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EVALUATION OF OECD COUNTRIES WITH MULTI-CRITERIA DECISION-MAKING METHODS IN TERMS OF ECONOMIC, SOCIAL AND ENVIRONMENTAL ASPECTS

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Abstract: *Exhausted natural resources and deteriorating ecological balance, together with the social privileges that people expect to have, are proof that the development of countries cannot be reduced to economic development alone. In this respect, this study aimed to evaluate the economic, social and environmental aspects of Organization for Economic Co-operation and Development (OECD) countries. Within this scope, the countries were firstly divided into two groups by performing cluster analysis in order to create more homogeneous country groups. Then, 12 criteria, consisting of four economic, four social and four environmental criteria, were determined by considering the literature and expert opinions. The criteria importance through intercriteria correlation (CRITIC) method was used to weight the determined criteria and using the calculated criterion weights, the countries in each cluster were then evaluated with the measurement of alternatives and ranking according to compromise solution (MARCOS) method. As a result, the most successful countries in the first cluster were determined as Switzerland, Denmark and Ireland with 68.8%, 62.7% and 62.5% performance scores, respectively. Whereas, the most unsuccessful countries were USA, Canada and Australia with 49.8%, 50.0% and 50.1% performance scores, respectively. The most successful countries in the second cluster were found as Slovenia, Spain and Portugal with 65.9%, 65.5% and 64.5% performance scores, while the most unsuccessful countries were Turkey, Chile and Colombia with 45.9%, 55.4% and 55.9% performance scores, respectively. Finally, in order to test the sensitivity of the MARCOS method, the solution was repeated with the MAIRCA, WASPAS, MABAC and CoCoSo methods using the weights obtained by the CRITIC method. A high correlation (greater than 80%) was found between the rankings acquired using the other methods and the rankings obtained by the MARCOS method.*

Key words: *OECD countries, economic- social- environmental development, CRITIC, MARCOS*

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1. Introduction

The continuous increase of the world population and the inequality in resource sharing drive countries into a constant growth war. This is because countries that strive to get the highest share of limited natural resources, especially oil, are aware that the primary way to achieve this is economic growth. However, the socio-environmental effects created by the economic growth of countries have brought forth increasing concerns in society. As developing countries begin to consume resources at the same level as developed countries, the planet is constantly being dragged into a disastrous situation. Economic growth is often accompanied by adverse environmental and social impacts such as excessive use of natural resources, income inequality, exploitation of manual labor and toxic gas emissions. Therefore, in order to evaluate the socio-economic performance of nations, economists have gradually started to address issues related to social welfare and environment as well as economic growth (Santana et al., 2014). However, it is still widely accepted to rank countries or regions by evaluating their performance and growth levels in terms of their gross domestic product (GDP).

GDP is useful for measuring and comparing market activity, as its intended purpose is to measure crude economic activity. However, in the last few decades GDP has been given a role that goes beyond its intended purpose. It has started to be used as a proxy indicator of economic competence as well as human progress and general social and economic well-being. Today, GDP is characterized as the most widely used indicator of a country's overall performance, even though it was never designed for such a purpose (Charles & D'Alessio, 2020). This is because societies with strong economic backgrounds are considered to be highly developed. However, obtaining and comparing the development level of societies only according to economic indicators can yield unrealistic and unreliable results. In fact, economic indicators cannot fully reflect the performance of countries in areas such as environment, public health, public education, etc. (Omrani et al., 2020). In any case, evaluating a country's performance should not be limited to only economic data or only non-economic data. Countries should be considered from both aspects simultaneously and in a coherent framework. More specifically, a country's GDP level of is seen as its ability to provide its citizens with the appropriate opportunities to take advantage of their economic, social and environmental conditions. Increase in per capita GDP can only be considered as a basic precondition for improving the living standards of a population (Cracolici et al., 2010). Therefore, in recent years, many indexes including the Social Progress Index (SPI), Human Development Index (HDI), Environmental Performance Index (EPI), Life Satisfaction Index (LSI), have been created in order to evaluate countries especially in terms of environmental and social aspects. However, although such indexes have been put forward by many different organizations, none of the indexes alone are sufficient for the social and environmental evaluation of countries.

Although economic growth, social development and environmental quality seem to be completely independent from each other, there are meaningful relationships between them. For instance, environmental constraints can lead to a decrease in regional growth, which is necessary for demographic development, and subsequently increased levels of unemployment (Fakher & Abedi, 2017), while population explosion and the struggle to improve economic growth can lead to more pollution and waste from industrial, agricultural and construction activities (Iram et al., 2020). In addition, healthy economic growth can be used as a social welfare tool for the citizens of that country. As can be understood from the examples, there are tight ties between the economic, social and environmental development of countries. Therefore, this study aimed to evaluate the Organization for Economic Co-operation and Development (OECD) countries in terms of economic, social and environmental aspects. It does not seem possible for a country to develop only economically or socially or environmentally. Economic development in a country means that a person living in that country earns more income. People who earn more income will want to have various social rights and privileges after their basic physiological needs are met. In addition, only people who can meet their basic physiological needs will be able to concern themselves with environmental issues. Therefore, all economic, social and environmental data should be taken into account when evaluating a country properly. From this point of view, as this study used economic, social and environmental data it yielded important results.

In recent years, there have been studies conducted with a tendency to evaluate the sustainability performance of countries. Using multiple-criteria decision-making methods, Tajbakhsh & Shamsi (2019) evaluated the sustainability performance of 133 countries while Antanasijevic et al. (2017) evaluated that of European countries, Ecer et al. (2019) evaluated that of 41 OPEC countries and Costa et al. (2019) evaluated that of 34 OECD countries. In this direction, the aim of contributing to the studies in the literature and evaluating the sustainability performances of OECD countries with regard to economic, environmental and social criteria constituted the main motivation of the present study. Differently from other studies in the literature, a cluster analysis was first performed in order to evaluate countries in more homogeneous groups. Following the cluster analysis, the sustainability performances of the countries were evaluated with a hybrid model using the CRITIC-MARCOS methods.

The particular goals of the present study specified to fill the gaps in the literature are listed below.

- Carrying out a performance evaluation for OECD countries with regard to the three main criteria of the concept of sustainability,
- Performing a cluster analysis in order to obtain homogeneous groups of countries prior to the performance evaluation,
- Comparatively presenting the outcomes of potential multiple-criteria decision-making methods that can be used for sustainable performance evaluation,
- Proposing an applicable methodology for the determination of the OECD country with the highest sustainability performance.

