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ASSESSING COUNTRY PERFORMANCES DURING THE COVID-19 PANDEMIC: A STANDARD DEVIATION BASED RANGE OF VALUE METHOD

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Abstract: *In this paper, we compare the pandemic management performance of 22 countries that belong to the middle-high income class based on criteria including the pandemic data, population characteristics, and health system capacity. The management of the COVID-19 pandemic requires considering many and often conflicting aspects at the same time which necessitates an MCDM approach. We use a standard deviation (SDV) based range of value (ROV) method which coincides with the black-box nature of the disease. The weights obtained from the SDV method reveal that the number of COVID-19 deaths, current health expenditure, and deaths due to cardiovascular diseases are the most important criteria. The ROV method indicates that most Asian countries are ranked in higher positions due to their strong healthcare systems and quick implementation of social distancing rules. The lowest performances belong to Bulgaria, Montenegro, and Bosnia and Herzegovina. They have experienced an elevated number of deaths due to having an elderly population and inefficient usage of healthcare resources. We also show that extreme poverty is an important determinant of country performance. In countries where poverty is higher, as the case with Indonesia, implementing the social distancing rules becomes almost impossible which affects the overall country performance significantly.*

Keywords: *COVID-19 pandemic, ROV method, SDV method, MCDM, middle-high income countries*

1. Introduction

It has been more than a year since the World Health Organization first declared the new Coronavirus disease (COVID-19) was a pandemic. After one year and several

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waves, COVID-19 caused 113,051,293 cases and more than 2,500,000 deaths[1]. Although we have learned many things about the disease, and several COVID-19 vaccines have been developed, the importance of the studies to clarify the effects of the disease has not been reduced. Any research that helps reduce the burden on the healthcare system and flatten the spread rate is still valuable. In this study, we aim to compare the performance of a relatively homogenous group of countries in their fight against the COVID-19 during the ongoing pandemic. More specifically, we rank the pandemic management performance of 22 countries that belong to the middle-high income class according to the World Bank classifications based on many criteria, namely pandemic data, population characteristics, and health system capacity. The existence of various factors and often conflicting criteria at the same time makes the issue of ranking country performances as a Multi-Criteria Decision Making (MCDM) problem. For this aim, we use a combination of two MCDM techniques, namely the standard deviation approach (SDV) for the criteria weights and range of value (ROV) method in order to compare country performances against COVID-19.

Regarding the aim of our study, we note two related fields of research: The first field investigates how well countries all over the world cope with the pandemic. Adabavazeh et al. (2020) note that benchmarking is essential for the healthcare systems to improve their working process and to be prepared for future public health crises. Hence, it is natural to observe a specific line of research in the COVID-19 literature. These studies concentrate on the performance rankings of different countries with various methodologies. Jamison et al. (2020) examine the performances of 35 countries according to the doubling times of confirmed cases and deaths at three different points in time during the beginning of the pandemic. They demonstrate that although the variation among the cross-country performances is modest initially, the difference between countries gets wider between later days. Aydin and Yurdakul (2020) rank the country performances against COVID-19 by using an extension of data envelopment analysis (DEA) and different machine learning algorithms. They aim to show which factors affect the number of confirmed cases and deaths the most. Maroko et al. (2020) aim to compare the neighborhoods in New York City, the USA, in terms of population characteristics. Olivia et al. (2020) evaluate the current pandemic management of Indonesia by comparing its performance with Lombardy (Italy) and New York (the USA) as well as other Asian countries.

The second group of related works is the ones that apply different decision-making approaches to COVID-19 studies. Among those studies, Shirazi et al., (2020) rank the performance of hospitals in Iran and their capability to meet patients' needs during the pandemic by using FAHP – PROMETHEE methods. Samanlioglu and Kaya (2020) evaluate the intervention strategies that countries have adopted to flatten the epidemiological curve by using the hesitant fuzzy AHP method. Kayapinar Kaya (2020) assesses the impact of COVID-19 on the sustainable development levels of the OECD countries by employing the MAIRCA technique and compares the findings with two other MCDM models, i.e. MABAC and WASPAS. Yiğit (2020) analyzed the performance of OECD countries during the current pandemic by employing the TOPSIS approach. In this study, the healthcare system performance proxies, such as health expenditures, the number of medical staff, and COVID-19 related indicators are employed as criteria,

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[1] Data from: https://www.worldometers.info/coronavirus/ Access Date: 24.02.2021

while 36 OECD countries constitute the alternatives. This study reveals that Asian Pacific countries are the more successful ones in this struggle whereas the European and Middle Eastern countries demonstrate bad performance.

Determining a good country performance against COVID-19 requires considering many types of criteria at the same time. Population characteristics, such as age, accompanying chronic diseases, the level of poverty are important factors in this struggle. Still, the biggest burden is on the healthcare system components. Among the primary determinants of pandemic management success, we can observe the timely detection of the newly infected ones, providing good healthcare, and limiting the number of deaths. The existence of various and conflicting criteria creates a need for MCDM techniques. Hence, we use two MCDM techniques combinedly, namely the SDV and the ROV approaches, to determine the rankings of the countries. To the extent of our knowledge, this is the first study that applies an SDV based ROV method to analyze the country's performances in the battle against the current pandemic. By doing so, we aim to contribute to both lines of the above-mentioned researches.

MCDM is a very common methodology to rank the decision options according to a group of criteria (Hajkowicz & Higgins, 2008). This particular nature allows us to compare the country's performances in the fight against COVID-19. In this sense, the aim of our study is related to the paper by Yiğit (2020). Here, we must mention the significant differences between this paper and ours. Yiğit (2020) considers the early phases of the pandemic with only healthcare-related criteria. However, COVID-19 created a very fast-changing environment in all areas. Therefore, re-evaluating the performance of the countries and showing the differences between the ongoing situation and the early stages even for a short period of time still adds to the efforts that aim to decrease its negative effects. It is also known that the struggle against the COVID-19 does not only depend on healthcare system, but also the characteristics of vulnerable population. These criteria must be added into country comparisons. Unlike Yiğit (2020), we consider population-related criteria such as the prevalence of chronic diseases and the percentage of elderly population. Besides, we focus on a different and more homogenous group of countries. It is natural to draw different conclusions from this comparison relative to a more heterogeneous country group. Last, we use a different combination of MCDM techniques. As a result, we believe that benchmarking the countries in the first year of the pandemic is still important to suggest policy changes for the worst-performing ones.

Bedford et al. (2020) indicate that the struggle against the COVID-19 pandemic is harder for the countries in the low and middle-income groups than the higher-income group countries. The literature, however, mostly concentrates on the USA and European countries where the pandemic hit hard initially. The burden of the pandemic on the healthcare workers and units is devastating even for the better prepared higher-income countries. De Nardo et al. (2020) state that the situation is, even more, overwhelming for low- and middle-income countries where the healthcare facilities are limited and mobility restrictions are difficult to be applied. In this study, we consider the middle-high income group countries, a less examined sample that also includes the origin of the pandemic, i.e. mainland China. We believe that such a comparison will help more disadvantaged countries to be prepared for future infection spreads, to decrease the economic and social effects of pandemics, and to allocate healthcare resources efficiently.

Our findings reveal that Asian countries like Thailand, mainland China and Malaysia produce better rankings in this comparison. These countries are more experienced in the management of infectious diseases due to previous epidemics, i.e. SARS. However, Bosnia and Herzegovina, Bulgaria, and Montenegro have more disadvantaged rankings. Their relative low performance can be attributed to the higher levels of the elderly population and their related co-morbidities as well as the inefficient management of the existing healthcare resources.

