a strategy weight, commonly used as v = 0.5.

$$Q_j = \frac{v\left(S_j - S^*\right)}{\left(S^- - S^*\right)} + \frac{(1 - V)\left(R_j - R^*\right)}{\left(R^- - R^*\right)} \tag{5}$$

where v = 0.5 and Q_j is the final score of an alternative j.

4) STEP 4

Classify the alternatives in a decreasing ordination, using the values obtained by S, R and Q. The results are three classification lists. However, only the values obtained by Q can be considered.

F. ELECTRE-MOR METHOD

The ELECTRE MOr, proposed by [19], is a multicriteria sorting method with ordinal weight input that includes multiple DM and distributes the alternatives into pre-defined categories. The ELECTRE MOr procedures are developed in two stages. To obtain the weights and evaluate qualitative criteria, the method uses an adaptation of the SAPEVO method [56], [57], transforming ordinal preferences of criteria into a vector of criteria weights and integrating the vector criteria of different DM.

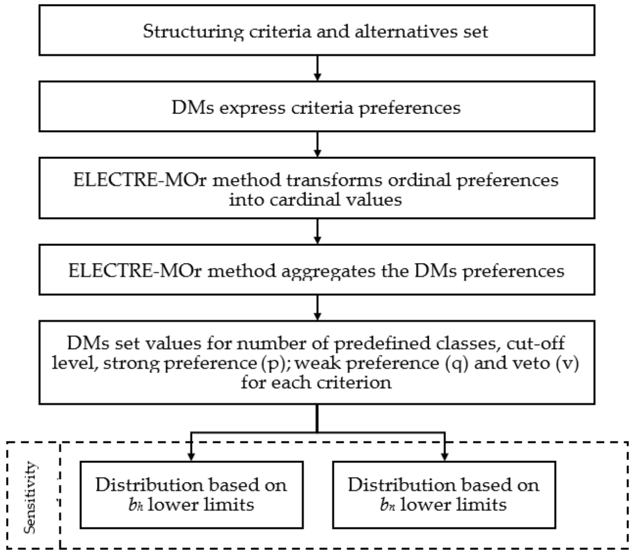

FIGURE 4. The steps of the ELECTRE-MOr method [71].

Fig. 4 shows the steps of ELECTRE-MOr method:

According to [19], ELECTRE-MOr has some advantages over the other methods of the ELECTRE family:

1. The elicitation of weights of the criteria by an ordinal form is not an easy task for a DM because it requires establishing a precise numerical value for such parameters as the importance coefficients of the criteria. The method also allows the evaluation of the criteria by multiple DM.
2. Two ways of obtaining the lower limits of the classes (bh and bn), which provides 4 different sorts (2 optimistic and 2 pessimistic), allowing a more robust and reliable sensitivity analysis of the results.

IV. RESULTS AND DISCUSSION

The application of the PROMETHEE-SAPEVO-M1 method in this work was supported by the software developed by [29] (present qualitative criteria). In structuring the problem, we have the evaluation matrix (Table 5).

To evaluate the criteria, preference functions were analyzed among the six presented by [63]. Because of the nature of the data, we opted for the V-Shape I preference function, where (6):

$$P(x) = \begin{cases} 0 & x \leq q \\ \dfrac{x - q}{p - 1} & q < x \leq p \\ 1 & x > p \end{cases} \tag{6}$$

When applying the V-Shape I preference function, we considered that the preference increases linearly from indifference to preference between the q and p limits. In this research,

TABLE 5. Evaluation matrix.

