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-RESEARCH ARTICLE-

ASSESSING AND CLUSTERING COUNTRIES BASED ON COVID-19 AND RELATED INDICATORS: CLUSTERING AND MULTIMOORA APPROACHES

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Abstract

The COVID-19 pandemic has been one of humanity's most difficult times. The pandemic spread and impact were not at the same level for all countries. Investigation of the variation of the countries is crucial for policymakers. Therefore, the study proposed to cluster countries according to the number of COVID-19 cases, deaths, vaccinations and related socioeconomic (life expectancy, elderly population, GDP per capita, health expenditure), health risk (smoking prevalence, alcohol consumption, environmental health index) and disease prevalence and mortality indicators (diabetes prevalence and mortality from cardiovascular disease, cancer, diabetes, or chronic respiratory disease) and rank them by using MULTIMOORA (MOORA plus the full multiplicative form) in an integrated way. The data set consists of 148 countries and 13 indicators. K-Means algorithm was used to cluster countries. The optimal cluster was found as six according to the Silhouette Index. The cluster consisted of mostly developed countries ranked as the best-performing cluster. It had the highest number of COVID-19 vaccinations, GDP per capita, share health expenditure in GDP, life expectancy, elderly population portion, and environmental performance index values, and the lowest mortality of chronic diseases. Moreover, Norway, Iceland, and Denmark were the best-performing countries in this cluster. In addition to this, Turkey was located in the second-ranked cluster. It was also determined that COVID-19 indicators (cases, deaths, and vaccinations) were related to GDP per capita, environmental index, and life expectancy. As a result, policymakers can develop pandemic policies for country groups separately, and assistance can be provided in this regard according to the priority order of the countries.

Keywords: *COVID-19, clustering analysis, K-means, MULTIMOORA*

JEL Codes: *C38, C44*

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ÜLKELERİN COVID-19 VE İLİŞKİLİ FAKTÖRLERE GÖRE KÜMELENMESİ VE DEĞERLENDİRİLMESİ: KÜMELEME VE MULTİMOORA ANALİZLERİ

Öz

COVID-19 pandemi dönemi insanlığın yaşadığı en zor dönemlerden bir tanesidir. Pandeminin yayılımı ve etkisi bütün ülkeler için aynı deredecede olmamış. Ülkeler arasındaki bu farklılıkların incelenmesi politika yapıcılar için önem arzetmektedir. Bu nedenle, çalışmanın amacı, ülkelerin COVID-19 vaka sayısı, vefat sayısı, aşılama sayısı ve ilişkili sosyoekonomik (politika sıklığı indeksi, doğumda beklenen yaşam süresi, yaşlı nüfus oranı, kişi başına düşen GSYH, sağlık harcamasının GSYH oranı), hastalık ve sağlık risk faktörlerini (yaşlı nüfus oranı, sigara içme sıklığı, alkol tüketimi, çevresel performans indeksi, diyabet prevelansı, kalp hastalığı, kanser ,diyabet ve KOAH'dan ölümlülük oranı) benzer özelliklerine göre kümelemek ve bir çok kriterli karar verme yöntemi olan MULTIMOORA (MOORA plus the full multiplicative form) yöntemi ile performanslarını sıralanmaktır. Çalışmanın verileri, halka açık kaynaklardan elde edilmiş, 148 ülke için elde edilen 13 değişkenden oluşmaktadır. Kümeleme analizi için K-Means algoritması kullanılmıştır. Optimal küme sayısı Silhoute Index kullanılarak altı olarak belirlenmiştir. Çoğunlukla gelişmiş ülkelerden oluşan küme en iyi performansa sahip olduğu belirlenmiştir. Bu kümedeki ülkeler en yüksek COVID-19 aşılama oranı, kişi başına düşen GSYH, sağlık harcamasının GSYH oranı, doğumda beklenen yaşam süresi, ve çevre performans indeksine, en düşük kronik hastalıklardan ölüm oranın sahiptir. Bunun yanında, Norveç, İzlanda ve Danimarka bu kümedeki en iyi performansa sahip ülkeler olarak bulunmuştur. Türkiye ise ikinci en iyi performansa sahip kümede yer almaktadır. COVID-19 değişkenleri (vaka sayısı, vefat sayısı, aşılama sayısı) kişi başına düşen GSYH, çevresel performans indeksi ve doğumda beklenen yaşam süresi ile ilişkili bulunmuştur. Sonuç olarak, politika yapıcılar ülke gruplarına yönelik politikalar geliştirebilir ve ülkelerin öncelik sırasına göre pandemi gibi olağanüstü durumlar için önlemler alabilir..

