



Health Efficiency Measurement of OECD Countries Against the COVID-19 Pandemic by Using DEA and MCDM Methods

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Abstract

Nowadays, it is seen that the COVID-19 virus has changed with mutation and the most effective method in combating this virus is vaccination. In addition to increasing the number of tests, the development and implementation of policies to increase vaccination rates also increase the efficiency of countries in the fight against the virus. This study aims to measure the efficiency levels of OECD countries in the fight against the COVID-19 pandemic in different periods with data envelopment analysis (DEA). To achieve this goal, efficiency analyses were conducted using the output-oriented DEA-constant return to scale (CRS) model with data for 2021. As a result, Colombia, Denmark, New Zealand, Slovakia, and the USA were efficient, while Slovenia, Hungary, and Chile were the countries with the lowest efficiency scores. For inefficient countries to be efficient in the future, it is suggested that policies should be developed and rapidly implemented to reduce the number of cases and deaths, as well as to increase the number of tests. With the study, it has been concluded that the use of the DEA method together with multi-criteria decision making (MCDM) methods such as TOPSIS, EDAS and CODAS for efficiency evaluation of OECD countries allows for a better ranking of efficient decision-making units.

Keywords OECD · COVID-19 · Health efficiency · DEA · MCDM

JEL Classification C44 · C81 · D61 · O57

1 Introduction

In the last two decades, the world has witnessed various diseases such as Zika, Nipah, Ebola, and Coronavirus that

emerged in various regions and affected the whole world. The disease, which was first observed in Wuhan, China, in December 2019 and named 2019 Novel Coronavirus (2019-nCoV) and Coronavirus Disease 2019 (COVID-19) by the World Health Organization (WHO), was declared a pandemic on February 12, 2020 [1]. As of 09.12.2021, more than 268.4 million (3.3 million on 04.05.2020) COVID-19 cases have been confirmed worldwide [2], including more than 5.3 million (238,000 on 04.05.2020) deaths. Compared to the previously known coronaviruses, namely, SARS and MERS 2019-nCoV infected a much larger population worldwide and affected more lives [3]. Today, it has been determined that this virus has undergone various mutations and infected more populations than other pandemics. Different studies have shown that this virus can affect even more, reaching 6.5 million [4]. It is inferred that these would be the new cases. The number of cases reached as of today (18.11.2022) is 641.9 million and the number of deaths is 6.6 million [2].

The importance of health services, which includes high technology-oriented R&D and innovation studies, which have a multiplier effect on the economy and social welfare

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of countries on an international scale, has become more evident during the pandemic period. In this context, innovation policies for health systems should be strengthened in OECD member countries, regardless of their level of development. The OECD is an international organization that creates the infrastructure to ensure the well-being of even the societies of countries [5]. 25 May 2021, Costa Rica has formally become an OECD Member, the 38th country to do so in the Organization's 60-year history [6]. The OECD has become one of the world's largest and most reliable sources of comparative economic and social data and statistics [7].

In the event of an epidemic in a country, the number of infected and death cases and the rate of their increase largely depend on the preparedness of that country and the strength of its health system. An indicator of countries' performance in epidemic response management is the number of confirmed cases, which is determined by the large number of tests performed. Although indicators such as the case recovery rate and death rate can be used as output data for countries to evaluate their efficiency against the COVID-19 pandemic, they can also fully reflect the impact of the situation in which a country is battling the disease.

In this study, the efficiency of OECD countries affected by the COVID-19 pandemic was evaluated using data envelopment analysis (DEA), taking into account their population density and health system infrastructures. As input variables in the study; number of doctors, nurses, and hospital beds per thousand people as output variables; health expenditure per capita in OECD countries, the number of tests per thousand people, the number of cases, and the number of deaths are used. Constant return to scale (CRS) model was used in the efficiency analysis, and then improvement suggestions were developed for inefficient countries.

It is predicted that the COVID-19 epidemic will have important social and economic consequences in the long term. Therefore, it is vital to evaluate the performance of countries against the COVID-19 pandemic [8]. Measuring the health efficiency of different countries during the COVID-19 epidemic is very important in determining which countries' health systems perform better. Thus, it is possible to assess which countries need to improve their performance [9]. As in many other sectors, the DEA method is widely used for efficiency assessment in the health sector [10–12]. MCDM methods are also widely used for performance evaluation [13–19].

It would be useful to compare the results of super-efficiency DEA analysis with the results of other MCDM methods in order to rank the efficient DMUs among themselves more clearly [18, 20–22]. In this study, the results of the super-efficiency CRS-DEA model were compared with the results of TOPSIS, EDAS and CODAS methods. In the literature, no study has been found in which the health efficiency assessment of OECD countries was made

by combining DEA, TOPSIS, EDAS and CODAS methods. Therefore, this study aims to contribute to the literature by using DEA, TOPSIS, EDAS and CODAS methods together. The main research question is how the COVID-19 pandemic has affected the health efficiency of OECD countries? The rest of the study is organized as follows. In the second part, the literature review is given. In the third chapter, the data set and the methods used in the research are explained. In the fourth section, the efficiency evaluation and ranking of OECD countries are included. In the fifth chapter, a general evaluation of the study was made.

2 Literature Review

In the literature review section, studies using the DEA method and MCDM methods are included. Some of the studies carried out using the DEA method are given in the following paragraphs.

In the study of Sel [23] the COVID-19 performance of the health system developments of the G-20 countries was evaluated by the DEA method, and according to the scale effectiveness scores, America, Argentina, Brazil, China, France, England and Turkey were efficient. Ozcelik and Yigit [24], Küçükaycan [25], Akbulut and Senol [26] and Kumru et al. [27] analyzed the relationship between COVID-19 morbidity and mortality rates in countries using demographic and socioeconomic factors.

Jouzdani and Shirouyehzad [3] investigated the effect of contact frequency between people during the COVID-19 epidemic in Iran using the system dynamics approach, using the capacity of the health system. Hadad et al. [28] created two models using the DEA method to calculate the efficiency of the health systems of OECD countries. As a result of the study, the health systems of nine countries with large and stable economies were found to be efficient in the 1st model and inefficient in the 2nd model. In addition, the relationship between socioeconomic and environmental indicators was found to be uncertain. Using the DEA method, Demir and Bakırcı [29] measured the economic efficiency of 34 OECD member countries with the data for the years 2006–2010 and revealed the changes in the activities over the years. As a result of the analysis made with the CRS method, 16 countries were efficient, and as a result of the analysis made with the VRS method, 18 countries were efficient. Kaya et al. [30] examined the determinants affecting the efficiency and activities of hospitals in 29 OECD countries between 2000 and 2010. Productivity scores were obtained by the DEA, panel tobit analysis methods to determine the factors affecting efficiency scores, and the changes in factor productivity were investigated through Malmquist Productivity Index. According to the findings obtained from the study, it was determined that the productivity scores obtained after 2000 decreased in

2004 and reached their lowest levels between 2009–2010. It has been shown that income from environmental factors, education and the number of private hospitals affect productivity positively, while the effect of public and private health expenditures and the number of public hospitals on this efficiency is negative.

Sener and Yigit [31] measured the technical efficiency of the health systems of 30 OECD countries with the DEA method and developed potential improvement suggestions for inefficient countries. According to the results of the input-oriented VRS model, 14 of the OECD countries were found to be productive. The average productivity score of all countries was calculated as 0.94, with Austria having the lowest score. Yilmaz and Şenel [32] calculated the efficiency of the health systems of 36 OECD member countries with the DEA method. As a result of the analysis made with the data of 2007, 10 countries were effective, and as a result of the analysis made with the data of 2017, 5 countries were efficient. Iceland, Mexico, Chile and Turkey were total efficient in the analyses made for both years. Sahinbas et al. [33] evaluated the efficiency levels of 35 OECD member countries in health services based on the assumption of constant (CRS) and variable returns to scale (VRS) of the DEA. As a result of the study, it was seen that 23 countries were effective in health services according to VRS. Australia, Belgium, Canada, Greece, Italy and Turkey were among these countries.

Yuksel [34] compared the health efficiencies of OECD countries with the window analysis method of the input-oriented data envelopment analysis technique for the years 2014–2018. According to the DEA window analysis results, it was seen that only Mexico was efficient, while Turkey, Japan, Korea and Luxembourg got the closest scores to efficiency. Bas Kaman and Yucel [35] applied DEA on the relationship between the living and educational conditions of children living in 23 OECD countries and alcohol and cigarette addiction. As a result of the study, 6 OECD countries were found to be relatively total efficient and 8 relatively technically efficient. Denmark, Iceland, the Netherlands, Norway, Sweden and Great Britain were efficient in the output-oriented CRS model. Konca et al. [36] evaluated the effectiveness of health expenditures of G-20 countries with the DEA. According to the CRS model, approximately half of the countries, and according to the VRS model, approximately 2/3 of the countries were relatively efficient.

Shirouyehzad et al. [37] have evaluated the performance of the most severely affected countries regarding transmission control and medical treatment of COVID-19 by using the DEA. In the study, efficacy values were first calculated according to country conditions and the number of confirmed cases, and then performance evaluation was carried out by considering the total number of confirmed cases, deaths and recovered cases to evaluate the effectiveness of

medical treatment in the countries. The results indicated that Singapore, Vietnam, and Belgium are the countries with the highest efficiency in both aspects. Selamzade and Ozdemir [38] examined the efficiency level of the COVID-19 epidemic struggles of OECD countries. In his study, he used CRS and VRS models of DEA based on output methods. In this way, the efficiency levels of the struggle applied by the countries were calculated. After determining the factors affecting productivity, some productivity-enhancing suggestions were also made. Ghasemi et al. [39] investigated the performance of 19 selected countries in their fight against the COVID-19 pandemic between February 2 and April 12, 2020, using dynamic data envelopment analysis. As a result of the research, it has been determined that the trend of inefficiency in preventing the spread of coronavirus has decreased in Singapore, South Korea, China and Australia.