We clearly show that countries that are successful in pandemic management have stronger healthcare systems and they have been more prepared for such a disaster. Countries that are ranked in the lower positions either have limited capacity or cannot manage their resources efficiently. Delaying to take necessary social distancing precautions is likely to increase the number of COVID-19 deaths and lowers the country's performance.

The success in pandemic management also depends on population characteristics. Having an elderly population increases the overall burden in the healthcare system because it increases the requirement for long term attention. In distressing times, like the COVID-19 pandemic, along with the co-morbidities, countries experience many difficulties to manage the crisis, no matter how high the level of the current expenditure is. In countries, where poverty is higher, implementing the social distancing rules becomes almost impossible. With that limited access to clean water and other hygiene products, the number of cases and deaths rapidly escalates. Authorities must adopt policies regarding elderly care and people living below the poverty line.

This paper continues with the literature review section that summarizes the related lines of research. The data and methodology section explains the details of the data and the selected MCDM method. Section 4 presents the findings and the policy discussions based on these results. We compare the robustness of our results in Section 5. The last section concludes.

2. Related Literature

Since the beginning of the COVID-19 pandemic, there has been vast literature discussing its effects in every aspect of our lives. Besides discussing the impact of the pandemic on our social and professional lives, many studies examine the effectiveness of different precautions to deal with the COVID-19. In this paper, we aim to compare the performances of countries in the battle against the current pandemic by using a combination of two MCDM techniques. Therefore, in this literature review we specifically focus on the two lines of research: First, we look at the literature that investigates how well countries all over the world cope with the pandemic. In this group, Jamison et al. (2020); Aydin and Yurdakul (2020); Adabavazeh et al. (2020) are highlighted. Second, we examine how different decision-making techniques are used in the COVID-19 studies. In the second group, the studies by De Nardo et al. (2020); Shirazi, et al. (2020); Yiğit (2020), and Kayapinar Kaya (2020) are stand out among the others.

The study by Jamison et al. (2020) is one of the first ones that investigate the county performances against COVID-19. They compare the performance of 35 countries with different characteristics in the early times of the pandemic depending on the doubling times of new cases and COVID-19 related deaths per 1,000,000 population. They aim to show which policy choices of different governments provide better health and economic results. Their results indicate that in the less populated countries, the pandemic started with more severity, but in time, the more populated countries were affected more. Brazil and India have always shown a bad performance in terms of controlling the pandemic. The cases in Iran and Indonesia doubled more quickly in the later comparisons than the initial times. Turkey showed a good performance and its ranking is above the average of 35 countries in terms of both new cases and deaths.

Aydin and Yurdakul (2020) and Adabavazeh et al (2020) employ the DEA method in the analysis of country efficiency. More specifically, Aydin and Yurdakul (2020) develop a novel three-stage DEA model called WSIDEA to identify country performances based on the number of COVID-19 cases and deaths and other population and economic characteristics. They cluster 142 countries into 3 groups and obtain their efficiencies according to the WSIDEA method. The factors that affect country efficiency levels are examined with decision trees and random forest algorithms. Adabavazeh, et al. (2020), on the other hand, employ the traditional DEA method to analyze the efficiency of healthcare units in 71 different countries where population, GDP per capita, day of infection, and the total number of cases are inputs and the number of total recovered patients and total deaths are outputs. They employ a BCC type output-oriented DEA model. Among them, 16 healthcare units including those located in mainland China and Iran are found efficient.

The second line of research applies different decision-making tools in COVID-19 studies, such as MCDM techniques, fuzzy sets, and artificial intelligence. These applications include many different fields, ranging from the prediction of future risks and the effectiveness of the non-healthcare precautions to medicine selection and hospital admissions.

Among the examples of fuzzy sets and artificial intelligence applications in the struggle against COVID-19, the following studies can be examined: Pal et al. (2020) benefit from artificial intelligence to predict long term country-specific risks and to group them as high-risk, low-risk, and recovering countries. Majumder et al. (2020) develop a decision-making tool based on TOPSIS. They try to identify the possible COVID-19 patients depending on their linguistic information in order to help early detection of newly infected people and to send them self-isolation or home quarantine. They replace the Euclidian distance computation of proximity to ideal solutions with supremum distance. Next, they apply an artificial neural network approach to provide real-time monitoring for death values. Si et al. (2021) propose a decision-making approach for appropriate medicine selection by employing fuzzy sets and grey relational analysis. Mishra et al. (2021), following Si et al. (2021), rank alternative medical treatments to apply for the mild cases of Covid-19. They employ an ARAS framework with hesitant fuzzy information. The attribute weights are obtained through the HF-divergence measure. Khatua et al. (2020) employ granular differentiability based fuzzy SEIAHRD model to control the current pandemic in India. Their results indicate that an optimal pandemic control requires more testing to detect the infections, hospital quarantine, and long-term partial lockdowns in the country.

The following group of studies constitutes examples for the application of MCDM techniques to the COVID-19 studies. Sayan et al. (2020) employ two different MCDM techniques, namely fuzzy PROMETHEE and fuzzy TOPSIS to rank seven diagnostic alternatives of COVID-19 based on different criteria such as test sensitivity, cost, usability, false result rates, accessibility, equipment.

Samanlioglu and Kaya (2020) assess the non-healthcare precautions, including mobility and border restrictions, lockdowns, school closures, declaration of a state of emergency in the struggle against the current pandemic by employing a hesitant fuzzy AHP method. De Nardo et al. (2020) use PAPRIKA as an MCDM technique to detect and prioritize the hospital admissions of COVID-19 patients with the potential of quick clinical deterioration in Italy. The criteria weights are based on a survey applied to the experts who deal actively with COVID-19 patients. The PAPRIKA method compares all combinations of criteria pairs. Shirazi, et al. (2020) examine patient satisfaction under normal terms and under times of health crisis, such as the current pandemic. To do so, they rate the hospitals in Iran and determine the factors of patient satisfaction by using a combination of the Fuzzy AHP-PROMETHEE approach. Kayapinar Kaya (2020) assesses the sustainable development performance of OECD countries before and during the COVID-19 pandemic by using MAIRCA as the main analysis method. She compared the rankings of MAIRCA with two other MCDM techniques namely WASPAS and MABAC. She showed that although the pandemic affects negatively all countries' sustainable development levels, developing countries are more negatively impacted. Sangiorgio and Parisi (2020) develop an index to forecast the contagion risk under different mobility scenarios in urban areas to support the decision-making process of local authorities. To do so, they collect data from 257 urban areas in Italy and they design the problem as AHP based multi-criteria approach. Next, they calibrate the model by using the GRG-optimization method and compared the results with an analysis based on the Artificial Neural Networks.

Yiğit (2020) compares the performance of 36 OECD countries by using the TOPSIS method in their struggle against the current disease. She considers the countries as alternatives to rank and employs healthcare indicators as equally weighted criteria. These criteria include the number of COVID-19 patients and deaths, healthcare system expenditures by governments, and current healthcare capacities, such as hospital beds and the number of physicians. She states that although one may observe a high correlation between healthcare expenditures and life expectancy, some countries do not comply with this anticipation. For example, Portugal, Spain, and Israel are among the countries with high life expectancy but their healthcare expenditures are lower than the OECD average. As a result, as indicated by Yiğit (2020), in a worldwide healthcare crisis, this situation leads to different performance rankings. The findings of Yiğit (2020) suggest that Asian countries in the OECD sample react more proactively to the ongoing pandemic relative to European countries and the USA.