The criteria importance through intercriteria correlation (CRITIC) method was used to determine the importance weights of the criteria used to evaluate the countries in the study. Since the CRITIC method reaches outcomes by performing processes that are based on real data, it eliminates the impact of decision-makers on the decision. Due to the inclusion of real data related to three main criteria and sub-criteria for the OECD countries in the present study and the importance of the correlations between these criteria, the CRITIC method was used for weighting criteria. Then, the criterion weights calculated with the CRITIC method were used in the measurement of alternatives and ranking according to compromise solution (MARCOS) method and the countries were ranked according to their performances. In the MARCOS method, the utility functions of decision alternatives are obtained and the performances of alternatives are revealed with compromise rankings based on reference values (ideal and anti-ideal solution values). It is a flexible method and the fact that it allows for the evaluation of a large number of criteria with compromise solution, that it can be used in the solution of complex problems despite being a simple solution algorithm and that it is a strong and reliable decision-making tool for the optimization of multiple purposes can be listed as its advantages in comparison with other similar methods. Finally, in order to test the sensitivity of the solution obtained by the CRITIC-MARCOS methods, solution values were obtained by using different MCDM methods and the obtained results were compared.

2. Literature Review

Studies in the literature have examined countries economically, socially and environmentally many times using different methods. Although methods such as structural equation modelling (Cracolici et al., 2010), fuzzy logic (Phillis et al., 2011) and multiple regression (Kaklauskas et al., 2020) have been used for the economic, social and environmental evaluation of countries, multi criteria decision making (MCDM) methods are often preferred for this assessment.

Table 1. MCDM studies in which economic, social and environmental criteria was used

Writer	Criteria			Methods*	Countries/Areas
	Eco.	Soc.	Env.		
Charles & D'Alessio (2020)	√	√	√	DEA	28 areas of Peru
Giannakitsidou et al. (2020)	√		√	DEA	26 European countries
Iram et al. (2020)	√		√	DEA	26 OECD countries
Iqbal et al. (2019)	√		√	DEA	20 industrial countries
Ecer et al. (2019)	√	√	√	CoCoSo	41 OPEC countries
Costa et al. (2019)	√	√		ELECTRE TRI-C	34 OECD countries
Tajbakhsh & Shamsi (2019)	√	√	√	DEA	133 countries
Kılıç Depren & Bağdatlı Kalkan (2018)	√	√	√	Entropy ve MULTIMOORA	37 OECD countries
Moutinho et al. (2018)	√		√	DEA	16 Latin American countries
Antanasijevic et al. (2017)	√	√	√	PROMETHEE	30 European countries
Skare & Rabar (2017)	√	√	√	DEA	30 OECD countries
Şahin & Öztel (2017)	√	√		COPRAS	BRICS countries and Turkey
Santana et al. (2014)	√	√	√	DEA	BRICS countries
Shmelev & Rodríguez-Labajos (2009)	√	√	√	NAIADE	Austria
Malul et al. (2008)	√	√	√	DEA	38 developed, 53 developing countries

*MCDM Methods name, *MULTIMOORA:* Full Multiplicative Form of Multi-Objective Optimization by Ratio Analysis, *ELECTRE:* ELimination Et Choix Traduisant la Realité, *DEA:* Data Envelopment Analysis *NAIADE:* Novel Approach to Imprecise Assessment and Decision Environments, *COPRAS:* Complex Proportional Assessment, *PROMETHEE:* Preference Ranking Organization Method For Enrichment Evaluations), *CoCoSo:* Combined Compromise Solution

Among these studies, there are studies that have examined countries using economic, social and environmental criteria as well as studies that have examined only economic and social or only economic and environmental criteria. Table 1 shows the criteria and methods used in the literature to examine countries.

Most decisions made in the real world have many criteria that often conflict. Therefore, MCDM methods have become an extremely necessary tool for decision makers (Benítez & Liern, 2020). In recent years, MCDM methods have been used in many decision problems. Panchal et al. (2017) used Fuzzy AHP, Fuzzy CODAS methods to evaluate maintenance decisions in the urea fertilizer industry; Panchal et al. (2019) used Fuzzy FMEA, Fuzzy TOPSIS, Fuzzy EDAS, Fuzzy VIKOR methods to analyze the performance problems of the chemical process plant; Chatterjee et al. (2020) used EDAS in biomaterial selection; Gopal & Panchal (2020) used Fuzzy COPRAS, Fuzzy TOPSIS methods for risk analysis and reliability assessment of the milk processing industry; Das et al. (2021) used PFMEA, TOPSIS, VIKOR methods for risk analysis in the milk industry. In this study, MCDM methods were preferred as there were many criteria, most of which were conflicting. First of all, the CRITIC method recommended by Diakoulaki et al. (1995) and used in many decision problems such as air conditioning selection (Vujicic et al., 2017), risk assessment (Ayrım & Can, 2017), third party logistics service provider selection (Keshavarz Ghorabaee et al., 2017), construction equipment evaluation (Keshavarz Ghorabaee et al., 2018), financial performance evaluation (Şenol & Ulutaş, 2018), bank performance evaluation (Akbulut, 2019), cargo company assessment (Ulutaş & Karaköy, 2019), corporate sustainability performance analysis (Yalçın & Karakaş, 2019), venture capital investment trusts assessment (Apan & Öztel, 2020), personnel selection process (Ayçin, 2020), R&D performance assessment of countries (Orhan & Aytekin, 2020) and 5G industry assessment (Peng et al., 2020) was preferred to weigh the selected criteria. Then, using these weights, the countries were evaluated with the MARCOS method developed by Stević et al. (2020) and used in decision problems such as project management software evaluation (Puška et al., 2020), human resources assessment in the transportation sector (Stević & Brković, 2020), supplier selection (Stević et al., 2020; Badi & Pamucar, 2020; Chattopadhyay et al., 2020; Madenoğlu, 2020), risk assessment of railway infrastructure (Simić et al., 2020), distribution channel selection (Dalić et al., 2020), stacker selection for logistics systems (Ulutaş et al., 2020), traffic risk analysis (Stanković et al., 2020), sanitary landfill selection for medical waste (Torkayesh et al., 2021), healthcare performance assessment of insurance companies (Ecer & Pamucar, 2021) and e-service quality assessment in the airline industry (Bakır & Atalık, 2021). As seen in the detailed literature review, the CRITIC and MARCOS methods were not used in studies conducted to evaluate countries. In this respect, the present study is the first of its kind in the literature.