Anahtar Kelimeler: *COVID-19, kümeleme analizi, K-means, MULTIMOORA*

JEL Kodları: *C38, C44*

"Bu çalışma Araştırma ve Yayın Etiğine uygun olarak hazırlanmıştır."

1. INTRODUCTION

The COVID-19 pandemic has been one of humanity's most challenging times. The first cases were initially documented in December 2019 in Wuhan, China; the World Health Organization (WHO) declared it a pandemic in March 2020. Until now, on August 22, 2022, globally, there were 769,774,646 confirmed cases and 6,955,141 confirmed deaths from the pandemic (WHO, 2023b). Although WHO declared that

COVID-19 has not been a Public Health Emergency of International Concern (PHEIC) since May 5, 2023, WHO still supports countries with COVID-19 health policy (WHO, 2023b). Also, it has been reported as the third leading cause of death in the world since 2020 (Christopher Troeger, 2023), and it is the fifth leading cause of death in Turkey(TÜİK, 2023).

Globally, people have struggled with health, economic, and social difficulties due to the pandemic. The governments restricted social life, like quarantine, social distancing, school arrangements, and travel to protect their people. COVID-19 lockdowns caused a global economic fall: increasing unemployment, a decline in trade, education, tourism, agriculture, food, entertainment, sports.. etc., sectors, sustainability, and quality of life (Naseer et al., 2023, p. 1).

Although the pandemic is a global issue, not all countries are affected by it equally. Several studies investigate its health, social, and economic reasons (Aydin & Yurdakul, 2020, p. 1; Rizvi, Umair, & Cheema, 2021, p. 1; Zarikas, Poulopoulos, Gareiou, & Zervas, 2020, p. 1). Clustering analysis, one of the machine learning methods, is a widely used analysis that investigates variations. Classifying countries according to distinctive features for COVID-19 helps decision makers to better health policies to deal with the disease. It is stated that the cluster analysis that is used the most in studies examining factors associated with COVID-19 outcomes is the K-Means analysis (Hussein & Abdulazeez, 2021).

In addition, it is complicated to order countries according to their needs due to its complex criteria. MCDM approaches have gained popularity for COVID-19 models due to their multicriteria of nature and the complexity of the health and socioeconomic systems (Sotoudeh-Anvari, 2022, p. 1). Therefore, MCDM methods can be used to evaluate the countries' relative performance through COVID-19 and related indicators.

The study proposes to cluster countries according to COVID-19 and related socioeconomic, disease, and health risk factors and rank them by using MULTIMOORA in an integrated way. Since the countries have different levels according to the COVID-19 pandemic, it is necessary to rank their performances in terms of indicators to provide better support. The study uses machine learning and MCDM methods to compare and determine the countries' needs objectively. Therefore, the study questions are summarized as follows:

1) What are the similarities and differences among countries based on COVID-19 outcomes and related variables?
2) Which countries are similar or dissimilar according to COVID-19 outcomes and associated indicators?
3) What is the performance ranking of countries in each cluster according to COVID-19 outcomes and related indicators?

Countries are initially clustered to COVID-19 and related indicators and characteristics for this aim. Then, the relative performance level of nations is determined according to the research variable.

The paper is organized as follows: Section 1.2 includes a literature review, Section 2 presents the proposed methodology, Section 3 consists of the findings, and Section 4 explains the discussion of the study; lastly there is a conclusion.