Sherpa [40] estimated the impact of governments' health policies on COVID-19 case fatality rates in OECD countries using Quantile regression. In the study, it was concluded that the policies of reducing health expenditures significantly increased the COVID-19 death rates. Ergulen et al. [41] investigated the effectiveness level of the Ministry of Health of the Republic of Turkey in combating the Covid-19 epidemic using DEA. As a result of the study, it was determined that the Ministry of Health was productive in April, May, July and September 2020, and inefficient in other months. Bas Kaman and Yucel [42] analyzed the performance of health-care workers in the 9 OECD countries most affected by the pandemic. As a result of the analysis, the Czech Republic, Poland and Portugal were found to be efficient in protecting health workers, while Italy was found to be inefficient.

MCDM methods are widely used in the literature in many fields such as education, health, energy, defense, and tourism [14, 43–49]. TOPSIS, EDAS and CODAS methods are some of the commonly used MCDM methods [18, 22, 50–58]. Some of the studies in which performance evaluation was carried out using MCDM methods are given in the following paragraphs. Sufiyan et al. [59] have used fuzzy DEMATEL and ANP methods for evaluating food supply chain performance. Abdel-Basset et al. [16] have used AHP, VIKOR and TOPSIS methods for the financial performance evaluation of 10 steel companies in Egypt. Prabhuram et al. [60] have used AHP, TOPSIS and fuzzy AHP methods for performance evaluation of Omni channel distribution network configurations in the Indian retail industry. Baydaş and Elma [61] have used the PROMETHEE and TOPSIS methods for the financial performance of 131 manufacturing companies in Turkey. Zhao et al. [62] have used anti-entropy weight method, grey-DEMATEL and DQGRA-TOPSIS methods for economy-environment-energy performance evaluation of combined cooling, heating and power micro-grid. Yiğit [63] has used the TOPSIS method for the health performance



analysis of 35 OECD countries. Ince et al. [64] have evaluated the policy performance of 18 different OECD countries in terms of rare diseases by using TOPSIS, MOORA and COPRAS methods. Acar [19] has evaluated the performance of OECD countries in terms of socio-economic global indices using CRITIC and CoCoSo methods. Aydin [65] has used ENTROPI, ARAS and TOPSIS methods for the relative assessment of the health systems of OECD countries during the COVID-19 pandemic.

There are many studies in the literature in which the DEA method and MCDM methods are used together [18, 20, 66–73]. Some of the studies in which performance evaluation was made by using the DEA method and MCDM methods together are given in the following paragraphs. Chitnis and Vaidya [74] have used the DEA method and TOPSIS for the efficiency of different branches of a bank in India. Lee et al. [71] have used the DEA method and VIKOR method for performance evaluation of 12 manufacturing industries in Taiwan. Ersoy [18] has used DEA method and TOPSIS method for the performance evaluation of distance education in Turkey. Guler et al. [17] have used the PROMETHEE method and DEA method for the evaluation of sustainable energy performance for OECD countries. Ersoy [22] has used the DEA method, TOPSIS and EDAS methods for the performance evaluation of 12 different international airports. Stevic et al. [75] have used the DEA method, MARCOS, EDAS, WASPAS and ARAS methods for the efficiency evaluation of transport companies. Altin and Filiz [76] have used the DEA method, EDAS, MAUT and MAUSRA methods for the performance evaluation of 8 railways logistics villages in Turkey. Gupta et al. [77] have used the DEA technique, AHP and TOPSIS techniques for the performance evaluation of green transportation alternatives in India.

3 Methodology

In this study, the health efficiency levels of OECD countries were evaluated with data envelopment analysis (DEA). Although the DEA method is a useful method used in efficiency measurement, it has some disadvantages. An important disadvantage is that DMUs cannot be ranked exactly in the DEA method [18, 22]. DEA also has some related disadvantages, such as low discrimination power and impractical weight distribution [9, 78, 79]. On the other hand, the weight assignment of DEA may be inconsistent with reality and thus cause many DMUs to be efficient [79]. Nevertheless, it is believed that MCDM methods will be combined with the DEA method so that a full ranking of DMUs can be made. Some researchers argued that the DEA method can be considered as a MCDM method [18, 22, 80, 81]. Although it was stated by Mousavi-Nasab and Sotoudeh-Anvari that the DEA method cannot be generally accepted as a MCDM method,

the applications of DEA models as MCDM methods are gaining increasing attention [78, 79]. DMUs that are efficient in DEA models are ranked according to their Super efficiency scores. In some cases, Super-efficiency scores may be insufficient for a clear ranking of efficient DMUs [18]. Therefore, in addition to DEA models, MCDM methods are widely used in the literature to evaluate efficient DMUs [18, 20, 82].

Firstly, the health efficiency scores of OECD countries were determined by the output-oriented CRS model. Later, the CRS-SE model and TOPSIS, EDAS and CODAS methods were used to rank the efficient DMUs. The input and output variables of the efficient DMUs are also used in TOPSIS, EDAS and CODAS methods. The criteria weights (weights of input and output variables) used in TOPSIS, EDAS and CODAS methods are equally considered [18, 22, 70, 74, 83, 84]. DEAP version 2.1 program was used for the analysis of the DEA method. Microsoft Excel 2016 program was used for TOPSIS, EDAS and CODAS methods.

The framework of the study can be seen in Fig. 1. The DEA, TOPSIS, EDAS and CODAS methods and data and variables of the study are explained below.

3.1 DEA Method

The nonparametric data envelopment analysis (DEA) method is a boundary-based linear programming optimization performance evaluation technique. This method evaluates the efficiency score obtained by the decision-making units (DMU) as a result of the production of more than one input and more than one output. The DEA technique is frequently used to compare national and international health systems [85]. The Constant Return to Scale (CRS) model developed by Charnes, Cooper, and Rhodes in 1978 [86] and variable returns to scale (VRS) models developed by Banker, Charnes, and Cooper in 1984 [87] is widely used to evaluate the efficiency of health systems. Input-oriented models are used to estimate how many inputs are needed with the number of available outputs, and output-oriented models are used to estimate how much output should be with the use of available inputs [88].

In the CRS model, the ratio of the final products (outputs) of DMUs to the resources (inputs) spent is as follows [86, 89]:

$$\max \Theta_0 = \frac{\sum_{r=1}^s u_r y_{ru}}{\sum_{i=1}^m v_i x_{io}} \quad (1)$$

$$\begin{aligned} \text{Constraint : } & \frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}} \leq 1; j = 1, \dots, nv_r, \\ & u_i \geq 0; r = 1, \dots, s, i = 1, \dots, m., \end{aligned} \quad (2)$$



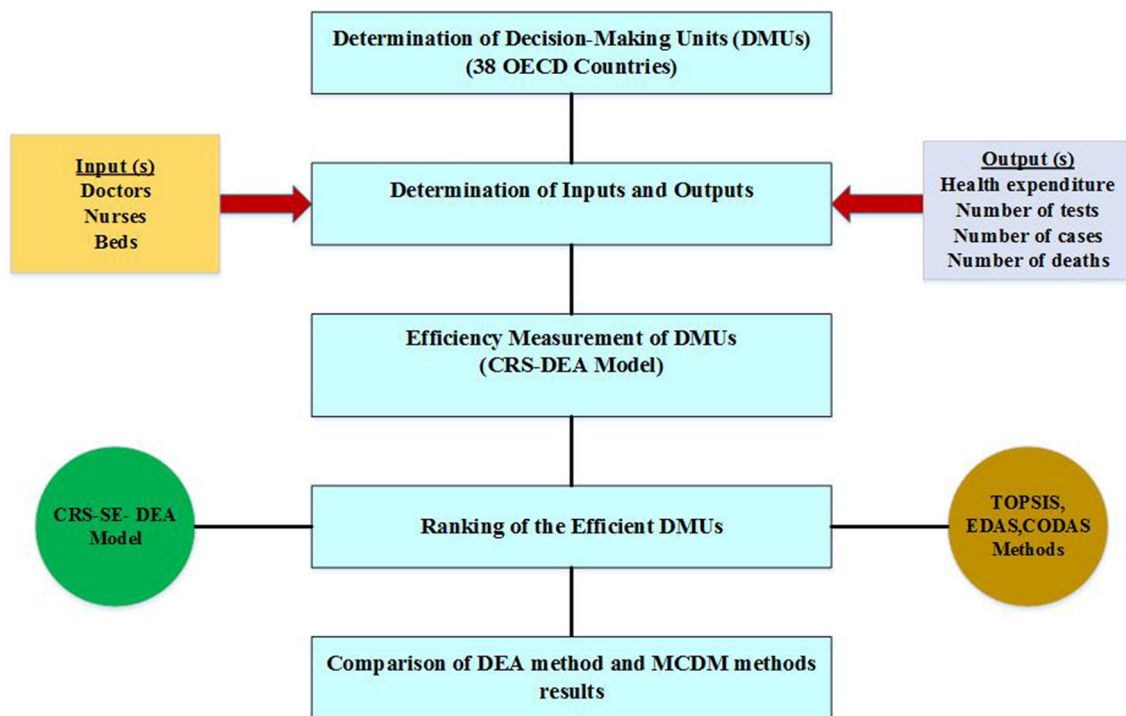


Fig. 1 The framework of the study

where n is the number of analyzed DMUs, s is the number of outputs, m is the number of inputs, y_{ij} is the r 'th output of the j th DMU, x_{ij} is the i th input of the j th DMU. u_r and v_i are the weighting coefficients of the corresponding inputs or outputs. Here Θ_o denotes the efficiency coefficient of that DMU. The main advantage of this model is that the weights u_r and v_i are automatically selected for each input and output. Equation (1) equating the denominator of the linear fractional programming formula to 1 and reducing it to a linear programming problem under constraint Eq. (2) is valid if all DMUs operate at the most appropriate output level with the available inputs [90]. The following formula was created for the output-oriented CRS analysis [86]:

$$\min h_o = \sum_{i=1}^m v_i x_{io} \quad (3)$$

$$\sum_{r=1}^s u_r y_{ro} = 1 \text{ Constraint : } \frac{\sum_{r=1}^s u_r y_{ro}}{\sum_{i=1}^m v_i x_{io}} \geq 1$$

$$(j = 1, \dots, n); \sum_{r=1}^s u_r y_{ro} = 1 : u_r > 0; v_i > 0. \quad (4)$$

In DEA model analysis, “Super Efficiency” (SE) is a model that is measured when DMU has a value higher than 1. Because in CRS and VRS models, DMUs do not allow itself to be used as a peer in calculating the efficiency of other active DMUs. The output oriented super-efficiency DEA model

based on the basic DEA models predicted by Seiford and Thrall in 1990 can be expressed as follows [91]:

$$\text{Max } \rho \sum_{i=1}^n v_i x_{ij} \quad (5)$$

$$\text{Constraint : } \sum_{j=1}^n \lambda_j x_j \geq \rho x_o; \sum_{j=1}^n \lambda_j y_j \leq y_o; \rho, \lambda_j \geq 0, j \neq 0.$$

With this linear programming, no add-on is needed when its super efficiency is used for the CRS model, but when it is used for the VRS model, $\sum_{j=1}^n \lambda_j = 1$ is added to the model.