The studies applying several decision-making tools on COVID-19 are summarized below in Table 1.

Our study aims to combine these two lines of research mentioned above. In particular, we aim to rank the countries in the middle-high income group based on their performances against the current pandemic while employing MCDM techniques. Although these techniques provide transparent and consistent comparisons as noted by De Nardo et al. (2020), the studies applying MCDM to the country performances are rather scarce. In this sense, our aim coincides most with the study by Yiğit (2020).

Table 1. The Studies Applied Decision-Making Tools in the Struggle Against COVID-19

Authors	The Aim of the Paper	The Decision-Making Tool
Yiğit (2020)	To compare the country performances based on the healthcare criteria in the battle against the current pandemic	TOPSIS
Sayan et al. (2020)	To compare the COVID-19 diagnostic tool alternatives	Fuzzy PROMETHEE and Fuzzy TOPSIS
Samanlioglu and Kaya (2020)	To rank the precautions other than the healthcare system measures against COVID-19	Hesitant Fuzzy AHP
De Nardo et al. (2020)	To prioritize the hospital admissions of not currently but potentially urgent patients.	PAPRIKA
Kayapinar Kaya (2020)	To rank the sustainable development levels of countries before and during the COVID-19 pandemic	MAIRCA results compared with WASPAS and MABAC
Shirazi, et al. (2020)	To rate the hospitals in Iran according to the patient satisfaction under normal and pandemic conditions	A combination of Fuzzy AHP-PROMETHEE
Sangiorgio and Parisi (2020)	To predict the contagion risk of COVID-19 based on different mobility restriction scenarios	AHP based multi-criteria approach and GRG-optimization method. The results are compared with those obtained from ANN.
Khatua et al. (2020)	To find the requirements for an optimal pandemic control in India	Granular differentiability based fuzzy SEIAHRD
Majumder et al. (2020)	To detect the potential COVID-19 patients based on their verbal information	Supremum distance TOPSIS method combined with ANN
Pal et al. (2020)	To determine the long term COVID-19 risks of a country	Artificial Intelligence
Si et al. (2021)	To choose appropriate medicine to treat COVID-19 patients	Fuzzy sets and grey relational analysis
Mishra et al. (2021)	To rank medical treatment alternatives of mild COVID-19 patients	ARAS framework with hesitant fuzzy information

However, there are important differences between these two papers. We consider a more homogenous and less investigated sample of countries than Yiğit (2020). Benchmarking of countries is more intuitive when the sample becomes less heterogeneous. In addition to the healthcare indicators employed in Yiğit (2020), we also consider population-based criteria, such as the elderly ratio, extreme poverty, and the existence of co-morbidities in our analysis. These criteria are also known as important determinants of the number of COVID-19 deaths and cases. Therefore, the performance comparison of countries in this battle must consider these criteria as well. The criteria ranking is done based on an objective weighting method called the SDV approach. The country comparisons are realized based on the ROV method. We believe that our selection of criteria weighting and alternative ranking methods overlap the black-box nature of the ongoing pandemic. Last, we employ a later time period for the ongoing pandemic to compare the performances. Such a comparison in this fast-changing environment is very valuable.

3. Data and Methodology

This study collects data for 22 countries that are classified as middle-high income group by the World Bank[2]. These countries are Albania, Argentina, Armenia, Bosnia and Herzegovina, Brazil, Bulgaria, mainland China, Columbia, Costa Rica, Dominican Republic, Ecuador, Georgia, Indonesia, Iran, Kazakhstan, Malaysia, Mexico, Montenegro, Paraguay, Russia, Thailand, and Turkey. As of the date of the analysis, this sample covers 25% of the total cases and 32% of the COVID-19 related deaths worldwide. These countries create a rather homogeneous group to provide a ranking for their performances and also contain mainland China, which is the origin of the pandemic and the most discussed country for its crisis management methods. The study begins with the identification of performance criteria and application of the SDV method to weight them. Next, the ROV method will be applied as the main analysis method, where the results are compared TOPSIS and EDAS approaches. For clarity, we show the general framework of our work in Figure 1.

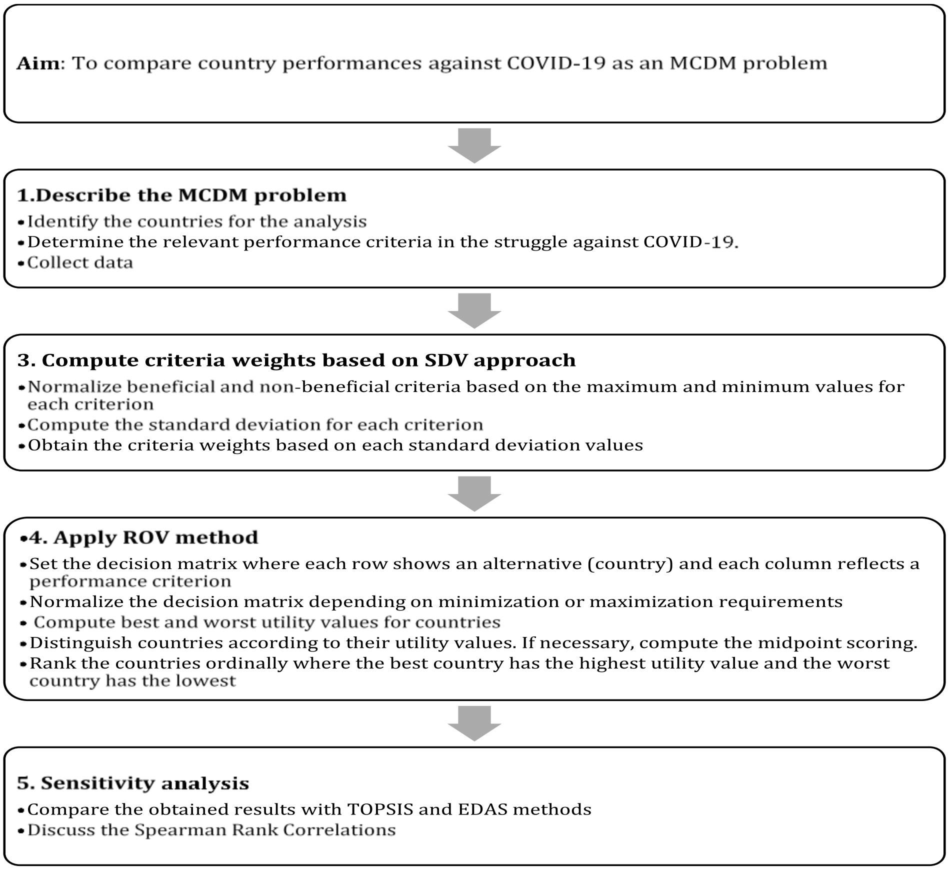

Figure 1. General working diagram of the study

[2] The World Bank, https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups, Access Date: 24.02.2020

For the comparisons, 12 evaluation criteria have been selected based on the studies by Adabavazeh et al. (2020), Aydin and Yurdakul (2020), George et al. (2020), and Khafaie and Rahim (2020). Those criteria, their codes, and the sources from which the data is obtained are provided in Table 2.