1.1. Literature Review

Due to the massive impact around the world of COVID-19, several studies have investigated country variations since the beginning of the pandemic.

Various studies are using different variables and countries. Rizvi et al. (Rizvi et al., 2021, p. 1) clustered countries according to COVID-19, socioeconomic, disease prevalence, and environmental performance indicators using K-Means. It determined that disease prevalence was highly related, whereas environmental health indicators were weakly related to COVID-19. Another work by Carrillo et al. (Carrillo-Larco & Castillo-Cara, 2020, p. 1) used K-Means clustering countries COVID-19 and air pollution, disease prevalence, socioeconomic and health system coverage features. They indicated that clusters stratify according to number of COVID-19 cases but not deaths. Using hierarchical clustering analysis, Zarikas et al. (Zarikas et al., 2020, p. 1) segmented countries according to daily COVID-19 cases. In another study, Gohari et al. (Gohari, Kazemnejad, Sheidaei, & Hajari, 2022, p. 1) applied K-Means algorithms to find different patterns of countries COVID-19 daily cases and deaths. They stated that clusters were formed according to government health policies. Aydın and Yurdakul (Aydin & Yurdakul, 2020, p. 1) used a three-stage model to assess countries' performance using clustering, data envelopment analysis, and random forest and decision tree models using COVID-19, risk factors, disease prevalence and mortality, socioeconomic and health system indicators. They indicated that smoking, diabetes rates, and GDP do not affect countries' performance in the pandemic. Malki (Malki et al., 2020, p. 1) also found a relationship between the location’s climate and COVID-19 indicators. In addition, Hussein and Abdulazeez (Hussein & Abdulazeez, 2021) reviewed COVID-19 studies using clustering analysis and found that the K-Means algorithm is the most widely used clustering analysis.

In addition to this, Tekin (Tekin, 2020, p. 336) used a hierarchical clustering method for clustering OECD countries with COVID-19, health systems, and financial features. Çağdaş (Çağdaş, 2020, p. 137) examined during, before, and after pandemic periods using financial variables by Hierarchical and K-Means clustering analysis. Küçükefe (Küçükefe, 2020, p. 280) investigated OECD countries' GDP and COVID-19 indicators by K-Means clustering. The study showed that the countries with the highest COVID-19 death rates had the most significant economic downfalls. Kocabıyık et al. (Kocabıyık, Karaatlı, & Bolat, 2022) segmented OECD countries by using economic variables. Demircioğlu and Eşiyok (Demircioğlu & Eşiyok, 2020, p. 369) examined OECD and EU countries using health indicators by hierarchical clustering. Kartal et al. (Kartal, Balaban, & Bayraktar, 2021, p. 9) used K-means algorithms to classify countries according to COVID-19 indicators.

Moreover, MCDM methods have been used in several studies evaluating COVID-19 terms. Anvari (Sotoudeh-Anvari, 2022, p. 1) reviewed 72 MCDM studies investigating 52 types of different aims. Some studies in the literature apply MCDM methods using COVID-19 variables in countries (Aydin & Yurdakul, 2020, p. 1; Kumru, Yiğit, & Hayran, 2022, p. 944).

2. METHODOLOGY

2.1. Data Collection

It was collected from 148 countries and 13 indicators, which were all continuous, displayed in Table 1. The data was obtained from the World Health Organization (WHO), World Bank, and World and Our World in Data websites. The analysis were performed based on the latest available data for the year 2021 for most variables since it was the latest year with all variables available. For this reason, cumulative numbers of 2021 for COVID-19 indicators were collected.