Alternatives	Criteria		
Country	Factor 1	Factor 2	Factor 3
Australia	0.930	0.930	0.112
Austria	0.784	0.760	0.112
Belgium	0.841	0.828	0.216
Brazil	0.291	0.302	0.358
Canada	0.892	0.916	0.031
Chile	0.385	0.409	0.286
Czech Republic	0.699	0.520	0.127
Denmark	1.000	0.896	0.101
Estonia	0.559	0.491	0.144
Finland	0.929	0.809	0.100
France	0.737	0.706	0.210
Germany	0.854	0.782	0.074
Greece	0.427	0.364	0.631
Hungary	0.386	0.358	0.244
Iceland	0.957	0.926	0.044
Ireland	0.798	0.796	0.183
Israel	0.572	0.578	0.171
Italy	0.563	0.552	0.368
Japan	0.696	0.621	0.073
Korea	0.497	0.405	0.121
Latvia	0.472	0.366	0.260
Luxembourg	0.763	0.873	0.111
Mexico	0.173	0.275	0.250
Netherlands	0.898	0.863	0.116
New Zealand	0.904	0.844	0.133
Norway	0.896	0.907	0.044
Poland	0.591	0.421	0.196
Portugal	0.488	0.497	0.291
Russia	0.363	0.269	0.257
Slovak Republic	0.582	0.425	0.279
Slovenia	0.666	0.566	0.158
South Africa	0.000	0.000	1.000
Spain	0.722	0.647	0.478
Sweden	0.894	0.887	0.109
Switzerland	0.936	0.920	0.000
Turkey	0.268	0.336	0.458
United Kingdom	0.819	0.783	0.082
United States	0.802	1.000	0.000

TABLE 6. Importance scale [30].

Relation	Degree
Absolutely worse/Absolutely less important	-3
Much worse/Much less important	-2
Worse/Less important	-1
Equivalent/As important as	0
Best/Most Important	1
Much better/ Much more important	2
Absolutely better/Absolutely more important	3

we used p as the criterion's standard deviation value. The q value was considered as p/2.

To evaluate the criteria weights, we applied the SAPEVO-M1, as mentioned by [30]. The importance scale was used according to Table 6.

Regarding evaluating the alternatives, the factors were scored by applying the scale above due to the variance for each factor. As Factor 1 had a variance of 51.165%, it was considered more important than Factor 2, which presented a variance of 15.375%.

Factor 1 was considered absolutely more important than Factor 3 since it obtained an explained variance of 6.725%.

TABLE 7. Countries ranking.

Ranking	Country	Grade	Ranking	Country	Grade
1	Denmark	7.226	20	Spain	−0.11
2	Iceland	7.089	21	Czech Republic	−0.904
3	Switzerland	7.02	22	Slovenia	−1.124
4	Australia	6.609	23	Israel	−2.544
5	Canada	6.471	24	Estonia	−3.636
6	United States	6.44	25	Poland	−3.852
7	Norway	6.43	26	Italy	−4.038
8	Finland	6.193	27	Slovak Republic	−4.443
9	Sweden	6.152	28	Korea	−4.961
10	Netherlands	6.081	29	Portugal	−5.257
11	New Zealand	5.988	30	Latvia	−6.088
12	Germany	5.448	31	Chile	−6.791
13	United Kingdom	5.181	32	Hungary	−6.827
14	Belgium	5.098	33	Greece	−7.42
15	Luxembourg	4.769	34	Russia	−7.607
16	Ireland	4.666	35	Brazil	−8.517
17	Austria	4.359	36	Turkey	−8.767
18	France	2.277	37	Mexico	−8.935
19	Japan	0.545	38	South Africa	−12.221

Factor 2 performed an explained variance of more than twice (absolutely better) when compared to Factor 3.

Therefore, it is possible to understand how much they are linked and influence the ordering. The criteria weights were distributed as follows: Factor 1, 0.5; Factor 2, 0.389; Factor 3, 0.111. It is worth noting that the weights obtained through the SAPEVO-M1 method were relatively proportional to the explained variance. It strengthens the analysis of the importance of each criterion, either by observation through factor analysis or qualitative comparison.

The next steps of the application, as well as the comments of the analysis, were performed based on the use of the software [29]. We emphasize that, as described above, the criteria represented by Factor 1 (personal development factors) and Factor 2 (financial balance) should be maximized because the highest possible value for these attributes is desirable. Factor 3 (insecurity with the labor market) should be minimized because greater insecurity with the labor market would negatively impact the quality of life.

A. RESULTS

After applying the method, we obtained the ranking of OECD countries in terms of quality of life, based on BLI variables (Table 7).

Analyzing the results, we observed that Denmark, Iceland and Switzerland stand out positively. Considering the countries with the lowest perception of the quality of life, we observed South Africa, Mexico, Turkey and Brazil. We emphasize an essential characteristic of the methodology presented because it provides, in addition to the ranking, a notion of the relative distance between countries. Given this, we see South Africa is far from the other countries, even as

TABLE 8. Application of the VIKOR method.