DMUs with an efficiency score of “1”, i.e. 100%, according to the results of the DEA method are considered efficient. The classical DEA model is insufficient to rank the efficient DMUs among themselves. Therefore, super-efficiency DEA models are used to rank the efficient decision-making units among themselves [18, 21, 22, 92]. TOPSIS, EDAS and CODAS methods used in addition to the CRS-SE DEA model in this study are explained below.



3.2 TOPSIS Method

The TOPSIS method was first developed by Hwang and Yoon in 1981 [93–95]. The method is based on the principle of identifying the distances of the alternatives subjected to evaluation from the positive ideal solution and negative ideal solution [94–98]. The steps of the TOPSIS method as follows [74, 93, 95–101].

Step 1: Creating the decision matrix.

There are $i, i = 1, 2, \dots, m$ alternatives in the rows of the decision matrix A_{ij} and $j, j = 1, 2, \dots, n$ criteria in the columns. The decision matrix is shown below.

$$A_{ij} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix} \quad (6)$$

Step 2: Creating the normalised decision matrix.

The normalised decision matrix is calculated using Eq. (7).

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^m a_{ij}^2}} \quad i = 1, 2, \dots, m \quad j = 1, 2, \dots, n \quad (7)$$

the normalised decision matrix is shown below.

$$R_{ij} = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \dots & r_{mn} \end{bmatrix} \quad (8)$$

Step 3: Creating the weighted normalised decision matrix.

First, the weight values (w_i) for the evaluation criteria are determined. Then the weighted normalised decision matrix is created by multiplying the elements in each column of the matrix by the corresponding value of w_i . The weighted normalised value y_{ij} is obtained as in Eq. (9).

$$y_{ij} = w_j \cdot r_{ij} \quad (9)$$

the weighted normalised decision matrix is shown below.

$$Y_{ij} = \begin{bmatrix} w_1 r_{11} & w_1 r_{12} & \dots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \dots & w_n r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_1 r_{m1} & w_2 r_{m2} & \dots & w_n r_{mn} \end{bmatrix}, \quad (10)$$

where y_{ij} is the weighted normalised value of the j th criterion of the i th alternative.

Step 4: Creating a positive ideal set (A^*) and negative ideal set (A^-).

To create the ideal solution set, the largest of the weighted column values in Y_{ij} matrix is chosen. The positive ideal solution set is obtained from Eq. (11).

$$A^* = \left\{ (\max_i y_{ij} | j \in J), (\min_i y_{ij} | j \in J') \right\} \quad (11)$$

The negative ideal solution set is created by choosing the smallest of the weighted column values in Y_{ij} matrix. The negative ideal solution set is obtained from Eq. (12).

$$A^- = \left\{ (\min_i y_{ij} | j \in J), (\max_i y_{ij} | j \in J') \right\} \quad (12)$$

In both equations, J benefit and J' loss value, where y_j^* represents the positive ideal solution of the j th criterion; y_j^- represents the negative ideal solution.

Step 5: Calculating the distance of each alternative to the positive ideal solution and the negative ideal solution.

The distance to the positive ideal solution is S_i^* and the distance to the negative ideal solution is S_i^- . The distance to the positive ideal solution is calculated using Eq. (13) and the distance to the negative ideal solution is calculated using Eq. (14).

$$S_i^* = \sqrt{\sum_{j=1}^n (y_{ij} - y_j^*)^2} \quad (13)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (y_{ij} - y_j^-)^2} \quad (14)$$

Step 6: Compute the relative proximity of each alternative to the ideal solution.

The relative closeness (C_i^*) of each alternative to the ideal solution is calculated as in Eq. (15).

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^*}, \quad (15)$$



where $0 \leq C_i^* \leq 1$.

3.3 EDAS Method

The EDAS method was first developed by Keshavarz Ghorabae et al. [22, 102–104]. In this method, the average solution is used to evaluate the alternatives. The positive distance average (PDA) and negative distance average (NDA) are two separate measures used to evaluate alternatives. The best alternative is chosen based on these two distances [22, 95, 101, 102, 105, 107]. The steps of the EDAS method were given below [22, 101, 102, 105–109]:

Step 1: Choosing alternatives and criteria and creating a decision matrix (X).

$$X = [x_{ij}]_{n \times m} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix}, \quad (16)$$

where x_{ij} demonstrates the performance value of i th alternative on j th criterion.

Step 2: Determine the average solution considering all criteria.

$$AV = [AV_j]_{1 \times m}, \quad (17)$$

where

$$AV_j = \frac{\sum_{i=1}^m x_{ij}}{m}. \quad (18)$$

Step 3: Calculate the positive distance from average (PDA) and the negative distance from average (NDA) matrices according to the type of criteria (cost and benefit).

$$PDA = [PDA_{ij}]_{n \times m} \quad (19)$$

$$NDA = [NDA_{ij}]_{n \times m} \quad (20)$$

If j th criterion is beneficial,

$$PDA_{ij} = \frac{\max(0, (x_{ij} - AV_j))}{AV_j} \quad (21)$$

$$NDA_{ij} = \frac{\max(0, (AV_j - x_{ij}))}{AV_j} \quad (22)$$

and if the j th criterion is non-beneficial

$$PDA_{ij} = \frac{\max(0, (AV_j - x_{ij}))}{AV_j} \quad (23)$$

$$NDA_{ij} = \frac{\max(0, (x_{ij} - AV_j))}{AV_j}, \quad (24)$$

where PDA_{ij} and NDA_{ij} demonstrate the positive and negative distance of i th alternative from the average solution in terms of the j th criterion respectively.

Step 4: Calculate the weighted sum of PDA and the weighted sum of NDA for all alternatives.

$$SP_i = \sum_{j=1}^m w_j PDA_{ij} \quad (25)$$

$$SN_i = \sum_{j=1}^m w_j NDA_{ij}, \quad (26)$$

where w_j is the weight of the j th criterion.

Step 5: Normalise the SP and SN values for all alternatives.

$$NSP_i = \frac{SP_i}{\max_i(SP_i)} \quad (27)$$

$$NSN_i = 1 - \frac{SN_i}{\max_i(SN_i)} \quad (28)$$

Step 6: Calculate the appraisal score (AS) for all alternatives.

$$AS_i = \frac{1}{2}(NSP_i + NSN_i), \quad (29)$$

where $0 \leq AS_i \leq 1$.

Step 7: Ranking of the alternatives considering the descending values of AS.

The alternative with the biggest AS value is the best.

3.4 CODAS Method

Combinative distance-based assessment (CODAS) method was first developed by Ghorabae et al. [95, 101, 102]. In the CODAS method, which is based on the choice of alternatives based on the distances to the negative ideal solution, the preference of the alternatives is determined by the Euclidean (Euclidean) and Taksicab (Taxicab) distances [101, 102, 110]. The application steps of the CODAS method were given below [52, 95, 101, 102, 111, 112]:

Step 1: Creating a decision matrix (X) with alternatives and criteria.

$$X = [x_{ij}]_{n \times m} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix}, \quad (30)$$

where $(x_{ij} \geq 0)$ denotes the performance value of i th alternative on j th criterion.



Step 2: Compute the normalized decision matrix.

$$n_{ij} = \begin{cases} \frac{x_{ij}}{\max_j x_{ij}} & \text{if } j \in N_b \\ \frac{\min_i x_{ij}}{x_{ij}} & \text{if } j \in N_c \end{cases} \quad (31)$$

The values N_b and N_c in Eq. (31) express the benefit and criteria, respectively.

Step 3: Compute the weighted normalized decision matrix.

This calculation, which is based on multiplying the column elements belonging to the normalized decision matrix with the relevant weight coefficients, is realized with Eq. (32).

$$r_{ij} = w_j n_{ij} \quad (32)$$

Step 4: Determine the negative-ideal solution point (NIS).

Using Eq. (33), the smallest values of the columns in the weighted matrix are selected.

$$ns = [ns_j]_{1 \times m} \quad ns_j = \min_i r_{ij} \quad (33)$$

Step 5: Calculate the Euclidean and Taxicab distances of alternatives from the negative-ideal solution.

Calculation of Euclidean distances (E_i) and Taxicab distances (T_i) values were shown in Eqs. (34) and (35), respectively.

$$E_i = \sqrt{\sum_{j=1}^m (r_{ij} - ns_j)^2} \quad (34)$$

$$T_i = \sum_{j=1}^m |r_{ij} - ns_j| \quad (35)$$

Step 6: Creation of comparative evaluation matrix.

A Comparative evaluation matrix is created from Eq. (36).

$$R_a = [h_{ik}]_{n \times n} \quad (36)$$

$$h_{ik} = (E_i - E_k) + (\psi(E_i - E_k) \times (T_i - T_k)),$$

where $k \in \{1, 2, \dots, n\}$ and ψ denotes a threshold function recognizes the equality of the Euclidean and as given Eq. (37).

$$\psi(x) = \begin{cases} 1, & \text{if } |x| \geq \tau \\ 0, & \text{if } |x| \leq \tau \end{cases} \quad (37)$$

In this function, τ is the threshold parameter that can be set by the decision-maker. It is recommended to set this parameter at a value between 0.01 and 0.05. If the difference between Euclidean distances of two alternatives is less than τ , these two alternatives are also compared by the Taxicab distance [95, 102, 111]. In this study τ value was taken 0.02.