Table 2. The Criteria used in the Analyses, Their Codes and Data Sources

Criteria	Codes	Definition	Data Source
Total Cases	C1	The number of patients that have positive PCR tests per 100.000 people	https://www.worldometers.info/coronavirus (Access Date: 20.01.2021)
Total Deaths	C2	Total number of deaths due to COVID-19 per 100.000 people	https://www.worldometers.info/coronavirus (Access Date: 20.01.2021)
Extreme Poverty	C3	The percentage of the population living less than daily $1.90	https://ourworldindata.org (Access Date: 20.01.2021)
Cardiovascular Death Rate	C4	The annual number of deaths due to cardiovascular diseases per 100.000 people in a given country.	https://ourworldindata.org (Access Date: 20.01.2021)
Diabetes Prevalence	C5	The rate of people aged between 20 and 79 with type 1 and type 2 diabetes	https://ourworldindata.org (Access Date: 20.01.2021)
Female Smokers	C6	The number of women who smoke in a given country.	https://ourworldindata.org (Access Date: 20.01.2021)
Population Aged 65 +	C7	The rate of people aged 65 and above to the total population in a given country.	The World Bank Database (2019)
Male Smokers	C8	The number of men who smoke in a given country.	https://ourworldindata.org (Access Date: 20.01.2021)
Current Health Expenditure	C9	The amount of health expenditures as a percentage of the GDP of a given country.	The World Bank Database (2018)
Total Recovered	C10	The number of patients recovered from COVID-19 infection per 100.000 people.	https://www.worldometers.info/coronavirus (Access Date: 20.01.2021)
Hospital Beds Per Thousand	C11	The number of hospital beds per 1000 people in a given country.	https://ourworldindata.org (Access Date: 20.01.2021)
Total Tests	C12	The number of total PCR tests to diagnose COVID-19 infections per 100.000 people.	https://www.worldometers.info/coronavirus (Access Date: 20.01.2021)

3.1. Standard Deviation Method

The standard deviation method is used to weight the criteria in this analysis. This method is developed by Diakoulaki et al. (1995) and the weights are determined according to the standard deviations of criteria. This is an objective weighting method in which decision-makers do not influence establishing the relative importance of criteria. This method gives lower weights to an attribute as long as the attribute has similar values in different alternatives. As a result, the contrasting attribute in the alternatives becomes much highlighted (Diakoulaki et al., 1995; Hassan et al., 2015). Diakoulaki et al. (1995) indicate that when the criteria are interdependent, the results might be misleading. However, removing some of these interdependent criteria might cause a loss of important information as well. In this case, using the standard deviation method in the weight determination might be a solution. This feature of the standard deviation method becomes more important when the nature of the COVID-19 pandemic is considered. As an example, the criteria in Table 2 include total confirmed cases, total tests, and deaths. Naturally, as more testing is performed, more cases will be confirmed and more COVID-19 deaths will be detected. However, the omission of any of these criteria will result in a loss of information.

While obtaining the weights into the standard deviation method, first, a normalization process is applied through Eq. (1) and Eq. (2) to provide a common and measurable basis for criteria that differ in scale and units (Diakoulaki et al., 1995; El-Santawy & Ahmed, 2012):

$$x'_{ij} = \frac{x_{ij} - \min_{i=1}^{m}(x_{ij})}{\max_{i=1}^{m}(x_{ij}) - \min_{i=1}^{m}(x_{ij})} \quad \text{i= 1,2,…,m; j = 1,2,… ,n (for beneficial)} \tag{1}$$

$$x'_{ij} = \frac{\max_{i=1}^{m}(x_{ij}) - x_{ij}}{\max_{i=1}^{m}(x_{ij}) - \min_{i=1}^{m}(x_{ij})} \quad \text{i=1,2,…,m; j=1,2,…,n (for non-beneficial)} \tag{2}$$

There are m alternatives and n criteria. Here, x_{ij} is the raw score of i^{th} alternative for criterion *j*. $(x')_{mxn}$ is the matrix after the normalization process, while max x_{ij} and min x_{ij} are the maximum and minimum values of x_{ij} respectively. The standard deviation for each criterion is computed with the aid of Eq. (3).

$$SDV_j = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(x'_{ij} - \overline{x'_j})^2} \tag{3}$$

$\overline{x'_j}$ is the average of the values of the j^{th} criterion after the normalization process, and j=1,2,…,n.

After obtaining standard deviation values, the weightings of criteria are computed by using Eq. (4).

$$w_j = \frac{SDV_j}{\sum_{j=1}^{n} SDV_j} \quad \text{j = 1,2,…, n} \tag{4}$$

3.2. Range of Value (ROV) Method

ROV approach is developed by Yakowitz and Szidarovxzky (1993). Hajkowicz and Higgins (2008) state that this method is especially beneficial when it is not possible or meaningful to provide quantitative weights. After one year of the pandemic, COVID-19 still protects its black box nature in many aspects. Therefore, instead of assigning quantitative weights, we find the ROV method more suitable to assess the country's performances during the pandemic. To the extent of our knowledge, this is to first paper that combines the ROV approach with the standard deviation method in both MCDM and COVID-19 literature.

ROV method basically computes the best and worst utility values for each alternative (Hajkowicz & Higgins, 2008). To calculate those values, the utility function is maximized and minimized, respectively. As a result, the performance rankings of alternatives are obtained.

The procedure for the application of the ROV method is simple which constitutes another strong point for this approach. The application steps are as follows (Madić et al., 2016):

Step 1: The relevant criteria to assess the existing alternatives are set.

Step 2: The decision matrix is formed. In this matrix, each row represents an alternative whereas each column reflects a criterion.

Step 3: The decision matrix is normalized at this stage. For beneficial criteria, where maximization is applied, the normalization is done by using Eq. (5) below:

$$\overline{x}_{ij} = \frac{x_{ij} - \min_{i=1}^{m}(x_{ij})}{\max_{i=1}^{m}(x_{ij}) - \min_{i=1}^{m}(x_{ij})} \tag{5}$$

For the non-beneficial criteria, however, where minimization is applied, the normalization is done by using Eq. (6) below:

$$\overline{x}_{ij} = \frac{\max_{i=1}^{m}(x_{ij}) - x_{ij}}{\max_{i=1}^{m}(x_{ij}) - \min_{i=1}^{m}(x_{ij})} \tag{6}$$

In both Eq (5) and (6), x_{ij} is the raw score of i^{th} alternative for criterion *j*. There are m alternatives. max x_{ij} and min x_{ij} are the maximum and minimum values of x_{ij}, and the $\overline{x}_{ij}$ is the normalized values.

Step 4: For each alternative, the best and worst utility values are computed as in Eq. (7) and (8).

$$\text{Max: } u_i^{+} = \sum_{j=1}^{n} \overline{x}_{ij} * w_j \tag{7}$$

$$\text{Min: } u_i^{-} = \sum_{j=1}^{n} \overline{x}_{ij} * w_j \tag{8}$$

Where u_i^{+} *and* u_i^{-} represent utility values and w_j reflects the criterion weight. The summation of the criterion weights must be equal to 1, and $w_j \geq 0$.

When u_i-≥u_i'+, the i^{th} alternative shows a better performance than the alternative *i'* without looking at the quantitative weights. If this basis is not sufficient to distinguish the alternatives, a midpoint scoring (u_i) can be used to allow the following ranking as such:

$$u_i = \frac{u_i^{-} + u_i^{+}}{2} \tag{9}$$

Step 5: In this last step, the alternatives are ordinally ranked based on their u_i values. The best alternative has the highest u_i, whereas the worst one has the lowest u_i.