3. Method

3.1. CRITIC

Diakoulaki et al. (1995) proposed the CRITIC method to overcome the problems of subjective weighting methods such as reliability and consistency (Diakoulaki et al., 1995). The procedure of the CRITIC method consists in the following steps:

Step 1: Forming the decision matrix

In the first step, the decision matrix includes a set of n criteria and m alternatives are constructed by using Equation (1).

$$X = A_1\ A_2\ \vdots\ A_m \left[x_{11}\ x_{12}\ \dots\ x_{1n}\ x_{21}\ x_{22}\ \dots\ x_{2n}\ \vdots\ \vdots\ \dots\ \vdots\ x_{m1}\ x_{m2}\ \dots\ x_{mn}\ \right] \quad (1)$$

Step 2: Normalization

The values of the criteria with different units in decision problems should be standardized to take a value in the range of [0,1] by the normalization process. The normalized decision-making matrix is calculated using Equations (2) and (3):

$$r_{ij} = \frac{x_{ij}-x_j^{min}}{x_j^{max}-x_j^{min}} \qquad j = 1,2,\dots,n \qquad if\ j \in B \quad (2)$$

$$r_{ij} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}} \qquad j = 1,2,\dots,n \qquad if\ j \in C \quad (3)$$

where B is a group of benefit criteria and C is a group of cost criteria.

Step 3: Constructing the correlation coefficient matrix

The correlation coefficient matrix consisting of linear relationship coefficients is created to measure the degree of the relationships between the criteria. The correlation coefficient is calculated by using Equation (4).

$$\rho_{jk} = \sum_{i=1}^{m}\left(r_{ij} - \overline{r_j}\right).\left(r_{ik} - \overline{r_k}\right) \Bigg/ \sqrt{\sum_{i=1}^{m}\left(r_{ij} - \overline{r_j}\right)^2 . \sum_{i=1}^{m}\left(r_{ik} - \overline{r_k}\right)^2} \quad j,k = 1,2,\dots,n \quad (4)$$

Step 4: Calculating the C_j Values

Information contained in MCDM problems is related to both the contrast intensity and conflict of the decision criteria. Hence, the amount of information C_j, emitted by the jth criterion can be determined by composing the measures that quantify the two notions using Equations (5) and (6).

$$C_j = \sigma_j \sum_{k=1}^{n}\left(1 - \rho_{jk}\right) \qquad j = 1,2,\dots,n \quad (5)$$

$$\sigma_j = \sqrt{\sum_{i=1}^{m}\left(r_{ij} - \overline{r_j}\right)^2 /(m-1)} \quad (6)$$

Step 5: Calculating the final criteria weights

In the last step of the CRITIC method, the objective weights are calculated by using Equation (7).

$$w_j = c_j / \sum_{k=1}^{n} c_k \tag{7}$$

3.2. MARCOS

Stevic et.al presented the main ideas of the MARCOS method, which is based on defining the relationship between alternatives and reference values (ideal and anti-ideal alternatives). On the basis of the defined relationships, the utility functions of the alternatives are determined and compromise ranking is made in relation to ideal and anti-ideal solutions. Decision preferences are defined on the basis of utility functions. Utility functions represent the position of an alternative with regards to an ideal and anti-ideal solution. The best alternative is the one that is closest to the ideal and furthest from the anti-ideal reference point (Stevic et al., 2020). The procedure of the MARCOS method consists of the following steps (Stevic et al., 2020, Ecer, 2020; Đalić et al. 2021):

Step 1: Forming the initial decision matrix.

The initial decision matrix includes a set of n criteria and m alternatives. In the case of group decision-making, expert evaluation matrices are aggregated into an initial group decision-making matrix.

Step 2: Forming the extended initial decision matrix.

The extended initial decision matrix is created by defining ideal (AI) and anti-ideal (AAI) solutions as shown in Equation (8).

$$C_1 \quad C_2 \quad \dots \ C_n$$
$$X = A_1 \ A_2 \ \vdots \ A_m \ A_{AAI} \ A_{AI} \ [x_{11} \ x_{12} \ \dots \ x_{1n} \ x_{21} \ x_{22} \ \dots \ x_{2n} \ \vdots \vdots \vdots \ \vdots \ x_{m1} \ x_{m2} \ \dots \ x_{mn} \ x_{aa1} \ x_{aa2} \ \cdots \ x_{aan} \ x_{ai1} \ x_{ai2} \ \cdots \ x_{ain} \ ] \tag{8}$$

AI and AAI are calculated by using Equations (9) and (10) depending on the nature of the criteria.

$$AI = x_{ij} \ \ if \ j \ \in B \ and \ x_{ij} \ \ if \ j \ \in C \tag{9}$$

$$AAI = x_{ij} \ \ if \ j \ \in B \ and \ x_{ij} \ \ if \ j \ \in C \tag{10}$$

where B is the benefit-based criteria and C is the cost-based criteria.

Step 3: Normalizing the extended initial decision matrix.

The normalized matrix N is calculated by using Equations (11) and (12).

$$n_{ij} = \frac{x_{ij}}{x_{ai}} \quad if \ j \ \in B \tag{11}$$

$$n_{ij} = \frac{x_{ai}}{x_{ij}} \quad if \ j \ \in C \tag{12}$$

where x_{ij} and x_{ai} are the elements of the extended initial decision matrix (X).

Step 4: Determining the weighted decision matrix (V).

The weighted matrix, V, is obtained by multiplying the normalized matrix elements with the weight coefficients of the criterion w_j as shown in Equation (13).

$$v_{ij} = n_{ij} \times w_j \tag{13}$$

Step 5: Forming the utility degrees of the alternatives (K_i).

The utility degrees of alternatives are calculated by using Equations (14) and (15).

$$K_i^{\ +} = \frac{S_i}{S_{ai}} \tag{14}$$

$$K_i^{\ -} = \frac{S_i}{S_{aai}} \tag{15}$$

S_i represents the sum of the elements of the weighted decision matrix (V) as shown in Equation (16).

$$S_i = \sum_{i=1}^{n} v_{ij} \tag{16}$$

Step 6: Forming the utility function of the alternatives f(K_i).