Step 7: Calculate the assessment score of each alternative.

$$H_i = \sum_{k=1}^n h_{ik} \quad (38)$$

By ranking the H_i scores of the alternatives in descending order, the alternatives are ranked from the best to the worst.

3.5 Data and Variables

In the selection of the input and output variables used in the study, the variables in the studies conducted to calculate the efficiency of the health systems of the OECD countries were examined and used. In addition, the variables used in the studies conducted to calculate the efficiency of the health systems of the countries during the COVID-19 pandemic were also used [3, 4, 7, 8, 11, 12, 23–42].

The current data of the input variables used in the study were obtained from the websites of the OECD [5], the World Bank [113], and the statistical institutions of the countries. The data of the output variables are provided by the European Center for Disease Prevention and Control [114], the Institute for Health Metrics and Evaluation [115], Worldometers [2], and the relevant institutions of the countries on the internet. obtained from the sites. The input and output variables used in the study are presented in Table 1.

Since the study aims to determine the most optimal output with the available inputs and to calculate the efficiency of the countries, analyses were made by taking the inverse of the number of COVID-19 cases and the number of deaths. While interpreting the potential improvement suggestions, the reversed data were translated into real data and interpreted [116–118].

In this study, data on the number of Doctors and Nurses could be obtained from the World Bank website for Chile, Colombia, Costa Rica in 2018, Greece, Netherlands, Portugal in 2017, and Australia and Finland in 2016 [113]. DEA-SOLVER-LV(V3) program was used for CRS, super efficiency, statistical and correlation analysis in the study.

Table 1 Input and output variables used in the study

Inputs	Outputs
Doctor—number of doctors (per 1000 pop)	HealthExp—health expenditure per capita USD
Nurse—the number of nurses (per 1000 pop)	Test—the number of tests (per 1000 pop)
Bed—number of hospital beds (per 1000 pop)	Case—number of cases (per 1000 pop)
	Death—the number of deaths (per 1000 pop)



Table 2 Statistics and correlation on input/output data

	Statistics						
	Inputs			Outputs			
	Doctor	Nurse	Bed	Exp	Tests	Case	Death
Max	5.48	18.05	12.84	10,948.48	15,885.90	198.95	3.52
Min	1.95	1.33	0.97	1197.65	54.11	1.19	0.008
Mean	3.56	9.17	4.38	4237.37	2445.97	92.01	1.46
Std. dev	0.90	4.21	2.63	2032.68	3073.34	56.48	0.94
	Correlation						
	Doctor	Nurse	Bed	Exp	Tests	Case	Death
Doctor	1.000						
Nurse	0.304	1.000					
Bed	0.008	0.106	1.000				
Exp	0.260	0.750	0.047	1.000			
Tests	0.360	0.107	− 0.052	0.268	1.000		
Case	− 0.035	− 0.093	0.087	− 0.149	− 0.145	1.000	
Death	− 0.029	0.103	− 0.055	0.013	− 0.093	0.445	1.000

The statistics of the input and output data used in the study are presented in Table 2. As can be seen from Table 2, the number of doctors per thousand people in the input variables used in the analysis was at least 1.95 (Turkiye) and at most 5.48 (Greece). The number of nurses and midwives per thousand people was at least 1.33 (Colombia), at most 18.05 (Norway), and the number of beds was at least 0.97 (Mexico) and at most 12.84 (Japan). Health expenditure per capita in 2020, which is one of the output variables, was at least 1197.65 USD (Mexico) and at most 10948.48 USD (USA). When the output variables used for the analysis presented in Table 2 are examined, it is seen that; the number of tests in OECD countries was min 54.11 (Colombia), max 15,885.90 (Denmark). The number of cases was min 1.19 (Slovakia) and max 198.95 (Slovenia). The number of death was min 0.008 (New Zealand) and max 3.52 (Hungary).

When the correlation relationship between the input and output variables presented in Table 2 is examined, it is seen that there is a high correlation relationship only between the number of nurses and health expenditure. It has been determined that the correlation relationship between all other variables is very weak and even close to zero. A negative correlation was found between number of cases and number of doctors, nurses, health expenditures and number of tests.

4 Results and Discussion

First of all, the efficiency of 38 OECD countries was evaluated according to the CRS DEA model and the countries

with an efficiency score of "1" were determined. In the study, TOPSIS, EDAS and CODAS methods were used as well as the CRS-SE model to rank the efficient DMUs among themselves. The results of the CRS-SE DEA model, TOPSIS, EDAS and CODAS methods are given below, respectively.

4.1 DEA Method Results

The efficiency analysis estimates made with CRS and CRS Super Efficiency methods are presented in Table 3. As can be seen from Table 3, in the CRS analysis made with the data for 2021, 5 OECD countries, Colombia, Denmark, New Zealand, Slovakia, and the USA were efficient. The country with the closest score to technical efficiency was Greece (0.927), while the countries with the lowest score were Finland (0.395), Slovenia (0.384), Hungary (0.353), and Chile (0.332).

Two countries of the OECD had an efficiency score of 40–49.99%, 16 of them 50–59.99%, three of them 60–60.99%, six of them 70–70.99% and one country between 80–80.99%. Turkiye took 14th place among 38 OECD countries with an efficiency score of 0.672. United Kingdom 0.796, Italy 0.718, Spain 0.712, and France 0.572, which are among the countries where the COVID-19 pandemic is most prevalent today, received an efficacy score. USA 32, New Zealand 26, Denmark 25, Colombia 23, and Slovakia 17 countries were referenced in the efficiency analysis using the CRS method.



Table 3 CRS and super efficiency scores

No.	Countries	CRS score	CRS-SE score
1	New Zealand	1	14.728
2	Slovakia	1	3.439
3	Denmark	1	2.856
4	USA	1	2.162
5	Colombia	1	1.122
6	Greece	0.927	0.927
7	Austria	0.875	0.875
8	Israel	0.799	0.799
9	United Kingdom	0.796	0.796
10	Luxembourg	0.734	0.734
11	Sweden	0.731	0.731
12	Italy	0.718	0.718
13	Spain	0.712	0.712
14	Turkiye	0.672	0.672
15	Latvia	0.628	0.628
16	Poland	0.542	0.616
17	Netherlands	0.609	0.609
18	Canada	0.594	0.595
19	S. Korea	0.594	0.592
20	Portugal	0.542	0.590
21	Czechia	0.571	0.585
22	France	0.572	0.572
23	Japan	0.572	0.572
24	Iceland	0.558	0.558
25	Belgium	0.553	0.553
26	Estonia	0.549	0.549
27	Australia	0.524	0.524
28	Ireland	0.524	0.524
29	Germany	0.522	0.522
30	Norway	0.522	0.522
31	Costa Rica	0.518	0.518
32	Mexico	0.513	0.513
33	Lithuania	0.456	0.456
34	Switzerland	0.429	0.430
35	Slovenia	0.384	0.401
36	Finland	0.395	0.395
37	Hungary	0.353	0.353
38	Chile	0.332	0.332
	Average	0.640	1.152

According to the results of the Super Efficiency analysis made for the efficient countries as a result of the analysis made with CRS method, New Zealand 14.728, Slovakia 3.439, the USA 2.162, Denmark 2.856 and Colombia 1.122, were Super Efficiency score. The average score of efficiency was 0.640 in the CRS analysis and 1.152 in the CRS super efficiency analysis.

The efficiency score distributions of OECD member countries made with the CRS and super CRS models are shown in Figs. 2 and 3.

Potential improvement suggestions for output variables for some of the inefficient countries are presented as a result of the efficiency analyses made on the output data for 2021 with the CRS method. Potential improvement suggestions were examined by choosing a country with an average value from each class, namely Chile, Lithuania, Belgium, Latvia, Sweden, Austria and Greece (Table 4).

It can be seen from Table 4 that all countries need to increase the number of tests to be efficient. In addition, more comprehensive and drastic measures should be taken to reduce the number of cases and deaths in Chile (0.332) and Lithuania (0.456), which have lower efficacy scores. Although Sweden (0.731) and Austria (0.875) had higher inefficiency scores than other countries, it can be said that they face higher rates of death with current inputs.

According to the results of the analysis made with the CRS method, it is seen that Greece should increase the number of tests by 7.90%. For Greece to be efficient, the current inputs and the number of Cases must be reduced by 15.36%, and the number of Deaths by 29.6%. It has been determined that Hungary's number of tests should be 1702.93% more, while the number of cases and deaths should be approximately 65% less.

According to the results of the DEA method, efficient and inefficient DMUs were determined and potential improvement suggestions were made. DMUs that were found efficient according to the results of the CRS DEA model were ranked among themselves according to the results of the CRS-SE model.

4.2 TOPSIS Method Results

The TOPSIS method results of DMUs that were efficient according to the results of the CRS-DEA model are shown in Table 5.

The countries are ranked according to the C_1^* values in Table 5. It is understood that Denmark is in first place and New Zealand is in last place.