4. Findings

Following the above procedure, the criteria that are presented in Table 2 are first weighted by using the standard deviation method. Next, the decision matrix is formed. Here, C1,…., C8 represent non-beneficial criteria to be minimized, while C9, C10, C11, and C12 are beneficial criteria, to be maximized. The decision matrix can be seen in Table 3.

Table 3. The Initial Decision Matrix

Countries	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
Albania	2381.8	44.8	1.1	304.2	10.1	7.1	14.2	51.2	5.3	1470.4	2.9	11105.5
Argentina	4021.9	101.9	0.6	191.0	5.5	16.2	11.2	27.7	9.6	3591.0	5.0	12677.7
Armenia	5567.6	101.3	1.8	341.0	7.1	1.5	11.5	52.1	10.0	5201.8	4.2	21246.1
Bosnia and Herzegovina	3577.1	135.8	0.2	329.6	10.1	30.2	17.2	47.7	8.9	2698.4	3.5	17304.2
Brazil	4033.0	99.6	3.4	178.0	8.1	10.1	9.3	17.9	9.5	3584.2	2.2	13551.3
Bulgaria	3044.5	122.7	1.5	424.7	5.8	30.1	21.3	44.4	7.3	2510.0	7.5	18543.8
Mainland China	7.0	0.3	0.7	261.9	9.7	1.9	11.5	48.4	5.4	5.8	4.3	11447.2
Colombia	3820.3	97.3	4.5	124.2	7.4	4.7	8.8	13.5	7.6	3548.2	1.7	18555.9
Costa Rica	3685.2	48.6	1.3	138.0	8.8	6.4	9.9	17.4	7.6	2870.2	1.1	11012.0
Dominican Republic	1815.5	22.7	1.6	266.7	8.2	8.5	7.3	19.1	5.7	1356.5	1.6	9065.9
Ecuador	1333.3	82.4	3.6	140.4	5.6	2.0	7.4	12.3	8.1	1147.3	1.5	4742.1
Georgia	6663.6	79.5	4.2	496.2	7.1	5.3	15.1	55.5	7.1	6368.2	2.6	54798.1
Indonesia	338.8	9.7	5.7	342.9	6.3	2.8	6.1	76.1	2.9	282.1	1.0	3138.1
Iran	1611.5	68.6	0.2	270.3	9.6	0.8	6.4	21.1	8.7	1372.2	1.5	10413.8
Kazakhstan	1171.8	15.6	0.1	466.8	7.1	7.0	7.7	43.1	2.9	839.3	6.7	32097.7
Malaysia	506.2	1.8	0.1	260.9	16.7	1.0	6.9	42.4	3.8	399.5	1.9	13036.4
Mexico	1292.9	110.7	2.5	152.8	13.1	6.9	7.4	21.4	5.4	981.2	1.4	3284.4
Montenegro	8969.5	119.9	1.0	387.3	10.1	44.0	15.4	47.9	8.4	7592.0	3.9	34205.6
Paraguay	1740.1	35.7	1.7	199.1	8.3	5.0	6.6	21.6	6.7	1420.7	1.3	8769.1
Russia	2460.8	45.0	0.1	431.3	6.2	23.4	15.1	58.3	5.3	2096.8	8.1	67602.4
Thailand	18.0	0.1	0.1	109.9	7.0	1.9	12.4	38.8	3.8	13.8	2.1	1749.1
Turkey	2868.2	28.9	0.2	171.3	12.1	14.1	8.7	41.1	4.1	2737.5	2.8	33402.3

The next step is to normalize each element in the decision matrix. This process is done according to Eq. (1) for beneficial criteria and according to Eq. (2) for non-beneficial criteria. The normalized decision matrix is presented in Table 4.

Table 4. Normalized Decision Matrix

	Criteria											
Countries	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**
Albania	0.74	0.67	0.82	0.50	0.59	0.85	0.46	0.39	0.33	0.19	0.26	0.14
Argentina	0.55	0.25	0.91	0.79	1.00	0.64	0.66	0.76	0.94	0.47	0.56	0.17
Armenia	0.38	0.25	0.70	0.40	0.86	0.98	0.64	0.38	1.00	0.68	0.45	0.30
Bosnia and Herzegovina	0.60	0.00	0.98	0.43	0.59	0.32	0.27	0.45	0.84	0.35	0.35	0.24
Brazil	0.55	0.27	0.41	0.82	0.77	0.78	0.79	0.91	0.93	0.47	0.17	0.18
Bulgaria	0.66	0.10	0.75	0.19	0.97	0.32	0.00	0.50	0.63	0.33	0.91	0.26
Mainland China	1.00	1.00	0.89	0.61	0.62	0.97	0.64	0.43	0.35	0.00	0.47	0.15
Colombia	0.57	0.28	0.21	0.96	0.83	0.91	0.82	0.98	0.67	0.47	0.10	0.26
Costa Rica	0.59	0.64	0.79	0.93	0.71	0.87	0.75	0.92	0.66	0.38	0.01	0.14
Dominican Republic	0.80	0.83	0.73	0.59	0.76	0.82	0.92	0.89	0.40	0.18	0.08	0.11
Ecuador	0.85	0.39	0.38	0.92	1.00	0.97	0.91	1.00	0.74	0.15	0.07	0.05
Georgia	0.26	0.42	0.27	0.00	0.86	0.90	0.41	0.32	0.59	0.84	0.22	0.81
Indonesia	0.96	0.93	0.00	0.40	0.93	0.95	1.00	0.00	0.00	0.04	0.00	0.02
Iran	0.82	0.50	0.98	0.58	0.64	1.00	0.98	0.86	0.81	0.18	0.07	0.13
Kazakhstan	0.87	0.89	1.00	0.08	0.86	0.86	0.89	0.52	0.01	0.11	0.81	0.46
Malaysia	0.94	0.99	1.00	0.61	0.00	1.00	0.94	0.53	0.12	0.05	0.12	0.17
Mexico	0.86	0.19	0.57	0.89	0.33	0.86	0.91	0.86	0.35	0.13	0.05	0.02
Montenegro	0.00	0.12	0.84	0.28	0.59	0.00	0.39	0.44	0.78	1.00	0.40	0.49
Paraguay	0.81	0.74	0.71	0.77	0.75	0.90	0.96	0.85	0.53	0.19	0.04	0.11
Russia	0.73	0.67	1.00	0.17	0.94	0.48	0.41	0.28	0.34	0.28	1.00	1.00
Thailand	1.00	1.00	1.00	1.00	0.86	0.97	0.58	0.58	0.13	0.00	0.15	0.00
Turkey	0.68	0.79	0.98	0.84	0.41	0.69	0.82	0.55	0.18	0.36	0.25	0.48

In the last step of this method, the standard deviation of each performance criterion and its relevant weight is computed by using Eq. (3) and Eq. (4). The results are shown in Table 5.