The utility function is the compromise of the observed alternative in relation to the ideal and anti-ideal solution. This function is calculated by using Equation (17).

$$f(K_i) = \frac{K_i^{\ +} + K_i^{\ -}}{1 + \frac{1 - f(K_i^{\ +})}{f(K_i^{\ +})} + \frac{1 - f(K_i^{\ -})}{f(K_i^{\ -})}} \tag{17}$$

Utility functions in relation to the ideal and anti-ideal solution are calculated by using Equations (18) and (19).

$$f(K_i^{\ +}) = \frac{K_i^{\ -}}{K_i^{\ +} + K_i^{\ -}} \tag{18}$$

$$f(K_i^{\ -}) = \frac{K_i^{\ +}}{K_i^{\ +} + K_i^{\ -}} \tag{19}$$

Step 7: Ranking the alternatives.

The final values of the utility function allow for a comparison between the alternatives. The best alternative has the highest rank in terms of the value of the utility function.

4. Data

When determining the criteria used in this study, the criteria used in previous studies that evaluated countries in terms of economic, social and environmental aspects were taken into consideration. Among these, the most used 12 criteria based on a comprehensive literature review, namely four economic, four social and four environmental criteria, were selected to evaluate the OECD countries. Information regarding the direction and unit of the selected criteria, in which study they are used and where they were obtained from are presented in Table 2.

Table 2. Criteria used in the study

	Criteria (abbreviation)	Aspect	Unit	Source	Data
Economical	GDP per capita (GDP)	Max	$	Antanasijevic et al., 2017; Ecer et al., 2019; Malul et al., 2008; Moutinho et al., 2018 ; Santana et al., 2014; Shmelev & Labajos, 2009; Chattopadhyay & Bose, 2015; Fare et al., 1994; Skare & Rabar, 2017; Karakış & Göktolga, 2016; Özbek & Demirkol, 2019	Worldbank, 2019
	Unemployment rate (UR)	Min	%	Antanasijevic et al., 2017; Cracolici et al., 2010; Phillis et al., 2011; Shmelev & Labajos, 2009; Chattopadhyay & Bose, 2015; Ela & Kurt, 2019; Eyüboğlu, 2016; Skare & Rabar, 2017; Podvezko, 2011; Karakış & Göktolga, 2016; Özbek & Demirkol, 2019	International Labor Organization (ILO), 2019
	Inflation rate (IR)	Min	%	Ecer et al., 2019; Chattopadhyay & Bose, 2015; Ela & Kurt, 2019; Eyüboğlu, 2016 ; Skare & Rabar, 2017; Karakış & Göktolga, 2016; Özbek & Demirkol, 2019	Worldbank, 2019
	Growth rate (GR)	Max	%	Ela & Kurt, 2019; Eyüboğlu, 2016; Podvezko, 2011; Karakış & Göktolga, 2016; Özbek & Demirkol, 2019	Worldbank, 2019
Social	Social progress index (SPI)	Max	0-100	Kaklauskas et al., 2020; Benitez & Liern, 2020; Giannakitsidou et al., 2020; Charles & D'Alessio, 2020	Social Progress Imperative, 2020
	Gini coefficient (GINI)	Min	0-1	Ecer et al., 2019; Malul et al., 2008; Shmelev & Labajos, 2009; Costa et al., 2019; Eren et al., 2017; Cravioto et al., 2011	Worldbank, OECD, 2015-2018
	Human development index (HDI)	Max	0-1	Malul et al., 2008; Krylovas et al., 2019; Şahin & Öztel, 2017; Eren & Kaynak, 2017; Eren et al., 2017; Bilbao-Terol et al., 2014; Cravioto et al., 2011	United Nations Development Programme (UNDP), 2020
	Life satisfaction index (LSI)	Max	0-10	Shmelev & Labajos, 2009; Kılıç Depren & Bağdatlı Kalkan, 2018; Cravioto et al., 2011	OECD Better Life Index , 2019
Environmental	Share of Renewable Energy in Gross Final Energy Consumption (SRE)	Max	%	Antanasijevic et al., 2017; Moutinho et al., 2018; Phillis et al., 2011	Worldbank, 2015

CO_2 emissions per capita (CO_2)	Min	Tones	Cracolici et al., 2010; Ecer et al., 2019; Moutinho et al., 2018; Phillis et al., 2011; Santana et al., 2014; Shmelev & Labajos, 2009	Our World in Data, 2019
Environmental performance index (EPI)	Max	0-100	Malul et al., 2008; Olafsson et al., 2014; Bilbao-Terol et al., 2014; Fakher & Abedi, 2017	EPI, 2020
Ecological footprint per capita (EA)	Min	Hectar	Olafsson et al., 2014; Bilbao-Terol et al., 2014; Blancard & Hoarau, 2013	Global Footprint Network 2019

The criteria used in the study consist of various economic, social and environmental indicators and indices. Definitions regarding these indicators and indices are given below.

Gross Domestic Product per capita (GDP): GDP per capita, which is used as a criterion in many economic performance studies, is obtained by dividing the GDP by the mid-year population. The data published annually by the World Bank are given in current US dollars.

Unemployment Rate (UR): The indicator obtained by proportioning the non-working people in the working population over the age of 15 to the total workforce is used in many studies to measure economic performance. The labor force rate is calculated annually by the International Labor Organization (ILO) using national estimates.

Inflation Rate (IR): Inflation, which is measured by the consumer price index, reflects the annual percentage change in the average cost of purchasing a basket of goods and services that can be fixed or changed at certain intervals such as every year. The inflation rate, which is frequently used in economic performance reviews and calculated annually by the International Monetary Fund (IMF), is published by the World Bank.

Growth Rate (GR): This is the annual GDP growth rate at constant local currency-based market prices. The indicator, calculated on the basis of constant 2010 USD, is shared annually by the World Bank.

Social Progress Index (SPI): It is an index calculated using basic indicators (access to food, personal security, etc.), welfare indicators (access to information, health rights, etc.) and opportunity indicators (personal freedoms, human rights, etc.). It is calculated by "The Social Progress Imperative" using 12 different indicators in three main headings.