Table 1: The Study Indicators and Data Sources

Variable name	Variable Code	Desirable Value	Data Source
Cumulative confirmed deaths per million	CCD	Min	
Cumulative confirmed cases per million	CCC	Min	COVID-19 indicators
Total vaccinations per hundred	TVC	Max	(Our World in Data, 2023)
Stringency Index	SI	Max	
Life expectancy	LE	Max	
Elderly population (% of aged 65 and over in the population)	EP	-	Socioeconomic indicators
		Max	(The World Bank, 2024)
GDP per capita	GDP		
Health expenditure (% of GDP)	HGDP	Max	
		Min	Health Risk indicators
Smoking prevalence	SP		(WHO, 2023a)
Alcohol consumption	AC	Min	
		Max	Health Risk indicator (Wolf,
Measure of Environmental Performance Index	EPI		Emerson, Esty, de Sherbinin, & Wendling, 2022)
Diabetes prevalence	DP	Min	Disease prevalence and
Mortality from cardiovascular disease, cancer, diabetes, or chronic respiratory disease	MCCDC	Min	mortality indicators (The World Bank, 2024)

The variables were determined through a literature review of studies examining the relationships between countries' COVID-19 outcomes and socioeconomic variables (Aydin & Yurdakul, 2020; Demircioğlu & Eşiyok, 2020; Kocabıyık et al., 2022;

Kumru et al., 2022; Rizvi et al., 2021; Valero & Valero-Gil, 2021). As a result, the indicators can be summarized as four headings: COVID-19 (COVID-19 cases and deaths, vaccinations, and stringency index), socioeconomic (life expectancy, elderly population, GDP per capita, health expenditure), health risk (smoking prevalence, alcohol consumption, environmental health index) and disease prevalence and mortality indicators (diabetes prevalence and mortality from cardiovascular disease, cancer, diabetes, or chronic respiratory disease). SI measures the strictness of the country's COVID-19 policies and is calculated from nine different categories such as stay-at-home, school, public place, and work restrictions. A higher score means higher restrictions. EPI is a measure of environmental challenges of a country calculated from 40 indicators with 11 subheadings and three headings such as air quality, climate change, water resources..etc. (Wolf et al., 2022).
In the data pre-processing process, all variables are standardized according to the mean is zero and standard deviation is one method. Outlier detection analysis was also performed, and outlier values changed with the min or maximum of the data.

2.2. Analysis

A two-step approach was developed to integrate cluster analysis and MCDM methods. Firstly, the countries were clustered according to study variables. Secondly, the MCDM model was employed to rank countries by considering study indicators for each cluster. Also, groups were ranked by using an MCDM method.

Table 2: Correlation of Study Variables

	CCD	CCC	TVC	SI	LE	EP	GDP	HGDP	SP	AC	EPI	DP	MCDC
CCD	1	0.665**	0.270**	0.059	0.328**	0.546**	0.114	0.388**	0.378**	0.455**	0.407**	0.03	-0.242**
CCC		1	0.536**	0.041	0.575**	0.627**	0.452**	0.441**	0.453**	0.555**	0.603**	0.095	-0.357**
TVC			1	0.142	0.824**	0.571**	0.604**	0.438**	0.249**	0.326**	0.525**	0.255**	-0.589**
SI				1	0.135	0.045	0.06	-0.094	0.072	0.09	-0.049	0.132	0.026
LE					1	0.720**	0.702**	0.482**	0.328**	0.386**	0.657**	0.271**	-0.738**
EP						1	0.574**	0.620**	0.474**	0.671**	0.769**	-0.089	-0.534**
GDP							1	.459**	0.101	0.405**	0.697**	0.01	-0.612**
HGDP								1	0.198*	0.445**	0.598**	-0.088	-0.416**

SP	1	0.276**	0.180*	0.084	0.058
AC		1	0.614**	-0.286**	-0.340**
EPI			1	-0.048	-0.581**
DP				1	0.003
MCDC					1

*p<0.05; **p<0.01

Correlation analysis was used to detect association between variables to find correlated variables (p<0.05) (Table 2). Significant, moderate, positive relationships exist between CCD-EP, CCD-AC, and CCD-EPI (0.546;0.455;0.407, respectively). There are significant strong correlations between CCC-EP and CCC-EPI (0.627;0.603, respectively). There are significant, moderate, positive relationships between CCC-LE, CCC-TVC, and CCC-AC, CCC-GDP, CCC-SP, and CCC-HGDP (0.575;0.536;0.555;0.453;0.452;0.441, respectively). There is a significant positive, very strong correlation between TVC and LE (0.824). A significant, strong, positive relationship exists between TVC and GDP (0.604). Significant, moderate, positive relationships exist between TVC-EP,TVC-EPI, and TVC-HGDP (0.571;0.525;0.438, respectively). There is a significant, moderate, negative relationship between TVC-MCDC (-0.589).