Table 5. Standard Deviations and Criterion Weights

	Total Cases (C1)	Total Deaths (C2)	Extreme Poverty (C3)	Cardiovascular Death Rate (C4)	Diabetes Prevalence (C5)	Female Smokers (C6)	Aged 65 + (C7)	Male Smokers (C8)	Current Health Expenditures (C9)	Total Recovered (C10)	Hospital Beds Per 1000 (C11)	Total Tests (C12)
SDV_j	0.25	0.33	0.30	0.31	0.24	0.27	0.27	0.27	0.31	0.27	0.30	0.25
w_j	0.07	0.10	0.09	0.09	0.07	0.08	0.08	0.08	0.09	0.08	0.09	0.08

SDV_j is the calculated standard deviation for each criterion.
W_j is the weight for each criterion

It is observed from the criteria weights in Table 5 that the most important criteria determining the country's performances are Total Deaths (C2), Current Health Expenditures (C9), and Cardiovascular Death Rate (C4). The least important criteria are, however, Diabetes Prevalence (C5), Total Cases (C1), and Total Tests (C12).

Table 6. Criteria Weights Comparison Matrix

	w_j	Total Cases (C1) 7.40%	Total Deaths (C2) 9.78%	Extreme Poverty (C3) 8.80%	Cardiovascular Death Rate (C4) 9.11%	Diabetes Prevalence (C5) 7.23%	Female Smokers (C6) 7.97%	Aged 65 + (C7) 8.06%	Male Smokers (C8) 8.10%	Current Health Expenditures (C9) 9.28%	Total Recovered (C10) 7.91%	Hospital Beds Per 1000 (C11) 8.84%	Total Tests (C12) 7.54%
Total Cases (C1)	7.40%		0.76	0.84	0.81	1.02	0.93	0.92	0.91	0.80	0.93	0.83	0.98
Total Deaths (C2)	9.78%	1.32		1.11	1.07	1.35	1.23	1.21	1.21	1.05	1.24	1.11	1.30
Extreme Poverty (C3)	8.80%	1.19	0.90		0.97	1.22	1.10	1.09	1.09	0.95	1.11	1.00	1.17
Cardio. Death Rate (C4)	9.11%	1.23	0.93	1.04		1.26	1.14	1.13	1.13	0.98	1.15	1.03	1.21
Diabetes Prevalence (C5)	7.23%	0.98	0.74	0.82	0.79		0.91	0.90	0.89	0.78	0.91	0.82	0.96
Female Smokers (C6)	7.97%	1.08	0.81	0.91	0.87	1.10		0.99	0.98	0.86	1.01	0.90	1.06
Aged 65 + (C7)	8.06%	1.09	0.82	0.92	0.88	1.11	1.01		1.00	0.87	1.02	0.91	1.07
Male Smokers (C8)	8.10%	1.09	0.83	0.92	0.89	1.12	1.02	1.00		0.87	1.02	0.92	1.07
Current Health Exp. (C9)	9.28%	1.25	0.95	1.05	1.02	1.28	1.16	1.15	1.15		1.17	1.05	1.23
Total Recovered (C10)	7.91%	1.07	0.81	0.90	0.87	1.09	0.99	0.98	0.98	0.85		0.89	1.05
Hospital Beds Per 1000 (C11)	8.84%	1.20	0.90	1.00	0.97	1.22	1.11	1.10	1.09	0.95	1.12		1.17
Total Tests (C12)	7.54%	1.02	0.77	0.86	0.83	1.04	0.95	0.94	0.93	0.81	0.95	0.85	

W_j is the weight for each criterion

As noted before, the standard deviation method determines the criteria weights based on the contrasting attributes. In other words, this method puts less importance if the attribute distributes more evenly among the alternatives, but places more emphasis if it differs significantly. From Table 5, it is seen that the number of cases and number of tests per one hundred thousand people are similar for the countries in the sample. However, the differences in the number of deaths per one hundred thousand and current health expenditures become prominent across countries.

Based on the weights in Table 5, we also construct the matrix in Table 6 to show the relative importance for any pair of criteria following De Nardo et al. (2020). This matrix is interpreted from left to right and it is not symmetric. For example, Table 6 indicates that the number of COVID-19 deaths is slightly more important than the deaths due to cardiovascular diseases (1.07) and the current health expenditures (1.05), but 1.32 times more important than the number of confirmed cases. The extreme poverty level is as important as the number of hospital beds. In fact, current health expenditures and the extreme poverty level are two of the criteria that show the biggest discrepancies among the sample countries. The diabetes level in a population, however, is the least important criterion in this analysis.

Table 7. The Results of the ROV Method

Countries	Results			
	u_i^-	u_i^+	u_i	Rankings
Thailand	0.59	0.03	0.60	1
Iran	0.52	0.11	0.58	2
Paraguay	0.54	0.08	0.58	3
Ecuador	0.52	0.09	0.57	4
Costa Rica	0.52	0.10	0.57	5
Dominican Republic	0.53	0.07	0.56	6
Mainland China	0.52	0.08	0.56	7
Argentina	0.46	0.19	0.55	8
Kazakhstan	0.49	0.12	0.55	9
Turkey	0.49	0.10	0.54	10
Malaysia	0.51	0.04	0.53	11
Colombia	0.45	0.13	0.52	12
Brazil	0.43	0.15	0.51	13
Russia	0.38	0.22	0.49	14
Armenia	0.37	0.21	0.48	15
Mexico	0.45	0.05	0.47	16
Albania	0.42	0.08	0.46	17
Indonesia	0.42	0.00	0.42	18
Georgia	0.28	0.20	0.38	19
Bosnia and Herzegovina	0.30	0.16	0.37	20
Bulgaria	0.28	0.18	0.37	21
Montenegro	0.22	0.22	0.33	22
Average			0.50	

After obtaining the criterion weights, we find the rankings of country performances in the struggle against COVID-19 by employing the ROV approach. Since the first three steps in the ROV approach are the same as the weighting procedure of the standard deviation model, the normalized decision matrix shown in Table 4 is used for the ROV method as well. The best and worst utility values are computed according to Eq. (7)

and Eq. (8). Next, for each alternative, the mid values (u_i) are calculated by using Eq. (9). According to these values, countries, which constitute the alternatives, are ranked. The overall results of the ROV method are given in Table 7.

The results in Table 7 demonstrate that Thailand, Iran, and Paraguay perform the best in the fight against the COVID-19 pandemic, while Bosnia and Herzegovina, Bulgaria, and Montenegro are the worst-performing countries. The average performance score is 0.4984. The starting point of the pandemic, mainland China has the 7th ranking.

From Table 7, it is seen that the high-performing countries have lower COVID-19 deaths, higher healthcare expenditures, lower poverty rates, and much lower rates of cardiovascular diseases. Bosnia and Herzegovina and Bulgaria, the countries with the lowest performance, have higher COVID-19 deaths and the highest elderly population in the sample. Montenegro is one of the countries with the lowest COVID-19 deaths. Since the beginning of the pandemic, Montenegro has applied strict physical distancing rules. However, when the population characteristics are closely observed, it is seen that smoking and diabetes are very common. The cardiovascular death rates are elevated. Together with the large elderly population, the struggle against the current pandemic becomes tougher.

Interestingly, the countries with the lowest performance have relatively high levels of current health expenditures and hospital bed capacity. In the case of Bulgaria, the lack of the medical workforce, especially in terms of nursing staff created difficulties for the treatment of COVID-19 disease. Particularly during the wave of October 2020, the number of infected medical professionals increased heavily and generated a shortage in workforce capacity[3]. The Bulgarian government was also criticized for not putting into force necessary non-healthcare precautions timely. The physical distancing rules were started to be applied late. Bosnia and Herzegovina, on the other hand, caught relatively short of the COVID-19 pandemic. There was no initial emergency action plan in the country for such a disaster. Although the healthcare resources are higher than the sample average in terms of expenditures and hospital beds, the resources seem to be inefficiently managed during the pandemic[4].