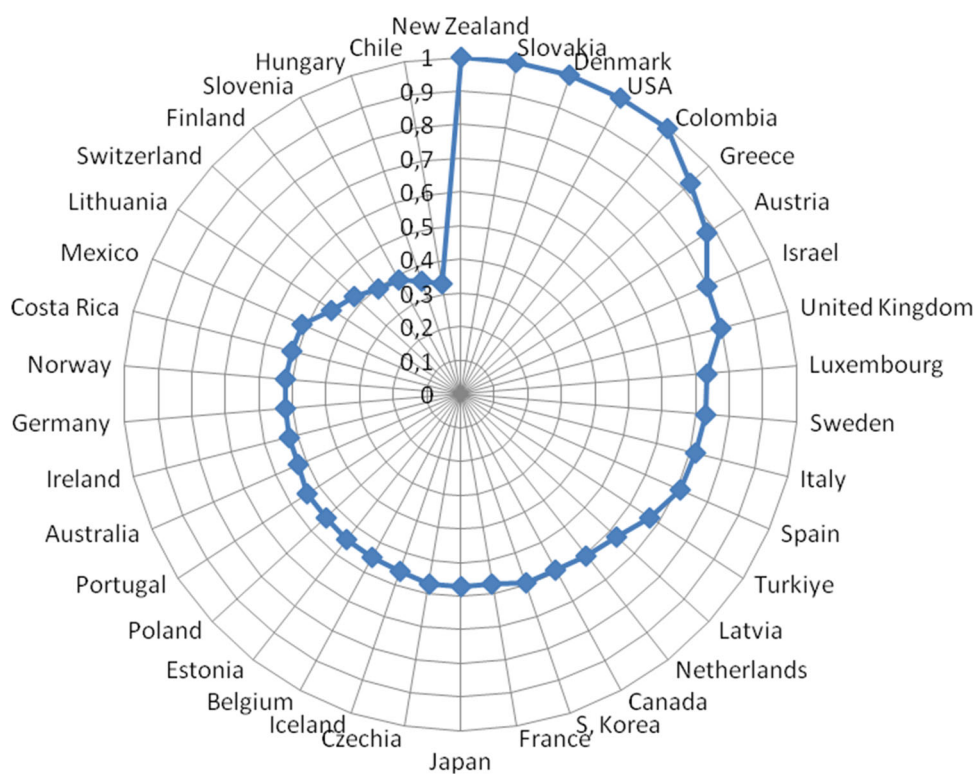
Fig. 2 CRS efficiency score distribution**Fig. 3** CRS—super efficiency score distribution

Table 4 Potential improvement suggestions for inefficient countries

Countries/score	Outputs	Data	Projection	Difference %
Chile	Tests	1,309,697	3,950,737	201.65
0.332	Case	90.685	30.063	– 66.85
	Deaths	1.977	0.123	– 93.80
Hungary	Tests	86,213	1,554,364	1702.9
0.353	Case	111.043	39.227	– 64.7
	Deaths	3.518	1.243	– 64.7
Lithuania	Tests	2,277,280	4,989,588	119.10
0.456	Case	174.076	55.805	– 67.94
	Deaths	2.492	0.905	– 63.68
Belgium	Tests	2,082,904	3,766,931	80.85
0.553	Case	144.065	79.660	– 44.71
	Deaths	2.298	1.271	– 44.71
Latvia	Tests	2,856,371	4,548,434	59.24
0.628	Case	135.176	75.868	– 43.87
	Deaths	2.215	1.099	– 50.39
Sweden	Tests	1,333,601	1,824,246	36.79
0.731	Case	117.676	86.026	– 26.90
	Deaths	1.483	0.466	– 68.57
Austria	Tests	12,029,623	13,746,061	14.27
0.875	Case	123.492	53.810	– 56.43
	Deaths	1.353	0.492	– 63.60
Greece	Tests	3,380,162	3,647,093	7.90
0.927	Case	88.376	74.799	– 15.36
	Deaths	1.718	1.209	– 29.60

Table 5 TOPSIS method results of efficient DMUs

Countries	S_i^*	S_i^-	C_i^*	Rank
Colombia	0.1781	0.1578	0.4698	3
Denmark	0.1263	0.1721	0.5767	1
New Zealand	0.2159	0.0720	0.2500	5
Slovakia	0.2132	0.0974	0.3135	4
USA	0.1450	0.1808	0.5550	2

4.3 EDAS Method Results

The EDAS method results of DMUs that were efficient according to the results of the CRS-DEA model are shown in Table 6.

The countries are ranked according to the AS_i values in Table 6. It is understood that Denmark is in first place and Slovakia is in last place.

4.4 CODAS Method Results

The CODAS method results of DMUs that were efficient according to the results of the CRS-DEA model are shown in Table 7.

The countries are ranked according to the H_i values in Table 7. It is understood that Colombia is in first place and New Zealand is in last place.

Table 6 EDAS Method Results of Efficient DMUs

Countries	SP_i	SN_i	NSP_i	NSN_i	AS_i	Rank
Colombia	0.228	0.247	0.480	0.251	0.366	3
Denmark	0.475	0.084	1.000	0.747	0.873	1
New Zealand	0.027	0.188	0.057	0.430	0.243	4
Slovakia	0.039	0.330	0.082	0.000	0.041	5
USA	0.211	0.133	0.443	0.597	0.520	2

Table 7 CODAS method results of efficient DMUs

Countries	E_i	T_i	H_i	Rank
Colombia	0.24155	0.52631	0.33192	1
Denmark	0.18234	0.36076	0.03468	3
New Zealand	0.06958	0.12086	– 0.52680	5
Slovakia	0.14487	0.19344	– 0.15225	4
USA	0.23972	0.50622	0.32261	2

4.5 Discussion

The results of the efficient DMUs according to the CRS-SE model and the results according to the TOPSIS, EDAS and CODAS methods were compared and are shown in Table 8.

When Table 8 is analyzed, while New Zealand ranks 1st according to the results of the CRS-SE model, it is in last place according to the TOPSIS and CODAS method results and 4th according to the EDAS method results. While the USA is in the 4th place according to the results of the CRS-SE model, it is in the 2nd place according to the TOPSIS, EDAS and CODAS method results. While Denmark is in the 3rd place according to the results of the CRS-SE model, it is in the 1st place according to the TOPSIS and EDAS method results and in the 3rd place according to the CODAS method results. According to all method results, it is possible to say that Denmark is in first place and the USA is in second place.

It should be noted that the results of the DEA analysis are relative. The results of DEA analysis may change when the number of input variables, number of output variables and DMU used in DEA analysis change. The increase or decrease in the amount of input variables and output variables affects the results of DEA analysis.

5 Conclusion

In the study, the efficiency of OECD countries against the COVID-19 pandemic was examined using Data Envelopment Analysis (DEA). At the end of the analysis, potential improvement rates were calculated for inefficient countries. In the study, DEA method was used together with multi-criteria decision making (MCDM) methods such as TOPSIS, EDAS and CODAS for efficiency evaluation of OECD countries to allow for a better ranking of efficient decision-making units.

Considering that it is not possible to reduce the number of doctors per thousand people, the number of nurses and midwives per thousand people, and the number of hospital beds per thousand people used as inputs to eliminate inefficiently in the fight against the COVID-19 pandemic, and even more input is needed. Outputs such as the number of deaths per thousand people, the number of tests per thousand people, and the health expenditure per capita (USD) need to be optimized. In this respect, the output of the number of tests per thousand people draws attention. It is considered the easiest to increase this output with the decisions to be taken according to the socio-economic status of the countries and the size of their health systems.

Table 8 Efficiency comparisons of efficient DMUs

Countries	CRS-SE	TOPSIS	EDAS	CODAS
Colombia	5	3	3	1
Denmark	3	1	1	3
New Zealand	1	5	4	5
Slovakia	2	4	5	4
USA	4	2	2	2



This study has several limitations. The most important limitation is that given the change in COVID-19 pandemic data, such as cases, deaths, and number of tests performed in countries, generalization of the results to other periods should be done with care. It can be said that the selection of indicators according to the dynamism of the number of cases affects the results of the model. Therefore, different results can be achieved with a different set of indicators. The disadvantage of this study is the lack of more effective indicators for evaluating performance. In the study, different models were used to make DEA efficiency score estimations of OECD countries. In the CRS model and CRS-SE model, the analyses were made with the input variables obtained from the current data in the statistics pages of the World Bank, World Health Organization and OECD institutions in 2021. In the analysis, the output variables obtained on 24.11.2021 were used. Another limitation of the study is that three inputs and four outputs were used in the study.

As a result of the efficiency analysis made with the CRS method Colombia, Denmark, New Zealand, Slovakia, and the USA were efficient. In the efficiency analyses, the countries with the closest technical efficiency score were Greece, and the countries with the lowest efficiency scores were Slovenia, Hungary, and Chile. New Zealand got the highest super-efficiency score in the Super-efficiency analyses made for the countries that were efficient in the CRS model.

According to the potential improvement rates estimated for the inefficient countries as a result of the DEA, Greece's number of cases per thousand people is 15.36% and the number of deaths is 29.60% less than the current input of Greece, which got the closest score to the full efficiency score in the output-oriented CRS analysis. It can be said that the number of tests should be increased by approximately 7.9%. It has been seen that Hungary, which is in last place according to the estimated efficiency score by both models, should have a low number of cases and deaths per thousand people by approximately 65%, and the number of tests per thousand people should be increased by more than 1500%.

When similar studies in the literature are examined, this is the case in the CRS analysis of Selamzade and Ozdemir [38] with the input and output variables obtained on April 24, 2020, in Australia, Austria, Israel, Iceland, Japan, Mexico, Slovakia, and New Zealand and VRS analysis. Besides these countries, S. Korea, Luxembourg, and Turkiye were efficient. In both models, the country with the least efficiency score was France. When the DEA analyses made by Shirouyehzad et al. [37] using 2 different models for countries severely affected by COVID-19 using the output variables of 25 March 2020 are examined, Canada, France, Iran, Singapore, and the USA in the 1st model. In the second model, Canada, China, France, Iran, Iraq, Italy, Lebanon, and Sweden were efficient. In the study conducted by Ayranci and Bagriacik [118] which is one of the most recent studies in 2021, for OECD and

EU countries, the Total Number of Cases and Total Number of Recoveries were used as input variables and the Total Number of Tests as the output variable. As a result of the input-oriented VRS Model study, Austria, Iceland, Finland, New Zealand, Czechia, Estonia, Israel, and Malta were efficient, while Chile and Poland had the least efficiency score.

Recently, it is seen that the COVID-19 virus is rapidly changing with mutation and the most effective method in combating this virus is vaccination. In addition to increasing the number of tests, the development and implementation of policies to increase vaccination rates are one of the important duties of the governments of the country. Considering all these, the study reveals the relative efficiency of OECD member countries against the COVID-19 virus. The performance evaluation of the epidemic response management applied in this study can be made for other countries and unions with similar data.

If a general evaluation of the study is made, it has been concluded that the results of the DEA super-efficiency model alone are not sufficient to rank and evaluate the DMUs that are efficient according to the results of the DEA analysis, and it will be useful to compare them with the results of other MCDM methods.