Clustering algorithms were performed by using the K-means algorithm. All analyses were performed R Studio 2022.07.2 with factoextra, clustertrend, NbClust, clValid packages. The number cluster, K, should be chosen by the researcher, as it might be challenging. There are methodologies to decide the optimal cluster.

In literature, internal cluster validity indices are used to decide the optimal cluster. These indices measure clusters according to the object's closeness in the cluster (compactness) and separation (separation of clusters). This study uses the Dunn Index (Dunn, 1974, p. 95) and the Silhouette Index (Rousseeuw, 1987, p. 53). Dunn Index aims to maximize interclass validity and minimize intra-cluster validity. The Silhouette Index quantifies the degree of similarity between an object and its own cluster relative to other clusters. These clusters were calculated using the clValid package in R. As a result, six cluster was chosen as an optimal cluster.

After that, discriminant analysis was used to test cluster validity. Table 3 shows the summary result of it. All discriminant functions are significant; the first discriminant function explains 96 % of the variance. Also, the discriminant function estimated the clusters with 100% accuracy. Therefore, it can be concluded that six groups are valid for this data set.

Table 3: Cluster validity result of discriminant analysis

Discriminant Function	Eigenvalue	Percentage of Variance (%)	Canonical Correlation	Wilk's Lambda	Chi-Square	Sig
1	11.671	63.40	0.96	0.002	836.704	p<0.001
2	3.599	19.60	0.885	0.029	487.548	p<0.001
3	1.834	10.00	0.804	0.133	277.738	p<0.001
4	0.917	5.00	0.7	0.376	134.482	p<0.001
5	0.387	2.10	0.528	0.721	44.976	p<0.001

MULTIOMOORA was applied to rank countries for each cluster separately also clusters. It determined the level of performance of countries and clusters according to research variables. To obtain MULTIMOORA, the decision matrix of the study contains 148 regions and 13 indicators, so it is a 148x13 matrix. It has 1924 elements. The desirable values of the indicators (which value is better for the country's performance: minimum or maximum) are given in Table 1.

2.2.1. K-Means Clustering

Clustering algorithms are type of unsupervised learning methods aiming to segment the data similar characteristic. The clusters should have high within-cluster homogeneity and high between-cluster heterogeneity (Hair et al., 2018, p. 218). There are three types of clustering algorithms: hierarchical, partitioning, and density-based. The major advantage of partitioning strategies is that they enhance the quality of the clustering, making it superior to the original form. The hierarchical methods are to gradually organize clusters by either splitting up the larger clusters or connecting the smaller ones with one another. Density-based clustering methods are another clustering technique that links subjects that mark enough high data points to form clusters (Hussein & Abdulazeez, 2021, p. 2675).

K-Means is a partitioning type of clustering algorithm. It partitioned data into K (user-defined) clusters with its centroid (mean of a cluster) and iteratively assign observations until its criteria were met. The purpose of the criteria is to make the distance between the observations in the cluster minimum and the distance between the other clusters maximum. Euclidean distance is used to calculate the distance. Since K-means clustering analysis is easy to implement, efficient and flexible compared to other algorithms, it is widely used in many areas.

2.2.2. MULTIMOORA

It used MULTIMOORA as an MCDM method because it is more robust than other single methods due to integrating three methods (Hafezalkotob, Hafezalkotob, Liao, & Herrera, 2019, p. 151). Initially, Brauers and Zavadskas (Willem Karel Brauers &

Kazimieras Zavadskas, 2006, p. 445) proposed MOORA (Multi-Objective Optimization by Ratio analysis), which combines ratio and reference point approaches. After that, They extended it as MULTIMOORA by adding a Full Multiplicative Form and applying dominance theory to obtain final raking (Willem Karel M. Brauers & Zavadskas, 2010, p. 5).