These findings indicate that each country struggles with this global health crisis with its own resources. Healthcare capacity and the amount of healthcare expenditure matter, albeit, are not enough. The efficient management of available resources and the existence of an emergency action plan are also necessary. In addition, these three countries have the highest elderly percentage in the sample. An older population increases the demand for long term healthcare attention (Yiğit, 2020). This situation raises the burden on the overall system particularly in times of crisis and limits the success of the "flattening the curve" efforts.

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[3] COVID-19 Health System Response Monitor (HSRM) https://www.covid19healthsystem.org/countries/bulgaria/livinghit.aspx?Section=2.2%20Workforce&Type=Chapter#7Physicalinfrastructure Access Date: 09.07.2021

[4] COVID-19 Health System Response Monitor (HSRM) https://www.covid19healthsystem.org/countries/bosniaandherzegovina/livinghit.aspx?Section=2.1%20Physical%20infrastructure&Type=Section Access Date: 09.07.2021

When we turn our attention to the Asian countries, we observe that Thailand, Malaysia, and mainland China are among the least affected countries by the COVID-19 pandemic in the world (Olivia et al., 2020). Thailand has a very low rate of COVID-19 deaths which brings the country to the first ranking. In fact, it is the only middle-high income country that has a position in the top ten health systems in the Global Health Security index ratings[5]. Together with mainland China, Thailand is among the countries that apply very strict measures since the beginning of the pandemic. The country had an influenza pandemic plan and people have been used to wear face masks because of previous epidemics and air pollution (Issac et al., 2021). Issac et al. (2021) indicate that the success behind Thailand's COVID-19 management is due to the primary healthcare workers that also surveil individual mobility and high usage of technological tools.

Mainland China has the 7th ranking in this comparison. China is known for its very restrictive measures since the beginning of the pandemic. On the global level, it has a low amount of total deaths due to effective coordination between its local and central administrations and the applied social control levels (Jiang, 2020). Comparing to the country figures in our sample, mainland China has COVID-19 deaths less than the sample average as well. It is position is mostly due to its averaged current healthcare expenditure levels and relatively higher cardiovascular death rates in society.

Malaysia has the average performance ranking according to our analysis (11th place). The country has lower COVID-19 deaths. Its population is relatively young and the cardiovascular deaths rates are close to the sample average. Hamzah et al. (2021) investigate the performance of Malaysia against COVID-19 very thoroughly with a network DEA approach. They examine the performance into three sub-areas, namely community surveillance, non-critical and critical medical care needs. They show that the highest inefficiency is originated from the medical care that must be applied to patients with critical conditions. The country demonstrates efficient contact tracking and surveillance, on the other hand. Hamzah et al. (2021) point out that this is mostly because of the existing emergency plans and the country's elevated preparedness levels. The inference of Hamzah et al. (2021) is also confirmed by our analysis. We observe that Malaysia has much lower current health expenditures than the sample average which lowers the position of the country and causes a middle ranking despite its high preparedness level.

In contrast to most Asian countries, Indonesia produces a much lower performance in the struggle against the pandemic. De Nardo et al. (2020) indicate that in low and middle-income countries, the poverty rates are higher, so implementing the social distancing rules is much difficult as well as accessing clean water. This is the case with Indonesia. It is mostly due to very high rates of extreme poverty, cardiovascular disease prevalence, low amount of hospital beds per capita (Olivia et al., 2020). Setiati and Azwar, (2020) point out that the number of beds in intensive care units per capita is among the lowest in Asian countries. They are mostly located in specific areas, so

[5] This global index compares 195 countries according to 6 categories, including disease prevention, detection and reporting, and health system capabilities. According to this index, Thailand has an 73.2 index score and had 6th place out of 195 countries in 2019. https://www.ghsindex.org/about/ and GHS Homepage https://www.ghsindex.org/ Access Date: 06.08.2021

not evenly distributed. Healthcare workers cannot reach enough protective suits while dealing with COVID-19 patients. The country has also been criticized for reacting late to the initial cases while its neighbors, Malaysia and Singapore, had already started mass testing (Olivia et al., 2020).

Turkey has 10th place in the performance ranking. The country has lower health expenditures and hospital bed capacity than the sample average. It owes its relatively high position to the low number of COVID-19 deaths, much lower cardiovascular disease rates, and younger population. It had an influenza pandemic plan before the current pandemic which facilitated being prepared for the spread of this disease.

As noted by Jamison et al. (2020), the efforts of "flattening the curve" play a significant role in those rankings. The delay in the implementation of such measures can also be a determinant. Brazil, for instance, does not have a high rate of chronic diseases or deaths, has a relatively younger population and expenditures for the healthcare system as a percentage of GDP are relatively higher. However, the Brazilian government has minimized the necessary precautions. The social distancing implementations are very weak and the extreme poverty in the country is high. This explains the very high rates of deaths related to COVID-19.

In contrast to Brazil, the countries located in central and south America mostly demonstrated good performance against COVID-19. Paraguay, Ecuador, Costa Rica, and the Dominican Republic have positions from 3rd to 6th in the sample. Among these countries, Ecuador and Costa Rica have advanced Global Health Index rankings[6]. The population percentage of 65 years and over is relatively small in Paraguay. The country also experiences a small number of COVID-19 deaths. UNDP Paraguay report (2020) reveals that the country was fighting the Dengue epidemic when the COVID-19 pandemic started. Because of the previous experience from the Dengue outbreak, the Paraguay government responded quickly to this new disease and applied physical distance measures and movement restrictions early.

We observe that a bigger healthcare capacity and lower poverty levels maintain a strong stance against health system crises even with higher levels of disease spread. As the healthcare system becomes larger and more evenly distributed, this battle gets easier. However, as we see from the Bosna and Herzegovina example, the efficient usage of the existing capacity is crucial to be successful. The initial preparedness of the countries and their willingness to apply social distancing measures are also important to limit the number of deaths. Brazil, for example, has a relatively greater overall score in the rankings of the Global Health Security Index. However, the government's reluctance to put in force necessary measures caused a significant number of deaths.

Poverty levels, on the other hand, determine the applicability of non-healthcare precautions. In the countries where most of the population lives below the poverty line, it is almost impossible to achieve physical distancing and personal hygiene. This environment accelerates the new numbers of COVID-19 cases. Taken together with the limited healthcare facilities, it is natural to observe a higher number of deaths.

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[6] https://www.ghsindex.org/country/ecuador/ and https://www.ghsindex.org/country/costarica/ Access Date: 06.08.2021.

5. Sensitivity Analysis

To show that our findings from the SDV based ROV approach are robust, we also conduct TOPSIS and EDAS analyses and compare the results. As discussed before, the ROV method depends on the comparison of best and worst utility functions for each alternative. Based on these utility functions, we obtain the rankings of alternatives in an easy manner. TOPSIS method, which is widely used in different areas (for example, Mimović et al. 2021), computes distances from positive ideal and negative ideal solutions. The alternative is ranked based on its proximity to the positive ideal and its remoteness from the negative ideal. The EDAS method, however, calculates the distances from average solutions. The positive and negative ideals are not required to be estimated (Ghorabaee et al., 2015).

We apply both TOPSIS and EDAS methods by employing the criteria weights obtained from SDV analysis. The comparisons of the rankings from these three methods are demonstrated in Figure 2.