	Factor 1	Factor 2	Factor 3	S_i	R_i	Q_i
Australia	0.035	0.02723	0.098568	0.074662	0.035	0.014255
Austria	0.20088	0.2232	0.099456	0.436624	0.2232	0.292568
Belgium	0.124656	0.13072	0.087808	0.279568	0.13072	0.163595
Brazil	0.596269	0.577944	0.138672	1.251541	0.596269	0.880716
Canada	0.031428	0.025368	0.346902	0.067894	0.031428	0.009011
Chile	0.54858	0.541356	0.022134	1.098802	0.54858	0.787359
Czech Republic	0.115885	0.19632	0.249678	0.348527	0.19632	0.239197
Denmark	0	0.05408	0.114173	0.066907	0.05408	0.025837
Estonia	0.441	0.456064	0.086456	0.911608	0.456064	0.64708
Finland	0.039689	0.093781	0.1296	0.14787	0.093781	0.086272
France	0.244327	0.237846	0.079	0.503173	0.244327	0.333509
Germany	0.107602	0.153908	0.19446	0.27705	0.153908	0.180255
Greece	0.489342	0.497352	0.027306	1.033388	0.497352	0.723993
Hungary	0.262178	0.233688	0.477036	0.64983	0.262178	0.40194
Iceland	0.016598	0.026492	0.233264	0.053826	0.026492	0
Ireland	0.193314	0.188904	0.035948	0.39027	0.193314	0.252536
Israel	0.341544	0.335912	0.151707	0.708749	0.341544	0.484235
Italy	0.249964	0.258944	0.108072	0.571836	0.258944	0.370299
Japan	0.171152	0.209208	0.341136	0.407224	0.209208	0.270945
Korea	0.350088	0.369495	0.064167	0.728416	0.369495	0.512813
Latvia	0.262416	0.25677	0.08954	0.550646	0.262416	0.365005
Luxembourg	0.111864	0.046482	0.23114	0.187206	0.111864	0.114719
Mexico	0.631001	0.632925	0.08325	1.291676	0.632925	0.92356
Netherlands	0.017646	0.037675	0.221	0.084321	0.037675	0.019901
New Zealand	0.086208	0.134628	0.100572	0.236264	0.134628	0.150357
Norway	0.094016	0.078492	0.127148	0.17836	0.094016	0.09786
Poland	0.366464	0.525153	0.035376	0.900241	0.525153	0.695273
Portugal	0.302592	0.211763	0.138964	0.571391	0.302592	0.403266
Russia	0.310856	0.363307	0.216213	0.74895	0.363307	0.515799
Slovak Republic	0.151734	0.154675	0.185297	0.378112	0.154675	0.218655
Slovenia	0.194388	0.18445	0.234918	0.42292	0.194388	0.265569
South Africa	0.666	0.566	0	1.39	0.666	0.985461
Spain	0	0	0.522	0.478	0.478	0.501474
Sweden	0.076532	0.073111	0.425898	0.201745	0.076532	0.093338
Switzerland	0.057216	0.07096	0.109	0.128176	0.07096	0.061578
Turkey	0.685152	0.61088	0	1.296032	0.685152	0.964837
United Kingdom	0.048508	0.072912	0.420444	0.158976	0.072912	0.074586
United States	0.162162	0	0.082	0.162162	0.162162	0.143529
Weights	0.5	0.389	0.111	S*, R*	0.053826	0.026492
				S-, R-	1.39	0.685152

countries with a lower perception of quality of life are far from the top positions.

B. COMPARATIVE ANALYSIS OF THE RESULTS

In order to verify the robustness and reliability of the results obtained, we also applied the VIKOR (Table 8) and ELECTRE-MOr (Table 9) methods. The methods were chosen for the comparative analysis because they are ranking and classification methods, respectively, in addition to being indicted for the analysis of cardinal data.

The VIKOR was applied by providing, as well as the PROMETHEE-SAPEVO-M1 method, a ranking of alternatives. The ELECTRE-MOr is a hybrid method, which distributes the alternatives in predefined classes, and was used to verify the robustness of the ranking obtained regarding positive and negative values. Therefore, when applying the ELECTRE-MOr method, we considered two classes (A and B), obtaining two clusters of alternatives. Table 10 presents the results obtained by applying the three methods.