***The Ratio System of MOORA*:** MOORA method starts with a decision matrix, X (its elements), xij, denote ith alternative of jth objective (i=1,2,⋯,m and j=1, 2,⋯, n). MOORA consists of two methods, ratio system and the refrence point system.
Ratio system specifies data normalization by comparing an objective's alternative to all of the objective's values.

$$x_{ij}^{*} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^{2}}} \quad (1)$$

where x_{ij}^{*} denotes ith alternative of jth objective. For optimization, these responses x_{ij}^{*} are added (if the optimum value is maximum) or subtracted (if the optimum value is minimum) to produce a sum for each alternative:

$$y_j^{*} = \sum_{j=1}^{g} x_{ij}^{*} - \sum_{j=g+1}^{n} x_{ij}^{*} \quad (2)$$

where g=1,⋯, n denotes number of objectives to be maximized. Each result per alternative is then ranked in descending order of the y_j^{*} shows the final preference.

***The Reference Point of MOORA*:** The reference point method relies on the ratios derived from the Ratio System. This theory starts from the already normalized ratios as defined in the formula (1). Every element of the normalized responses matrix is recalculated, and the ranks are assigned based on deviations from the reference point and the Tchebycheff Min-Max by giving formula

$$\text{Metric:} \underset{(j)}{min} \left\{ \underset{(i)}{max} \left| r_j - x_{ij}^{*}) \right| \right\} \quad (3)$$

The outcomes for each alternative are then ranked in ascending order.

The Full Multiplicative Form and MULTI-MOORA: Full Multiplicative Form method (Willem Karel M. Brauers & Zavadskas, 2010, 2011) incorporates both the maximization and minimization of a multiplicative utility function. The i-th alternative's overall utility can be expressed as a dimensionless number:

$$U_i = \frac{A_i}{B_i} \quad (4)$$

where $A_i = \prod_{j=1}^{g} x_{ij}$, i=1,2….n denotes the product of objectives of the i-th alternative to be maximized with g = 1,..., m being the number of objectives to be maximized and $B_i = \prod_{j=g+1}^{m} x_{ij}$ denotes the product of objectives of the i-th alternative to be minimized with $m - g$ being the number of objectives to be minimized.

Thus, MULTIMOORA is a summary of MOORA and the Full Multiplicative Form. The theory of dominance (Willem Karel M. Brauers & Zavadskas, 2011) allows for the classification of the final MULTIMOORA ranks.

For implementation, all the features are used to rank the country's conditions. Firstly, it is determined the optimal values for the indicators: confirmed deaths (minimum value better the performance), confirmed cases (minimum value better the performance), the total vaccinations (maximum the value better the performance), stringency index (maximum the value better the performance), life expectancy (maximum the value better the performance), GDP per capita and health expenditure (maximum the values better the performances), smoking prevalence and alcohol consumption (minimum values better the performances), environmental performance index (maximum the value better the performance), diabetes prevalence and mortality from chronic diseases (minimum values better the performances). Brauers et al. (Willem K. M. Brauers, Baležentis, & Baležentis, 2012) used to criticize the subjects in MULTIMOORA in 3 groups: best condition countries (best performance), less favorable countries (medium performance), and the least favorable countries (low performance) for studies. Then, normalized the indicators using Equation (1), Equations (2) for Ratio System. Thirdly, Equation (3) applicated the ratios obtained in Equation (1) to obtain the distances to the Reference Point of MOORA. Then, the Full Multiplicative Form calculated using the decision matrix to rank the countries. Finally, the final classification was made with dominance theory.

The K-Means algorithm was chosen as a clustering tool because it is practical, flexible, and easy to implement compared to other methods. MULTIMOORA is preferred because it is a more robust MCDM method that uses three methods together.