Gini Coefficient (GINI): It measures the extent to which the distribution of income (or, in some cases, consumption expenditures) deviates from an exactly even distribution among individuals or households in an economy. A GINI coefficient of 0 represents perfect equality while a coefficient of 1 indicates perfect inequality. The most up-to-date data on the GINI coefficient, which is not calculated for each year, varies between 2015 and 2018 according to country.

Human Development Index (HDI): This index is published annually by the United Nations Development Program and includes indicators related to income, life expectancy and educational opportunities. The HDI consists of three dimensions: the long and healthy life dimension, which is measured by life expectancy at birth; the knowledge dimension, which is measured by schooling times for adults aged 25 and over, and the expected education period for children at school starting age, and the decent standard of living dimension, which is measured by gross national income per capita.

Life Satisfaction Index (LSI): This index is based on the results of a survey that measures how people evaluate their lives as a whole rather than their current emotions. It is based on the average of the answers given to the question "how happy are you?", which is asked to the participants to determine the Better Life Index. It is calculated annually for all OECD member countries.

Share of Renewable Energy in Gross Final Energy Consumption (SRE): This is the share of renewable energy in the total energy consumption in the country where the data is provided. This indicator is frequently used to measure environmental performance, as it is thought that the increase in renewable energy consumption will have positive environmental consequences.

CO_2 Emission per capita (CO_2): The contribution of the citizens of each country to the CO_2 emission can be obtained by dividing the total emissions of that country by the total population. The achieved value is called CO_2 emissions per capita. CO_2 emission per capita is one of the most frequently used indicators in environmental performance measurements.

Environmental Performance Index (EPI): This index is calculated using 32 performance indicators under 11 dimensions and ranks countries in terms of environmental health and ecosystem vitality. The EPI provides a national scale indicator of how close countries are to setting environmental policy goals. Due to the large number of performance indicators it contains, it can be used on its own in many environmental performance evaluation studies.

Ecological Footprint (EF): Ecological Footprint per person is obtained by dividing a nation's total ecological footprint by the nation's total population. To live within the resources of our planet, the Earth's ecological footprint must equal the available biocapacity per person on our planet, currently 1.7 global hectares. Thus, if a country's EF is 6.8 global hectares per person, it means that the citizens of that country demand four times the resources and waste that our planet can regenerate and absorb in the atmosphere.

OECD members consist of countries that are economically, socially and environmentally different from each other. These differences can reduce the quality of the evaluations made. In the present study, the countries were grouped in order to prevent this and to reveal more homogeneous country groups. Accordingly, cluster analysis was performed using the two-step cluster method. The silhouette, which was examined in order to test the consistency and accuracy within the data sets in the clustering analysis, revealed that the grouping was at a "fair" level. The country groups formed as a result of the cluster analysis are shown in Table 3.

Table 3. OECD country clusters

First cluster countries		Second cluster countries
USA	Sweden	Estonia
Germany	Switzerland	Spain
Australia	Japan	Italy
Austria	Canada	Colombia
Belgium	Luxemburg	Latvia
Czech Republic	Norway	Lithuania
Denmark		Hungary
Finland		Poland
France		Portugal
South Korea		Slovakia
Holland		Slovenia
England		Chile
Ireland		Turkey
Israel		Greece

When conducting the cluster analysis, 12 criteria were taken into account to evaluate OECD countries economically, socially and environmentally. As Mexico's growth rate was negative, it was excluded from the analysis and only 34 countries were included in the cluster. Of these 34 countries, 20 were in the first cluster and 14 were in the second cluster.

5. Results

When evaluating the countries, the criteria were weighted with the CRITIC method. Then, using the obtained weights, the countries were evaluated using the MARCOS method. In this section, the solution values calculated with the CRITIC and MARCOS methods are shown respectively.

5.1. CRITIC Results

The decision matrix used in both the CRITIC method and the MARCOS method was created as shown in Equation (1). As a result of the clustering analysis, the decision matrices created with the values taken by the OECD countries, which were divided into two clusters, according to the criteria shown in Table 2 are presented in Table 4.

The normalization process was implemented primarily to the maximization and minimization criteria by using the values in the decision matrix given in Table 4. Then, the correlation coefficient matrix was created by using the criterion values in the normalized decision matrix. Finally, the criterion weights were calculated using the C_j values representing the amount of information of the criteria. The criteria weights for each cluster of countries obtained after the operations seen in Equations (2)-(7) were carried out are shown in Table 5.