When the results of this study are examined, it is understood that DEA and MCDM methods can be used together in future studies. The results of the MCDM method seem to support the results of the DEA. There are very few studies in the literature where DEA and MCDM methods are used together in the field of health. Therefore, this study may contribute to the literature in the field of health.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

1. Zu, Z.Y.; Jiang, M.D.; Xu, P.P.; Chen, W.; Ni, Q.Q.; Lu, G.M., et al.: Coronavirus disease 2019 (COVID-19): a perspective from China. *Radiology* **296**(2), E15–E25 (2020). <https://doi.org/10.1148/radiol.202000490>
2. Worldometer: COVID-19 coronavirus pandemic. (2022). <https://www.worldometers.info/coronavirus>. Accessed 18 Nov 2022
3. Jouzdani, J.; Shirouyehzad, H.: Fight against COVID-19: what can be done in the case of Iran? *J. Appl. Res. Ind. Eng.* **7**(1), 1–12 (2020)

4. Riou, J.; Althaus, C.L.: Pattern of early human-to-human transmission of Wuhan 2019 novel coronavirus (2019-nCoV). *Euro Surveill.* **25**(4), 2000058 (2020)
5. OECD: Health, OECD data. (2021). <https://data.oecd.org/health.htm>. Accessed 20 Nov 2021
6. OECD: List of OECD member countries—ratification of the convention on the OECD. (2021). <https://www.oecd.org/about/document/ratification-oecd-convention.htm>. Accessed 20 Nov 2021
7. Alptekin, N.; Yesilaydin, G.: Classifying OECD countries according to health indicators using fuzzy clustering analysis. *J. Bus. Res. Turk.* **7**(4), 137–155 (2015)
8. Doğan, M.İ.; Özsoy, V.S.; Örkücü, H.H.: Performance management of OECD countries on Covid-19 pandemic: a criticism using data envelopment analysis models. *J. Facil. Manag.* **19**(4), 479–499 (2021). <https://doi.org/10.1108/JFM-01-2021-0005>
9. Pereira, D.S.; de Mello, J.C.: Efficiency evaluation of Brazilian airlines operations considering the Covid-19 outbreak. *J. Air Transp. Manag.* **91**, 1–6 (2021). <https://doi.org/10.1016/j.jairtraman.2020.101976>
10. Değirmenci, N.: Evaluation of health efficiency of OECD countries with data envelopment and inverse data envelopment analyses. *Int. J. Econ. Adm. Stud.* **30**, 171–182 (2021). <https://doi.org/10.18092/ulikidince.786089>
11. Pereira, M.A.; Dinis, C.D.; Ferreira, D.C.; Figueira, J.R.; Marques, R.C.: A network data envelopment analysis to estimate nations' efficiency in the fight against SARS-CoV-2. *Expert Syst. Appl.* **210**, 1–18 (2022). <https://doi.org/10.1016/j.eswa.2022.118362>
12. Ersoy, Y.; Aktaş, A.: Health system efficiency of OECD countries with data envelopment analysis. *Probl. Zarz. Manag. Issues* **20**(4), 90–109 (2022). <https://doi.org/10.7172/1644-9584.98.4>
13. Vavrek, R.; Chovancova, J.: Assessment of economic and environmental energy performance of EU countries using CV-TOPSIS technique. *Ecol. Ind.* **106**, 1–8 (2019). <https://doi.org/10.1016/j.ecolind.2019.105519>
14. Chowdhury, P.; Paul, S.K.: Applications of MCDM methods in research on corporate sustainability. A systematic literature review. *Manag. Environ. Qual. Int. J.* **31**(2), 385–405 (2020). <https://doi.org/10.1108/MEQ-12-2019-0284>
15. Li, T.; Li, A.; Guo, X.: The sustainable development-oriented development and utilization of renewable energy industry—a comprehensive analysis of MCDM methods. *Energy* **212**, 1–17 (2020). <https://doi.org/10.1016/j.energy.2020.118694>
16. Abdel-Basset, M.; Ding, W.; Mohamed, R.; Metawa, N.: An integrated plithogenic MCDM approach for financial performance evaluation of manufacturing industries. *Risk Manag.* **22**, 192–218 (2020). <https://doi.org/10.1057/s41283-020-00061-4>
17. Guler, E.; Kandemir, S.Y.; Acikkalp, E.; Ahmadi, M.H.: Evaluation of sustainable energy performance for OECD countries. *Energy Sources Part B* **16**(6), 491–514 (2021). <https://doi.org/10.1080/15567249.2021.1909673>
18. Ersoy, Y.: Performance evaluation in distance education by using data envelopment analysis (DEA) and TOPSIS Methods. *Arab. J. Sci. Eng.* **46**, 1803–1817 (2021). <https://doi.org/10.1007/s13369-020-05087-0>
19. Acar, E.: Comparison of the performances of OECD countries in the perspective of socio-economic global indices: CRITIC-based CoCoSo method. *Dumlupınar Univ. J. Soc. Sci.* **73**, 256–277 (2022). <https://doi.org/10.51290/dpusbe.1122650>
20. Lotfi, F.H.; Fallajnejad, R.; Navidi, N.: Ranking efficient units in DEA by using TOPSIS method. *Appl. Math. Sci.* **5**(1), 805–815 (2011). <http://www.m-hikari.com/ams/ams-2011/ams-17-20-2011/lotfiAMS17-20-2011-1.pdf>. Accessed 10 May 2022
21. Nayeibi, M.; Lotfi, F.H.: The methods of ranking based super efficiency. *Int. J. Res. Ind. Eng.* **5**(1–4), 43–66 (2016). <https://doi.org/10.22105/riej.2017.49169>
22. Ersoy, Y.: Performance evaluation of airports during the COVID-19 pandemic. *Pol. J. Econ.* **4**(308), 23–53 (2021). <https://doi.org/10.33119/GN/143335>
23. Sel, A.: Measuring the efficiency of health system developments in the Covid 19 pandemic: a study on the G-20. *Kırklareli Univ. J. Fac. Econ. Adm. Sci.* **10**(2), 181–202 (2021)
24. Özçelik, M.; Yiğit, P.: The health system efficiency analysis of OECD countries. In: Kaya, H.; Söner, A. (Eds.) *Health and Science 2021-III*. Efe Academy Publication, Istanbul (2021)
25. Küçükaycan, D.: Universal health coverage combating covid-19 pandemic from global public goods perspective and researching of OECD countries' performance. *Maliye Dergisi* **181**, 234–263 (2021)
26. Akbulut, F.; Senol, O.: Evaluation of the Covid-19 fighting of top income countries with data envelopment analysis. *Gümüşhane Üniversitesi Sosyal Bilimler Dergisi* **13**(2), 679–689 (2022)
27. Kumru, S.; Yiğit, P.; Hayran, O.E.: Demography inequalities and Global Health Security Index as correlates of COVID 19 morbidity and mortality. *Int. J. Health Plan. Manag.* **37**(2), 944–962 (2022)
28. Hadad, S.; Hadad, Y.; Simon-Tuval, T.: Determinants of health-care system's efficiency in OECD countries. *Eur J Health Econ.* **14**, 253–265 (2013). <https://doi.org/10.1007/s10198-011-0366-3>
29. Demir, A.; Bakirci, F.: Measuring the economical efficiency of the OECD countries by using data envelopment analysis. *Ataturk Univ. J. Econ. Adm. Sci. (JEAS)* **28**(2), 109–132 (2014)
30. Kaya Samut, P.; Cafri, R.: Analysis of the efficiency determinants of health systems in OECD countries by DEA and panel Tobit. *Soc. Indic. Res.* **129**, 113–132 (2016)
31. Sener, M.; Yiğit, V.: Technical efficiency of health systems: a research on the OECD countries. *J. Süleyman Demirel Univ. Inst. Soc. Sci.* **26**, 266–290 (2017)
32. Yılmaz, F.; Senel, I.K.: Assessing health system efficiency of OECD countries. In: *3rd International 13th National Congress on Health and Hospital Administration*, Sakarya-10–13 October, 1052–1062 (2019)
33. Sahinbas, F.; Konca, M.; Yetim, B.: Evaluating the health care efficiency in OECD countries. In: *3rd International 13th National Congress on Health and Hospital Administration*, Sakarya-10–13 October, 366–372 (2019)
34. Yuksel, O.: Comparison of healthcare system performances in OECD countries. *Int. J. Health Serv. Res. Policy* **6**(2), 251–261 (2021). <https://doi.org/10.33457/ijhsrp.935170>
35. Bas Kaman, F.; Yucel, A.: An efficiency analysis on the evaluation of smoking and alcohol consumption in children in OECD countries. *Hacettepe Univ. J. Soc. Sci.* **3**(1), 44–63 (2021)
36. Konca, M.; Gozlu, M.; Cakmak, C.: The evaluation of G-20 countries efficiencies in terms of health expenses. *J. Prod.* **2019**(2), 119–141 (2019)
37. Shirouyehzad, H.; Jouzdani, J.; Karimvand, M.: Fight against COVID-19: a global efficiency evaluation based on contagion control and medical treatment. *J. Appl. Res. Ind. Eng.* **7**(1), 13–24 (2020)
38. Selamzade, F.; Ozdemir, Y.: Evaluation of the efficiency of OECD countries against COVID-19 by DEA. *Turk. Stud.* **15**(4), 977–991 (2020)
39. Ghasemi, A.; Boroumand, Y.; Shirazi, M.: How do governments perform in facing COVID-19? MPRA Pap (2020). <https://doi.org/10.1314/RG.2.2.16576.48649>
40. Sherpa, D.: Estimating impact of Austerity policies in COVID-19 fatality rates: examining the dynamics of economic policy and case fatality rates (CFR) of COVID-19 in OECD countries. *SSRN Electron. J.* (2020). <https://doi.org/10.2139/ssrn.3581274>