Comparing the results obtained using the PROMETHEE-SAPEVO-M1 with the VIKOR method, we observe a remarkable similarity in the orderings, both in the best-ordered and worst-ranked countries. We emphasize that the first 15 countries are the same in both methods, with few variations in the rankings. Analyzing the worst countries, we found that 14 of the 15 worst are repeated in the ordering obtained by the VIKOR method.

TABLE 9. Application of the ELECTRE-MOr method.

Country	Factor 1	Factor 2	Factor 3	b_h		b_n	
Australia	0.93	0.93	0.112	A	A	A	A
Austria	0.784	0.76	0.112	A	A	A	A
Belgium	0.841	0.828	0.216	A	A	A	A
Brazil	0.291	0.302	0.358	B	B	B	B
Canada	0.892	0.916	0.031	A	A	A	A
Chile	0.385	0.409	0.286	B	B	B	B
Czech Republic	0.699	0.52	0.127	A	A	B	B
Denmark	1	0.896	0.101	A	A	A	A
Estonia	0.559	0.491	0.144	B	B	B	B
Finland	0.929	0.809	0.1	A	A	A	A
France	0.737	0.706	0.21	A	A	A	A
Germany	0.854	0.782	0.074	A	A	A	A
Greece	0.427	0.364	0.631	B	B	B	B
Hungary	0.386	0.358	0.244	B	B	B	B
Iceland	0.957	0.926	0.044	A	A	A	A
Ireland	0.798	0.796	0.183	A	A	A	A
Israel	0.572	0.578	0.171	A	A	B	B
Italy	0.563	0.552	0.368	B	B	B	B
Japan	0.696	0.621	0.073	A	A	B	B
Korea	0.497	0.405	0.121	B	B	B	B
Latvia	0.472	0.366	0.26	B	B	B	B
Luxembourg	0.763	0.873	0.111	A	A	A	A
Mexico	0.173	0.275	0.25	B	B	B	B
Netherlands	0.898	0.863	0.116	A	A	A	A
New Zealand	0.904	0.844	0.133	A	A	A	A
Norway	0.896	0.907	0.044	A	A	A	A
Poland	0.591	0.421	0.196	B	B	B	B
Portugal	0.488	0.497	0.291	B	B	B	B
Russia	0.363	0.269	0.257	B	B	B	B
Slovak Republic	0.582	0.425	0.279	B	B	B	B
Slovenia	0.666	0.566	0.158	A	A	B	B
South Africa	0	0	1	B	B	B	B
Spain	0.722	0.647	0.478	A	A	A	A
Sweden	0.894	0.887	0.109	A	A	A	A
Switzerland	0.936	0.92	0	A	A	A	A
Turkey	0.268	0.336	0.458	B	B	B	B
United Kingdom	0.819	0.783	0.082	A	A	A	A
United States	0.802	1	0	A	A	A	A
b_h	0.5	0.5	0.5				
b_n	0.722	0.647	0.158				
Weights	0.5	0.389	0.111				
Q	0.05	0.05	0.05				
P	0.2	0.2	0.2				
V	1	1	1				

Regarding the comparison with the ELECTRE-MOr method, which distributed the countries into two groups, we observed that the transition range from class A to B is practically the same as the change of positive to negative values (Japan/Spain). This comparative analysis shows that the results obtained in this article preserve good coherence, both in the ordering of countries and in their distribution in classes.

We also emphasize that the method applied in this article presents advantages related to the VIKOR method (scale ranging from 0 to 1) and ELECTRE-Mor (divides the alternatives into classes) because it presents a more well-defined

TABLE 10. Comparative analysis of the results.