Table 4. Decision matrix of the clusters

	Countries	Economic Criteria				Social Criteria				Environmental Criteria			
		GDP	UR	IR	GR	SPI	GINI	HDI	LSI	SRE	CO_2	EPI	EF
		max	min	min	max	max	min	max	max	max	min	max	min
First Cluster	USA	65118	3.7	1.8	2.3	85.7	0.39	0.92	6.9	8.72	16.2	69.3	8
	Germany	46258	3.1	1.4	0.6	90.5	0.28	0.93	7	14.21	9.6	77.2	4.7
	Australia	54907	5.2	1.6	1.9	91.2	0.32	0.93	7.3	9.18	16.9	74.9	7.3
	Austria	50277	4.5	1.5	1.6	89.5	0.27	0.91	7.1	34.39	7.9	79.6	6
	Belgium	46116	5.4	1.4	1.4	89.4	0.26	0.91	6.9	9.2	8.5	73.3	6.6
	Czech Republic	23101	2	2.8	2.6	86.6	0.24	0.89	6.7	14.83	9.9	71	5.5
	Denmark	59822	5	0.8	2.4	92.1	0.26	0.93	7.6	33.17	6.0	82.5	6.9
	Finland	48685	6.7	1	1	91.8	0.26	0.92	7.6	43.24	8.1	78.9	5.8
	France	40493	8.4	1.1	1.5	88.7	0.29	0.89	6.5	13.5	5.3	80	4.6
	South Korea	31762	3.7	0.4	2	89.0	0.35	0.90	5.9	2.71	12.5	66.5	6.2
	Holland	52447	3.4	2.6	1.8	91.0	0.28	0.93	7.4	5.89	9.6	75.3	5
	England	42300	3.7	1.7	1.4	88.5	0.36	0.92	6.8	8.71	5.8	81.3	4.2
	Ireland	78661	4.9	0.9	5.5	90.3	0.29	0.94	7	9.08	8.1	72.8	5
	Israel	43641	3.8	0.8	3.5	83.6	0.34	0.90	7.2	3.71	7.8	65.8	5.5
	Sweden	51610	6.8	1.8	1.2	91.6	0.27	0.93	7.3	53.25	4.2	78.7	6.1
	Switzerland	81993	4.4	0.4	0.9	91.4	0.29	0.94	7.5	25.29	4.5	81.5	4.5
	Japan	40246	2.4	0.5	0.7	90.1	0.33	0.91	5.9	6.3	9.3	75.1	4.7
	Canada	46194	5.7	1.9	1.7	91.4	0.31	0.92	7.4	22.03	15.5	71	8.1
	Luxemburg	114704	5.6	1.7	2.3	89.5	0.32	0.90	6.9	9.03	15.6	82.3	12.8
	Norway	75419	3.7	2.2	1.2	92.7	0.26	0.95	7.6	57.77	8.2	77.7	5.8
Second Cluster	Estonia	23659	4.4	2.3	4.3	87.2	0.30	0.88	5.7	27.48	14.1	65.3	7.2
	Spain	29613	14.1	0.7	2	88.7	0.33	0.89	6.3	16.25	5.8	74.3	4
	Italy	33189	10	0.6	0.3	87.3	0.33	0.88	6	16.52	5.7	71	4.4
	Colombia	6432	10	3.5	3.3	74	0.50	0.76	6.3	23.56	1.9	52.9	1.9
	Latvia	17836	6.3	2.8	2.2	83.1	0.35	0.85	5.9	38.1	3.7	61.6	6.1
	Lithuania	19455	6.3	2.3	3.9	83.9	0.37	0.86	5.9	28.96	4.7	62.9	5.9
	Hungary	16475	3.4	3.3	4.9	81.0	0.28	0.84	5.6	15.56	5.1	63.7	3.7
	Poland	15595	3.3	2.2	4.1	84.3	0.27	0.87	6.1	11.91	8.8	60.9	4.7
	Portugal	23145	6.5	0.3	2.2	87.7	0.32	0.85	5.4	27.16	5.3	67	4.4
	Slovakia	19329	5.8	2.7	2.4	83.1	0.22	0.85	6.2	13.41	6.6	68.3	4.4
	Slovenia	25739	4.4	1.6	2.4	87.7	0.24	0.90	5.9	20.88	6.8	72	4.9
	Chile	14896	7.3	2.6	1.1	83.3	0.46	0.84	6.5	24.88	4.5	55.3	4.3
	Turkey	9042	13.7	15.2	0.9	68.2	0.40	0.80	5.5	13.37	5.2	42.6	3.5
	Greece	19582	17.3	0.3	1.9	85.7	0.31	0.87	5.4	17.17	7.0	69.1	4.1

Table 5. Criteria weights of the clusters determined using the CRITIC method

First Cluster w_j	Economic Criteria			
	GDP	UR	IR	GR
	0.072	0.099	0.103	0.089
	Social Criteria			
	SPI	GINI	HDI	LSI
	0.069	0.081	0.072	0.082
	Environmental Criteria			
	SRE	CO_2	EPI	EF
	0.083	0.087	0.088	0.075
Second Cluster w_j	Economic Criteria			
	GDP	UR	IR	GR
	0.071	0.094	0.058	0.099
	Social Criteria			
	SPI	GINI	HDI	LSI
	0.065	0.079	0.068	0.107
	Environmental Criteria			
	SRE	CO_2	EPI	EF
	0.100	0.093	0.063	0.104

When the criteria weights in Table 5 are examined, it can be seen that the most important criteria for the first cluster were inflation rate (IR), unemployment rate (UR) and growth rate (GR), while the most important criteria for the second cluster were the life satisfaction index (LSI), ecological footprint (EF) and the share of renewable energy in gross final energy consumption (SRE).

5.2. MARCOS Results

In the next step, the MARCOS method was used to evaluate the economic, social and environmental performance of the OECD countries. The mathematical steps of the MARCOS method as shown in Equations (8)-(19) were followed respectively and the results are shown in Table 6.

Table 6. Results of the MARCOS method for the clusters

	Country	S_i	K_i-	K_i+	$f(K_i$-)	$f(K_i$+)	$f(K_i)$	Rank
First Cluster	USA	0.5620	1.3157	0.5620	0.2993	0.7007	0.4983	20
	Germany	0.6230	1.4585	0.6230	0.2993	0.7007	0.5524	13
	Australia	0.5659	1.3249	0.5659	0.2993	0.7007	0.5018	18
	Austria	0.6472	1.5152	0.6472	0.2993	0.7007	0.5738	8
	Belgium	0.5862	1.3724	0.5862	0.2993	0.7007	0.5198	17
	Czech Republic	0.6462	1.5129	0.6462	0.2993	0.7007	0.5730	9
	Denmark	0.7072	1.6557	0.7072	0.2993	0.7007	0.6270	2
	Finland	0.6581	1.5407	0.6581	0.2993	0.7007	0.5835	6
	France	0.6250	1.4633	0.6250	0.2993	0.7007	0.5542	12
	South Korea	0.6187	1.4483	0.6187	0.2993	0.7007	0.5485	14
	Holland	0.6143	1.4381	0.6143	0.2993	0.7007	0.5446	15
	England	0.6280	1.4703	0.6280	0.2993	0.7007	0.5568	11
	Ireland	0.7054	1.6514	0.7054	0.2993	0.7007	0.6254	3
	Israel	0.6334	1.4828	0.6334	0.2993	0.7007	0.5616	10
	Sweden	0.6933	1.6232	0.6933	0.2993	0.7007	0.6148	5