41. Ergulen, A.; Bolayir, B.; Unal, Z.; Harmankaya, I.: In Covid-19 process evaluation with data envelopment analysis efficiency of Turkey. *Gumushane Univ. J. Soc. Sci. Inst.* **11**, 275–286 (2020)
42. Bas Kaman, F.; Yucel, A.: A study on the effectiveness of healthcare workers in the 9 most-affected OECD countries by COVID-19. *J. Appl. Soc. Sci. Fine Arts* **3**(5), 14–25 (2021)
43. Mardani, A.; Jusoh, A.; Nor, K.M.D.; Kahalifah, Z.; Zakwan, N.; Valipour, A.: Multiple criteria decision-making techniques and their applications—a review of the literature from 2000 to 2014. *Econ. Res.* **28**(1), 516–571 (2015). <https://doi.org/10.1080/1331677X.2015.1075139>
44. Rezaei, J.: A systematic review of multi-criteria decision-making applications in reverse logistics. *Transport. Res. Procedia* **10**, 766–776 (2015). <https://doi.org/10.1016/j.trpro.2015.09.030>
45. Huang, Y.; Jiang, W.: Extension of TOPSIS method and its application in investment. *Arab. J. Sci. Eng.* **43**, 693–705 (2018). <https://doi.org/10.1007/s13369-017-2736-3>
46. Shao, M.; Han, Z.; Sun, J.; Xiao, C.; Zhang, S.; Zhao, Y.: A review of multi-criteria decision making applications for renewable energy site selection. *Renew. Energy* **157**, 377–403 (2020). <https://doi.org/10.1016/j.renene.2020.04.137>
47. Jamwal, A.; Agrawal, R.; Sharma, M.; Kumar, V.: Review on multi-criteria decision analysis in sustainable manufacturing decision making. *Int. J. Sustain. Eng.* **14**(3), 202–225 (2021)
48. Al-Hawari, T.; Khanfar, A.; Mumani, A.; Bataineh, O.: A Simulation-Based Framework for evaluation of healthcare systems with interacting factors and correlated performance measures. *Arab. J. Sci. Eng.* **47**, 3707–3724 (2022). <https://doi.org/10.1007/s13369-021-05937-5>
49. Mandal, S.; Khan, D.A.: Cloud-CoCoSo: cloud model-based combined compromised solution model for trusted cloud service provider selection. *Arab J Sci Eng* **47**, 10307–10332 (2022). <https://doi.org/10.1007/s13369-021-06512-8>
50. Kumar, R.R.; Mishra, S.; Kumar, C.A.: Novel framework for cloud service evaluation and selection using hybrid MCDM methods. *Arab. J. Sci. Eng.* **43**, 7015–7030 (2018). <https://doi.org/10.1007/s13369-017-2975-3>
51. Mathew, M.; Sahu, S.: Comparison of new multi-criteria decision making methods for material handling equipment selection. *Manag. Sci. Lett.* **8**(3), 139–150 (2018). <https://doi.org/10.5267/j.msl.2018.1.004>
52. Yalçın, N.; Uncu, N.: Applying EDAS as an applicable MCDM method for Industrial robot selection. *Sigma J. Eng. Nat. Sci.* **37**(3), 779–796 (2019)
53. Mathew, M.; Thomas, J.: Interval valued multi criteria decision making methods for the selection of flexible manufacturing system. *Int. J. Data Netw. Sci.* **3**, 349–358 (2019). <https://doi.org/10.5267/j.ijdns.2019.4.001>
54. Li, Y.; Wang, J.; Wang, T.: A Linguistic neutrosophic multi-criteria group decision-making approach with EDAS method. *Arab. J. Sci. Eng.* **44**, 2737–2749 (2019). <https://doi.org/10.1007/s13369-018-3487-5>
55. Batool, B.; Abosuliman, S.S.; Abdullah, S.; Ashraf, S.: EDAS method for decision support modeling under the Pythagorean probabilistic hesitant fuzzy aggregation information. *J. Ambient Intell. Hum. Comput.* **13**, 5491–5504 (2021). <https://doi.org/10.1007/s12652-021-03181-1>
56. Chen, L.; Gou, X.: The application of probabilistic linguistic CODAS method based on new score function in multi-criteria decision-making. *Comput. Appl. Math.* **41**, 1–25 (2022). <https://doi.org/10.1007/s40314-021-01568-6>
57. Chakraborty, S.; Chakraborty, S.: A scoping review on the applications of MCDM techniques for parametric optimization of machining processes. *Arch. Comput. Methods Eng.* **29**, 4165–4186 (2022). <https://doi.org/10.1007/s11831-022-09731-w>
58. Biswas, S.; Singh, Y.; Mukherjee, M.; Datta, S.; Barman, S.; Raja, M.: Design of multi-material model for wire electro-discharge machining of SS304 and SS316 using machine learning and MCDM techniques. *Arab. J. Sci. Eng.* (2022). <https://doi.org/10.1007/s13369-022-06757-x>
59. Sufiyan, M.; Haleem, A.; Khan, S.; Khan, M.I.: Evaluating food supply chain performance using hybrid fuzzy MCDM technique. *Sustain. Prod. Consum.* **64**, 1–18 (2019). <https://doi.org/10.1016/j.websem.2020.100592>
60. Prabhuram, T.; Rajmohan, M.; Tan, Y.; Johnson, R.R.: Performance evaluation of Omni channel distribution network configurations using multi criteria decision making techniques. *Ann. Oper. Res.* **288**, 435–456 (2020). <https://doi.org/10.1007/s10479-020-03533-8>
61. Baydaş, M.; Elma, O.E.: An objective criteria proposal for the comparison of MCDM and weighting methods in financial performance measurement: an application in Borsa Istanbul. *Decis. Mak. Appl. Manag. Eng.* **4**(2), 257–279 (2021). <https://doi.org/10.3118/dmame.210402257b>
62. Zhao, H.; Li, B.; Lu, H.; Wang, X.; Li, H.; Guo, S.; Xue, M.: Economy-environment-energy performance evaluation of CCHP microgrid system: a hybrid multi-criteria decision-making method. *Energy* **240**, 1–17 (2022). <https://doi.org/10.1016/j.energy.2021.122830>
63. Yiğit, A.: Performance analysis of OECD countries based on health outcomes and expenditures indicators. *J. Int. Sci. Manag.* **5**(9), 114–123 (2019)
64. Ince, Ö.; Güre, M.D.P.: Evaluation of rare diseases policy performance of oecd countries using mcdm methods. *Health Policy Technol.* **10**(3), 1–12 (2021). <https://doi.org/10.1016/j.hlpt.2021.100537>
65. Aydin, G.Z.: Evaluation of Covid-19 pandemic in OECD countries by multi-criteria decision making methods. *Samsun Ondokuz Mayıs Univ. J. Health Sci.* **7**(3), 713–730 (2022)
66. Çelen, A.; Yalçın, N.: Performance assessment of Turkish electricity distribution utilities: an application of combined FAHP/TOPSIS/DEA methodology to incorporate quality of service. *Util. Policy* **23**, 59–71 (2012)
67. Lai, P.-L.; Potter, A.; Beynon, M.; Beresford, A.: Evaluating the efficiency performance of airports using an integrated AHP/DEA-AR technique. *Transp. Policy* **42**, 75–85 (2015). <https://doi.org/10.1016/j.tranpol.2015.04.008>
68. Babaei, S.; Bagherikahvarin, M.; Sarrazin, R.; Shen, Y.; Hermans, E.: Use of DEA and PROMETHEE II to assess the performance of older drivers. *Transp. Res. Procedia* **10**, 798–808 (2015). <https://doi.org/10.1016/j.trpro.2015.09.033>
69. Keskin, B.; Köksal, C.D.: A hybrid AHP/DEA-AR model for measuring and comparing the efficiency of airports. *Int. J. Prod. Perform. Manag.* **68**(3), 525–541 (2019). <https://doi.org/10.1108/IJPPM-02-2018-0043>
70. Fan, J.-P.; Li, Y.-J.; Wu, M.-Q.: Technology selection based on EDAS cross-efficiency evaluation method. *IEEE Access* **7**, 58974–58980 (2019). <https://doi.org/10.1109/ACCESS.2019.2915345>
71. Lee, Z.Y.; Chu, M.T.; Wang, Y.T.; Chen, K.J.: Industry performance appraisal using improved MCDM for next generation of Taiwan. *Sustainability* **12**(13), 5290 (2020). <https://doi.org/10.3390/su12135290>
72. Ersoy, Y.; Dogan, N.Ö.: An integrated model of fuzzy AHP/fuzzy DEA for measurement of supplier performance: a case study in textile sector. *Int. J. Supply Oper. Manag. (IJSOM)* **7**(1), 17–38 (2020). <https://doi.org/10.2203/IJSOM.2020.1.2>
73. Prasad, K.G.D.; Subbaiah, K.V.; Prasad, M.V.: Supplier evaluation and selection through DEA-AHP-GRA integrated approach—a case study. *Uncertain Supply Chain Manag.* **5**(4), 369–382 (2017). <https://doi.org/10.5267/j.uscm.2017.4.001>