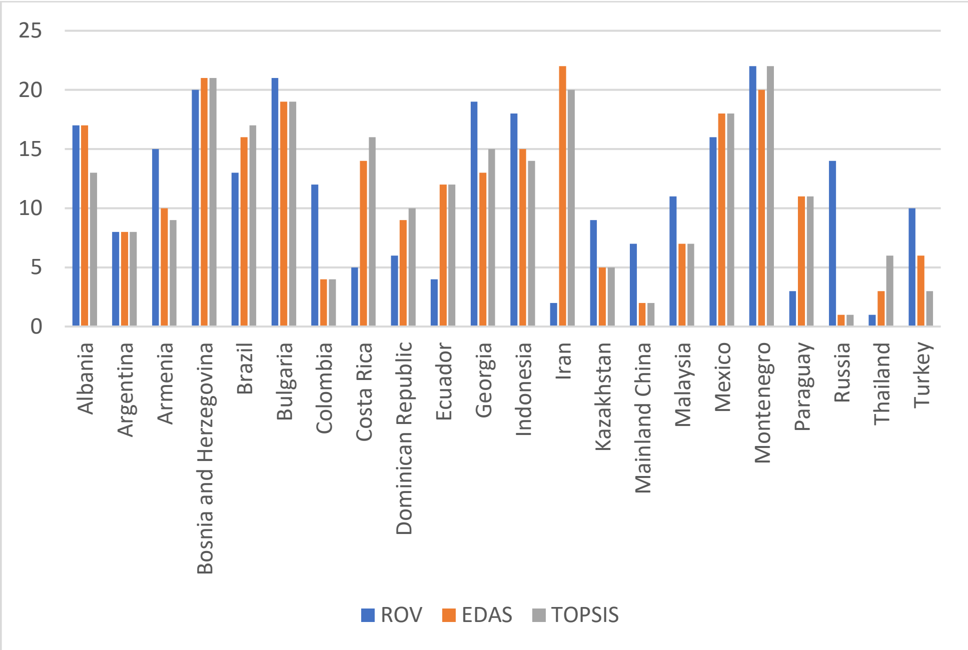

Figure 2: The rankings from ROV, EDAS, and TOPSIS methods respectively

The comparisons show that the rankings from these three methods are quite parallel to each other. Particularly, the rankings of the low-performing countries stay very similar. In addition to the visual analysis, we also look at the Spearman rank correlations and Wilcoxon rank tests. The former one is applied to observe the direction and strength of the relation between the ranks obtained from these three methods. The latter test shows whether the mean ranks are statistically different. Both are non-parametric tests since MCDM analysis provides results that are not normally distributed. The findings are presented in Table 8.

Table 8. The Results for Spearman Rank Correlations and Wilcoxon Rank Tests

Spearman Rank Correlations			
	ROV	EDAS	TOPSIS
ROV	1		
EDAS	0.69	1	
TOPSIS	0.61	0.97	1

Wilcoxon Rank Tests		
H_0	ROV=EDAS	ROV=TOPSIS
Z	0.488	0.261
p-value	0.626	0.806

The findings from Spearman rank correlations indicate that the ROV method produces positive and fairly high association with EDAS and TOPSIS methods (0.69 and 0.61 respectively). In the second part of Table 8, the mean ranking of ROV is tested against EDAS and TOPSIS. The null hypotheses here are the mean ranking of ROV is not different than the mean ranking of EDAS and TOPSIS respectively (first and second columns). The p-values for both tests are much higher than any acceptable significance levels, so the null hypotheses cannot be rejected.

The overall results suggest that the ROV method has a computational advantage over more popular methods such as TOPSIS and EDAS and offers similar rankings.

6. Conclusion

This study aims to shed light on the black-box nature of the COVID-19 pandemic by comparing the country's performances in this global struggle. To do so, the performance of 22 countries, which all belong to high–middle income group according to the World Bank classifications, are assessed. Since several and conflicting criteria are used, the performance ranking against managing the current pandemic is considered a multicriteria decision-making problem. The benchmarking is made with the standard deviation-based ROV approach. To the extent of our knowledge, this is the first study that combines these two methods and applies them to the COVID-19 pandemic.

In the struggle against COVID-19, there are some important parameters such as the properties of the healthcare system, application of physical distancing rules and mobility restrictions, and the population characteristics. Among them, particularly the healthcare capacity, proxied by the number of hospital beds and the current healthcare expenditures, becomes prominent. Our analysis confirms this expectation and demonstrates that Thailand has the highest ranking in our sample. The country's very high position in the Global Health Security Index and the very low number of COVID-19 deaths are no surprise, in this sense. However, the findings from the lowest ranking countries reveal that the efficient usage of healthcare resources matters as much as its amount. These countries have a relatively high amount of healthcare resources, but they have still experienced elevated numbers of COVID-19 deaths. As seen from the Bosnia and Herzegovina case, the lack of an emergency healthcare plan makes much more difficult to obtain efficiency in the usage of resources.

We also observe that the high-ranked countries are mostly praised for their quick response to take necessary non-healthcare restrictive precautions and the low-ranked ones are highly criticized for the same reason. It is seen that many Asian countries, for instance, Thailand, mainland China, and Malaysia, applied strict social distancing rules, whereas Brazil, Bulgaria, and Indonesia are the ones where these rules are weak or sometimes non-existent.

Our analysis also confirms that population characteristics are other determinants of country performances against COVID-19. The low-ranking countries mostly have an elder population. Age brings co-morbidities with itself which increases the likelihood of COVID-19 deaths. It also boosts the requirement of long-term healthcare attention, which creates another burden on the already overwhelmed healthcare system. Another population characteristic that affects country rankings is the level of poverty. In countries, where the poverty level is higher, implementing the social distancing rules and distant working becomes almost impossible. In fact, we show that extreme poverty is as crucial as the number of hospital beds in this battle. Combining the fact that these areas have diminished access to clean water, the spread of the disease is inevitable. This is one of the social consequences of COVID-19: It contributes to the gap between rich and poor. Policymakers should consider policies that decrease the level of poverty to control future pandemics as well. The vaccination policies against COVID-19 will also have importance. Since the delivery of vaccines requires more time in the middle-high income countries in comparison to their developed counterparts, the public must comply with the social distancing rules to avoid future deaths.

For future pandemics, countries that manage their healthcare resources more efficiently and that are quick to apply social distancing rules will be more successful to eliminate the negative impacts. However, policymakers must also focus on elderly care and poverty levels in their countries.

There are some limitations of this study that must be mentioned: First, the very quick changes in the pandemic landscape restrict the generalizability of the findings to some extent. This is why the COVID-19 studies that compare the beginning of the pandemic to the ongoing situation are valuable. Second, we have only used quantitative data in this analysis. Further researches may consider qualitative data and appropriate techniques such as fuzzy MDCM to compare the performance of countries. Last, at the beginning of the pandemic, the definitions of COVID-19 deaths and patients were not clear for all countries[7]. In time, there has been a convergence in these definitions. However, this situation may create a limitation for this study in terms of comparability.

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[7]Some countries have made a distinction between "deaths *from* COVID-19" and "deaths *with* COVID-19". The same difference was valid at the beginning of the pandemic for the positive cases. Some counted a person as COVID-19 patient depending on the clinical diagnosis, others required a positive test result.
Source:https://eurohealthobservatory.who.int/monitors/hsrm/analyses/hsrm/how-comparable-is-covid-19-mortality-across-countries Access Date: 05.08.2021

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