	Switzerland	0.7769	1.8188	0.7769	0.2993	0.7007	0.6888	1
	Japan	0.6562	1.5362	0.6562	0.2993	0.7007	0.5818	7
	Canada	0.5647	1.3221	0.5647	0.2993	0.7007	0.5007	19
	Luxemburg	0.5888	1.3785	0.5888	0.2993	0.7007	0.5221	16
	Norway	0.7033	1.6465	0.7033	0.2993	0.7007	0.6236	4
Second Cluster	Estonia	0.6807	1.7267	0.6807	0.2828	0.7172	0.6125	8
	Spain	0.7289	1.8489	0.7289	0.2828	0.7172	0.6558	2
	Italy	0.6358	1.6126	0.6358	0.2828	0.7172	0.5720	11
	Colombia	0.6220	1.5776	0.6220	0.2828	0.7172	0.5596	12
	Latvia	0.6932	1.7582	0.6932	0.2828	0.7172	0.6236	5
	Lithuania	0.6904	1.7512	0.6904	0.2828	0.7172	0.6211	6
	Hungary	0.7170	1.8187	0.7170	0.2828	0.7172	0.6451	4
	Poland	0.6815	1.7287	0.6815	0.2828	0.7172	0.6132	7
	Portugal	0.7179	1.8208	0.7179	0.2828	0.7172	0.6459	3
	Slovakia	0.6555	1.6628	0.6555	0.2828	0.7172	0.5898	9
	Slovenia	0.7329	1.8591	0.7329	0.2828	0.7172	0.6594	1
	Chile	0.6164	1.5636	0.6164	0.2828	0.7172	0.5546	13
	Turkey	0.5106	1.2950	0.5106	0.2828	0.7172	0.4593	14
	Greece	0.6381	1.6185	0.6381	0.2828	0.7172	0.5741	10

Results were obtained for each cluster with the MARCOS model. When Table 6 is examined it can be observed that for the first cluster Switzerland, Denmark and Ireland had the highest performance score, while USA, Canada and Australia had the lowest performance score and for the second cluster Slovenia, Spain and Portugal had the highest performance score, while Turkey, Chile and Colombia had the lowest performance score.

6. Examination of Results

In this section, the sensitivity analysis of the CRITIC-MARCOS methodology is presented. For this purpose, the reliability and validity of the proposed model were analyzed by using the multi-attribute ideal-real comparative analysis (MAIRCA), attributive border approximation area comparison (MABAC), weighted aggregated sum product assessment (WASPAS) and combined compromised solution (CoCoSo) methods. The comparative results of these MCDM methodologies for the first and second cluster are shown in Figures 1 and 2, respectively.

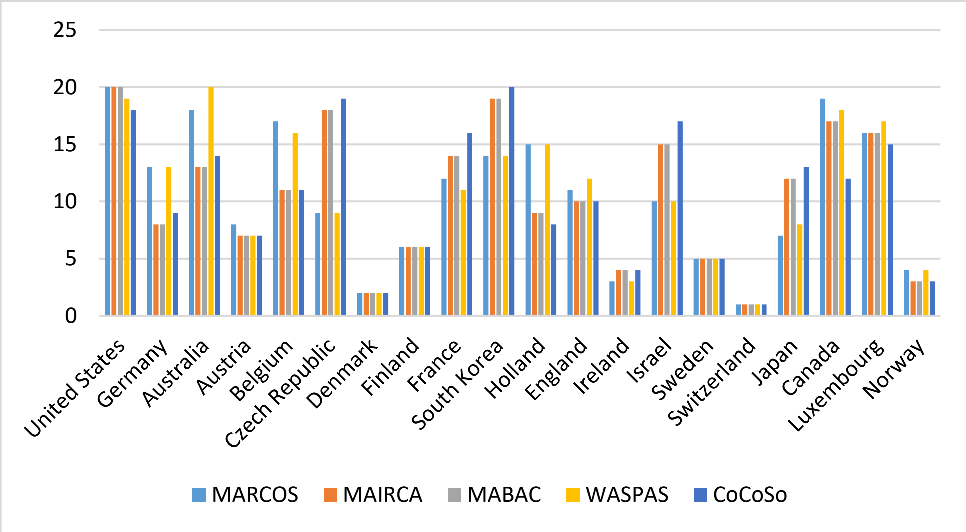

Figure 1. Sensitivity results of the first cluster

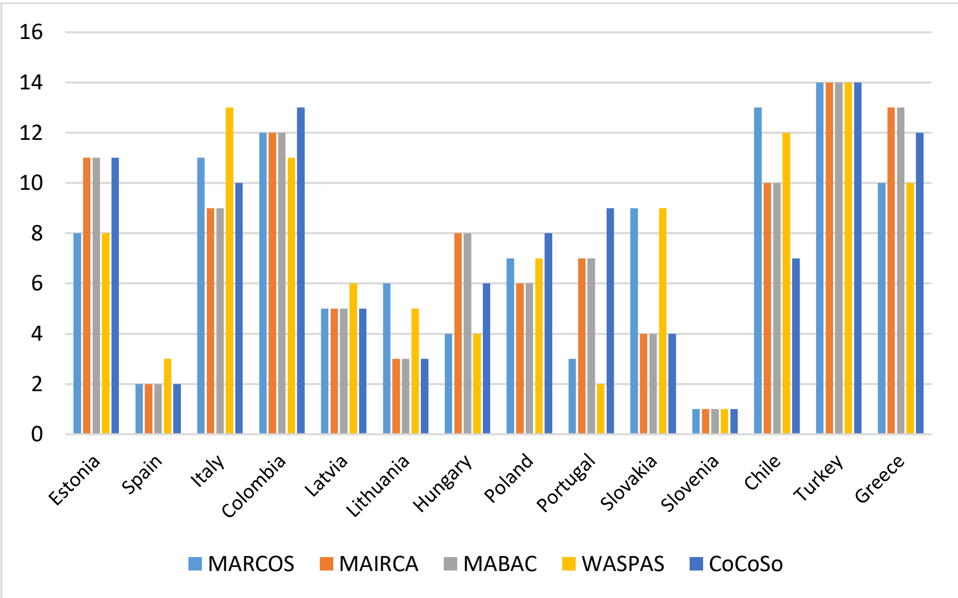

Figure 2. Sensitivity results of the second cluster

Spearman's correlation coefficient was used to determine the ranking position of the difference between the results of the CRITIC-MARCOS methodology and the all other mentioned MCDM methods. The Spearman correlation coefficients for both clusters are shown in Table 7.

Table 7. Spearman correlation results

Cluster/Method	MAIRCA	MABAC	WASPAS	CoCoSo	Average Value
Cluster-1 (CRITIC-MARCOS)	0.782*	0.782*	0.991*	0.690*	0.811
Cluster-2 (CRITIC-MARCOS)	0.785*	0.785*	0.978*	0.723*	0.818

According to Table 10, the correlation coefficients of each cluster was above 80.0%. These results show a significant correlation between the ranks of the proposed CRITIC-MARCOS methodology and all other mentioned MCDM methods in both clusters. This confirms that the ranking results suggested by the CRITIC-MARCOS methodology were valid and credible.