74. Chitnis, A.; Vaidya, O.S.: Efficiency ranking method using DEA and TOPSIS (ERM-DT): case of an Indian bank. *Benchmarking Int. J.* **23**(1), 166–182 (2016). <https://doi.org/10.1108/bij-09-29013-0093>
75. Stevic, Z.; Miskic, S.; Vojinovic, D.; Huskanovic, E.; Stankovic, M.; Pamucar, D.: Development of a model for evaluating the efficiency of transport companies: PCA–DEA–MCDM model. *Axioms* **11**(3), 1–33 (2022). <https://doi.org/10.3390/axioms11030140>
76. Altın, F.G.; Filiz, T.: Assessment of the performance of logistics villages operated by the Turkish state railways using MCDM and DEA methods. *Ege Acad. Rev.* **22**(2), 169–182 (2022). <https://doi.org/10.21121/eab.983220>
77. Gupta, N.; Saini, C.P.; Dangi, A.; Akthar, Md.T.: Unified AHP-TOPSIS and DEA technique for the adoption and performance evaluation of green transportation alternatives in India. *Int. J. Veh. Des.* **88**(2–4), 260–282 (2022). <https://doi.org/10.1504/IJVD.2022.127019>
78. Mousavi-Nasab, S.H.; Sotoudeh-Anvari, A.: A comprehensive MCDM-based approach using TOPSIS, COPRAS and DEA as an auxiliary tool for material selection problems. *Mater. Des.* **121**, 237–253 (2017). <https://doi.org/10.1016/j.matdes.2017.02.041>
79. Anvari-Sotoudeh, A.: The applications of MCDM methods in COVID-19 pandemic: a state of the art review. *Appl. Soft Comput.* **126**, 1–40 (2022). <https://doi.org/10.1016/j.asoc.2022.109238>
80. Somogyi, R.M.: Ranking efficient and inefficient decision making units in data envelopment analysis. *Int. J. Traffic Transp. Eng.* **1**(4), 245–256 (2011). <http://ijtte.com/uploads/2011-12-19/d4c8811d-2d60-b00a245-256.pdf>. Accessed 14 May 2022
81. Azadfallah, M.: Multi-criteria decision making for ranking decision making units. *Int. J. Prod. Manag. Assess. Technol. (IJPMAT)* **6**(1), 17–36 (2018). <https://doi.org/10.4018/IJPMAT.2018010102>
82. Su, W.; Wang, D.; Xu, L.; Zeng, S.; Zhang, C.: A nonradial super efficiency Dea framework using a MCDM to measure the research efficiency of disciplines at Chinese universities. *IEEE Access* **8**, 86388–86399 (2020). <https://doi.org/10.1109/ACCESS.2020.2993108>
83. Mehdiabadi, A.; Rohani, A.; Amirabdollahiyan, S.: Ranking industries using a hybrid of DEA-TOPSIS. *Decis. Sci. Lett.* **2**(4), 251–256 (2013)
84. Yalçın, N.; Bayraktaroglu, A.; Kahraman, C.: Application of fuzzy multi-criteria decision making methods for financial performance evaluation of Turkish manufacturing industries. *Expert Syst. Appl.* **39**(1), 350–364 (2012). <https://doi.org/10.1016/j.eswa.2011.07.024>
85. Kutlar, A.; Salomov, F.: Evaluation of activities of Azerbaijan regional public hospitals with data envelopment analysis. *Balkan Near Eastern J. Soc. Sci.* **4**(2), 65–75 (2018)
86. Charnes, A.; Cooper, W.W.; Rhodes, E.: Measuring the efficiency of decision-making units. *Eur. J. Oper. Res.* **2**, 429–444 (1978)
87. Banker, R.D.; Charnes, A.; Cooper, W.W.: Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manag. Sci.* **30**(9), 1078–1092 (1984)
88. Abankina, I.; Aleskerov, F.; Belousova, V.; Zinkovsky, K.; Petrushchenko, S.: Evaluating performance of universities using data envelopment analysis. *Educ. Stud. Moscow* **2**, 15–48 (2013). <https://doi.org/10.17323/1814-9545-2013-2-15-48>
89. Charnes, A.; Cooper, W.W.: Programming with linear fractional functional. *Nav. Res. Logist. Q.* **9**(4), 181–186 (1962)
90. Coelli, T.; Rao, D.; O'Donnell, C.; Battese, G.: *An Introduction to Efficiency and Productivity Analysis*. Springer, Berlin (2005)
91. Seiford, L.M.; Thrall, R.M.: Recent developments in dea: the mathematical programming approach to frontier analysis. *J. Econometr.* **4**, 7–38 (1990)
92. Ghasemi, M.R.; Ignatius, J.; Rezaee, B.: Improving discriminating power in data envelopment models based on deviation variables framework. *Eur. J. Oper. Res.* **278**(2), 442–447 (2019). <https://doi.org/10.1016/j.ejor.2018.08.046>
93. Hwang, C.L.; Yoon, K.: *Multiple Attributes Decision Making Methods and Applications*. Springer, Berlin (1981) <https://doi.org/10.1007/978-3-642-48318-9>
94. Chen, C.T.: Extensions of the TOPSIS for group decision-making under fuzzy environment. *Fuzzy Sets Syst.* **114**(1), 1–9 (2000). [https://doi.org/10.1016/S0165-0114\(97\)00377-1](https://doi.org/10.1016/S0165-0114(97)00377-1)
95. Ersoy, Y.: Equipment selection for an e-commerce company using entropy-based topsis, edas and codas methods during the COVID-19. *LogForum* **17**(3), 341–358 (2021). <https://doi.org/10.17270/J.LOG.2021.603>
96. Ghaleno, M.R.D.; Meshram, S.G.; Alvandi, E.: Pragmatic approach for prioritization of flood and sedimentation hazard potential of watersheds. *Soft. Comput.* **24**, 15701–15714 (2020). <https://doi.org/10.1007/s00500-020-04899-4>
97. Rouyendegh, B.D.; Öztürk, B.N.; Cebeci, K.: Performance management of supervisors in railway company: a case study. *Manag. Bus. Res. Q.* **7**, 10–20 (2018). <https://doi.org/10.32038/mbqr.2018.07.02>
98. Zhu, Y.; Chen, C.; Zhang, G.; Lin, Z.; Meshram, S.G.; Alvandi, E.: Investigation of west lake ecotourism capabilities using SWOT and TOPSIS decision-making methods. *Sustainability* **15**(3), 1–21 (2023). <https://doi.org/10.3390/su15032464das>
99. Shih, H.S.; Shyur, H.-J.; Lee, E.S.: An extension of TOPSIS for group decision making. *Math. Comput. Model.* **45**(7–8), 801–813 (2007). <https://doi.org/10.1016/j.mcm.2006.03.023>
100. You, P.; Guo, S.; Zhao, H.; Zhao, H.: Operation performance evaluation of power grid enterprise using a hybrid BWM-TOPSIS method. *Sustainability* **9**(12), 1–15 (2017). <https://doi.org/10.3390/su9122329>
101. Adalı, E.A.; Tuş, A.: Hospital site selection with distance-based multi-criteria decision-making methods. *Int. J. Healthc. Manag.* **14**(2), 534–544 (2021). <https://doi.org/10.1080/20479700.2019.1674005>
102. Ghorabae, M.K.; Zavadskas, E.K.; Olfat, L.; Turskis, Z.: Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (EDAS). *Informatica* **26**(3), 435–451 (2015). <https://doi.org/10.15388/Informatica.2015.57>
103. Mishra, A.R.; Rani, P.; Pandey, K.: Fermatean fuzzy CRITIC-EDAS approach for the selection of sustainable third-party reverse logistics providers using improved generalized score function. *J. Ambient. Intell. Humaniz. Comput.* **13**, 295–311 (2022). <https://doi.org/10.1007/s12652-021-02902-w>
104. Zhang, N.; Su, W.; Zhang, C.; Zeng, S.: Evaluation and selection model of community group purchase platform based on WEPLPA-CPT-EDAS method. *Comput. Ind. Eng.* **172**, 1–12 (2022). <https://doi.org/10.1016/j.cie.2022.108573>
105. Kahraman, C.; Ghorabae, M.K.; Zavadskas, E.K.; Onar, S.C.; Yazdani, M.; Oztaysi, B.: Intuitionistic fuzzy EDAS method: an application to solid waste disposal site selection. *J. Environ. Eng. Landsc. Manag.* **25**(1), 1–12 (2017). <https://doi.org/10.3846/16486897.2017.1281139>
106. Stanujkic, D.; Zavadskas, E.K.; Ghorabae, M.K.; Turskis, Z.: An extension of the EDAS method based on the use of interval grey numbers. *Stud. Inform. Control* **26**(1), 5–12 (2017). <https://doi.org/10.24846/v26i1y201701>
107. Aggarwal, A.; Choudhary, C.; Mehrotra, D.: Evaluation of smart-phones in Indian market using EDAS. *Procedia Comput. Sci.* **132**, 236–243 (2018). <https://doi.org/10.1016/j.procs.2018.05.193>
108. Das, P.P.; Chakraborty, S.: Application of grey correlation-based EDAS method for parametric optimization of non-traditional machining processes. *Sci. Iran.* **29**(2), 864–882 (2022). <https://doi.org/10.2420/sci.2020.53943.3499>



109. Mitra, A.: Selection of cotton fabrics using EDAS method. *J. Nat. Fibers* **19**(7), 2706–2718 (2022). <https://doi.org/10.1080/15440478.2020.1821289>
110. Bakır, M.; Alptekin, N.: A new approach in service quality assessment: an application on airlines through CODAS method. *Bus. Manag. Stud. Int. J.* **6**(4), 1336–1353 (2018). <https://doi.org/10.15295/bmij.v6i4.409>
111. Badi, I.; Ballem, M.A.; Shetwan, A.G.: Site selection of desalination plant in Libya by using combinative distance-based assessment (CODAS) method. *Int. J. Qual. Res.* **12**(3), 609–624 (2018). <https://doi.org/10.18421/IJQR12.03-04>
112. Sivalingam, V.; Poogavanam, G.; Natarajan, Y.; Sun, J.: Optimization of atomized spray cutting fluid eco-friendly turning of Inconel 718 alloy using ARAS and CODAS methods. *Int. J. Adv. Manuf. Technol.* **120**, 4541–4564 (2022). <https://doi.org/10.1007/s00170-022-09047-w>
113. The World Bank: Data. 2021. <https://data.worldbank.org/indicator>. Accessed 20 Nov 21
114. European Centre for Disease Prevention and Control—ECDC: Data on the daily number of new reported COVID-19 cases and deaths by EU/EEA country. (2021). <https://www.ecdc.europa.eu/en/publications-data/data-daily-new-cases-covid-19-eueea-country>. Accessed 24 Nov 21
115. Institute for Health Metrics and Evaluation-IHME: COVID-19 projections. (2021). <https://covid19.healthdata.org>. Accessed 24 Nov 21
116. Dinc, M.; Haynes, K.E.: Sources of regional inefficiency: an integrated shift-share, data envelopment analysis, and input–output approach. *Ann. Reg. Sci.* **33**, 469–489 (1999)
117. Ozden, U.H.: Efficiency evaluation of foundation universities in Turkey by using data envelopment analysis (DEA). *Istanbul Univ. J. Sch. Bus. Adm.* **37**(2), 167–185 (2008)
118. AyranciBagriacik, E.: Evaluation of Turkey's effectiveness against OECD and EU member countries in fighting COVID-19. *Erciyes Univ. J. Econ. Adm. Sci.* **60**, 215–233 (2021)

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