PROMETHEE-SAPEVO-M1			VIKOR		ELECTRE-MOr			
Country	Grade	Ranking	Q_i	Ranking	b_k		b_n	
Denmark	7.226	1	0.0258	5	A	A	A	A
Iceland	7.089	2	0	1	A	A	A	A
Switzerland	7.02	3	0.0615	6	A	A	A	A
Australia	6.609	4	0.0142	3	A	A	A	A
Canada	6.471	5	0.0090	2	A	A	A	A
United States	6.44	6	0.1435	12	A	A	A	A
Norway	6.43	7	0.0978	10	A	A	A	A
Finland	6.193	8	0.0862	8	A	A	A	A
Sweden	6.152	9	0.0933	9	A	A	A	A
Netherlands	6.081	10	0.0199	4	A	A	A	A
New Zealand	5.988	11	0.1503	13	A	A	A	A
Germany	5.448	12	0.1802	15	A	A	A	A
United Kingdom	5.181	13	0.0745	7	A	A	A	A
Belgium	5.098	14	0.1635	14	A	A	A	A
Luxembourg	4.769	15	0.1147	11	A	A	A	A
Ireland	4.666	16	0.2525	18	A	A	A	A
Austria	4.359	17	0.2925	21	A	A	A	A
France	2.277	18	0.3335	22	A	A	A	A
Japan	0.545	19	0.2709	20	A	A	B	B
Spain	−0.11	20	0.5014	28	A	A	B	B
Czech Republic	−0.904	21	0.2391	17	A	A	B	B
Slovenia	−1.124	22	0.2655	19	A	A	B	B
Israel	−2.54	23	0.4842	27	A	A	B	B
Estonia	−3.63	24	0.6470	31	B	B	B	B
Poland	−3.85	25	0.6952	32	B	B	B	B
Italy	−4.03	26	0.3702	24	B	B	B	B
Slovak Republic	−4.44	27	0.2186	16	B	B	B	B
Korea	−4.96	28	0.5128	29	B	B	B	B
Portugal	−5.25	29	0.4032	26	B	B	B	B
Latvia	−6.08	30	0.3650	23	B	B	B	B
Chile	−6.79	31	0.7873	34	B	B	B	B
Hungary	−6.82	32	0.4019	25	B	B	B	B
Greece	−7.42	33	0.7239	33	B	B	B	B
Russia	−7.60	34	0.5157	30	B	B	B	B
Brazil	−8.51	35	0.8807	35	B	B	B	B
Turkey	−8.76	36	0.9648	37	B	B	B	B
Mexico	−8.93	37	0.9235	36	B	B	B	B
South Africa	−12.2	38	0.9854	38	B	B	B	B

relative distance between the alternatives, which provides additional information to the DM, particularly in case studies with a large number of alternatives, such as the one proposed in this research.

V. CONCLUSION

This paper applied a hybrid methodology composed of multivariate analysis and the PROMETHEE-SAPEVO-M1 MCDM method. The approach had two main objectives. The first was reducing the number of variables present in the BLI, which has 11 dimensions and is composed of 24 variables. The factor analysis allowed the decrease of the original variables in three factors, representing a 94% reduction in the number of decision makers' pairwise comparisons. It greatly facilitated the evaluation of the countries, requiring much less cognitive effort of the DM.

The second objective was to obtain the ranking of the 38 countries for which BLI is calculated. This ranking was obtained by applying the PHROMETHEE-SAPEVO-M1 method, analyzing the countries considering the abovementioned factors.

As a result, European countries such as Denmark, Iceland, and Switzerland presented the best rankings because they presented good performances in all the analyzed criteria. On the other hand, countries in Africa and America presented the worst rankings due to their poor performance in the light of the evaluated criteria. The result proved to be very consistent with the conditions of the countries, providing transparency and robustness to the decision-making process.

We also emphasize the possibility of analyzing the results from a clustering perspective since the PROMETHEE-SAPEVO-M1 method presents a difference between alternatives with negative and positive flows, providing additional information to the decision-maker. Such classification and the final ranking were compared with MCDA sorting and classification methods, with very similar results.

Another critical point is to obtain a quantified ranking, which makes it possible to verify how much one alternative is superior to the other. This feature can show minimal differences, which in practice would represent indifference; on the other hand, it can present relevant differences, which would justify the choice of an alternative in relation to the others.

This paper proposed an innovative methodology that can be replicated in several other academic applications, providing a decrease in variables through a robust and based factor analysis.

Regarding the impact on society, the work is relevant because it can be applied to public policies based on the grades of each country and also on the weight of each criterion since this approach can be used to prioritize investments in each area. We highlight the ease, flexibility and robustness of the PROMETHEE-SAPEVO-M1 method, which presents several analyses of the results, providing additional information to the DM. The software allows the reader to apply the methodology intuitively to tactical, operational, managerial and strategic problems.

Finally, as future studies, the authors suggest:

The construction, expansion and creation of a model that can be applied to more countries, not just OECD countries; the implementation of other approaches for dimension reduction and aggregation in an index; evaluation and comparison of the results with other methodologies in terms of variables/criteria that can be compared according to other sensitivity analyses.

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