7. Discussion

Firstly, the countries were divided into two clusters using cluster analysis in order to make the heterogeneous structure of the countries homogeneous and evaluate the countries with similar characteristics together. There were 20 developed countries including USA, Germany, Denmark and Switzerland in the first cluster, while there were 14 relatively less developed countries including Estonia, Lithuania, Slovenia and Colombia included in the second cluster.

After the countries were clustered, 12 criteria used for the economic, social and environmental evaluation of each cluster were weighted using the CRITIC method. The most important criteria for the first cluster were determined as inflation rate (IR: 0.103), unemployment rate (UR: 0.099) and growth rate (GR: 0.089), while the most important criteria for the second cluster were found as the life satisfaction index (LSI: 0.107), ecological footprint (EF: 0.104) and the share of renewable energy in gross final energy consumption (SRE: 0.100), respectively. Kılıç Depren & Bağdatlı Kalkan (2018) used both unemployment rate and the life satisfaction index criteria to evaluate OECD countries. In the study where 24 criteria were weighted using the entropy method, the life satisfaction index was determined as the ninth most important criterion while unemployment rate was determined as the twentieth most important criterion. In the present study, unemployment rate was determined as the second most important criterion for the countries in the first cluster while the life satisfaction index was determined as the most important criterion for the second cluster. This result is proof that different combinations of criteria produce different results in the evaluation of countries.

The countries were evaluated using the criterion weights obtained by the CRITIC method in the MARCOS method. Among the countries in the first cluster, Switzerland, Denmark and Ireland had the best performances, respectively, while Australia, Canada and USA had the worst performances. It is noteworthy that the economic data of countries with good performance in particular were higher than the other countries in the first cluster. Even though the economic data of the poor performing countries were similar to the other countries in the first cluster, the GINI coefficient representing the income equity and the CO_2 emissions representing the air quality were worse than the other countries in the cluster. Therefore, these countries should focus on policies that will ensure income justice and take steps to improve air quality.

Among the countries in the second cluster, Slovenia, Spain and Portugal performed the best, while Colombia, Chile and Turkey performed the worst. The GDP values of the most successful countries in the second cluster were relatively better than the other countries in the cluster. Likewise, the social progress and human development index values of these countries were higher than the other countries in the cluster. The economic data of the most unsuccessful countries were noticeably worse than the other countries in the cluster.

In previous studies in the literature, similar results emerged although countries were not evaluated in two different clusters. In many recent studies, Switzerland and Denmark, which are at the top of the first cluster, demonstrated the highest performance while Chile and Turkey, which are at the bottom of the second cluster, were among the countries with the lowest performance (Skare & Rabar, 2017; Kılıç Depren & Bağdatlı Kalkan, 2018; Costa et al., 2019; Iram et al., 2020). Australia, Canada and USA, which are among the countries in the first cluster with the lowest performance, demonstrated high performance in some studies (Kılıç Depren & Bağdatlı Kalkan, 2018; Costa et al., 2019; Iram et al., 2020) and lower performance in others (Skare & Rabar, 2017). Therefore, the findings obtained in the present study support the current literature.

The country rankings obtained using the CRITIC and MARCOS methods were rankings belonging to this combination of criteria. It is possible to reach different rankings under different criteria. In order to test the accuracy and consistency of the criteria used in this study and the rankings acquired, a sensitivity analysis was performed. By using the criterion weights obtained by the CRITIC method, the model was re-solved using MAIRCA, MABAC, WASPAS and CoCoSo methods and country rankings were achieved. The Spearman rank correlations between the country rankings obtained with the MARCOS method and those acquired with the other methods were calculated. The calculated correlation values revealed that there were significant relationships between the rankings. An average of over 80% similarity was found between the rankings obtained with MARCOS and the rankings acquired by the other methods. This shows that the analysis made was a consistent and accurate analysis.

8. Conclusion

In general, when trying to determine the development levels of countries economic data are taken into consideration. However, economic development alone is not often sufficient for the people of a country to live in tranquility and prosperity. Income increase resulting from economic development can be considered as a tool to support the social development of people. Moreover, socially developed individuals are also more likely to be more interested in the environment. These meaningful connections between economic, social and environmental development were the main motivation for the present study. Therefore, OECD member countries with heterogeneous characteristics in terms of economic, social and environmental aspects were evaluated in this study.

The findings obtained include those that policymakers of countries will refer to when developing economic, social and environmental policies. Based on these findings, certain managerial implications were proposed for policymakers to utilize.

For many years, decision-makers tend to rank countries based on their GDP. However, the results of the present study serve as proof that countries should not be ranked based on GDP only. For example, although the GDP of the USA, which ranks last in the first cluster, is approximately three times that of the Czech Republic, Czech Republic ranked ninth. Therefore, GDP alone is not enough to reflect national welfare. Furthermore, in the findings of the present study, economic criteria were determined as the most important criteria for the first cluster, which consists of countries that completed their social and environmental development, while social and environmental criteria stood out for countries in the second cluster. Based on this, it is necessary for particularly the countries in the second cluster to develop economic policies towards increasing their GDP while focusing on developing policies to improve their social and environmental performance by increasing medical and educational expenditures. Both the data on the countries and the results of the present study indicate that countries that were regarded as the greatest global forces in the past are beginning to lose importance against countries that were previously ineffective. The great powers of the past such as the USA, England, France and Germany are unable to provide their citizens with the opportunities that countries such as Switzerland, Sweden, Denmark and Ireland offer to their citizens. This situation cannot be explained by the difference in population between the countries or the richness of national resources alone. In addition to economic data, national welfare depends on a number of non-economic factors such as income equality, freedom of speech, gender equality and CO2 emissions, as well. Therefore, countries that are unable to demonstrate high performance in economic, social and environmental terms should use benchmarking processes based on successful countries while developing policies.

Although the present study produced original results in terms of the criteria, methodology and methods used, it has certain limitations in terms of scope and content. The most apparent limitation of the present study is the number of countries. The present study, in which only OECD countries were evaluated due to time and resource constraints, can be used to evaluate all countries in the future. Another limitation in the present study is regarding the criteria used. 12 criteria were used to evaluate OECD countries in the present study. In future studies, different countries can be evaluated under the same criteria. In addition, different results can be obtained by using different combinations of criteria or MCDM methods based on expert opinions.

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