3. RESULTS

The K-Means clustering approach for COVID-19 and related variables led to six clusters. Table 4 shows the summary statistics of clusters. The clustered countries using K-Means and their MULTIMOORA rankings are displayed in Table 5 and Table 6. Among 148 countries, 30 countries (20%) belong to Cluster-1, 11 countries (7%) belong to Cluster-2, 36 (24%) countries belong to Cluster-3, and 20 (14%), 30 (20%), and 21 (14%) countries belong to the Cluster-4, Cluster-5 and Cluster-6, respectively. Clusters are also evaluated according to MULTIMOORA methodology; as a result, the fifth cluster ranked as the first, and the sixth cluster ranked as the last.

Table 4: Summary Statistics of the Clusters

	Cluster-1			**Cluster-2**			**Cluster-3**		
	Min	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**
CCD	1,952	111,383	55,430	15,255	191,142	80,901	281	57,981	7,189
CCC	3.83	5949.68	1405.42	135.86	979.61	543.98	10.21	1520.37	154.16
TVC	28.89	155.01	108.19	133.69	240.19	180.19	0.34	69.26	18.60
SI	8.33	77.78	47.29	31.29	54.63	45.17	6.48	73.15	37.87
LE	63.63	78.72	72.84	72.54	83.44	77.05	52.53	71.59	61.44
EP	3.81	14.95	7.54	1.14	12.92	5.07	2.17	5.34	3.18
GDP	2,065	28,260	7,685	9,063	77,710	32,078	364	8,636	1,755
HGDP	3.82	10.31	6.98	2.39	6.66	5.05	2.01	15.53	5.40
SP	5.00	34.80	14.07	8.00	30.70	16.98	3.50	27.80	11.56
AC	0.43	9.69	4.90	0.00	4.35	1.57	0.04	15.09	4.46
EPI	28.00	56.20	42.62	26.30	52.40	40.10	24.90	50.90	34.46
DP	2.42	17.11	9.33	10.99	22.02	15.56	0.99	15.67	4.67
MCCDC	9.50	22.70	15.12	9.50	23.20	16.80	16.10	42.70	23.65
	Cluster-4			**Cluster-5**			**Cluster-6**		
	Min	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**
CCD	72,557	249,638	143,034	2,651	215,507	111,132	93	203,956	34,806
CCC	583.22	4501.36	2673.95	9.84	2872.38	1247.31	4.00	1658.00	411.48
TVC	54.28	203.91	114.99	130.29	275.36	182.56	5.04	198.85	101.24
SI	19.44	69.44	41.47	26.85	74.28	46.24	29.63	85.08	56.83
LE	68.85	77.37	73.58	73.68	84.45	81.66	65.35	78.21	70.14
EP	8.61	20.80	16.28	11.09	27.05	17.77	3.19	10.64	5.56
GDP	4,828	27,944	14,808	9,500	133,590	52,106	1,211	12,618	3,975
HGDP	6.27	9.98	7.78	5.77	18.82	10.63	2.53	9.85	4.97
SP	20.20	39.80	30.27	12.00	35.10	22.16	14.50	44.10	27.38
AC	6.92	20.50	11.06	4.21	12.94	10.11	0.02	8.66	3.67
EPI	37.40	61.40	50.35	46.70	77.90	60.68	18.90	40.90	29.51
DP	3.67	10.55	6.79	3.28	10.79	6.44	4.00	17.65	8.74
MCCDC	14.30	25.50	20.13	7.30	16.60	10.10	15.90	37.70	24.92

Cluster-1 consisted of developing countries. It had the fourth-highest number of confirmed COVID-19 cases and vaccinations and the second-highest number of COVID-19 deaths and stringency index. It also had the fourth-highest GDP per capita and life expectancy values. According to MULTIMOORA, Trinidad and Tobago ranked as the first country, and Honduras ranked as the last country in this cluster.

Table 5: Clustered Countries According to K-Means and Their MULTIMOORA Ranking Results (Clusters1-4)

Cluster-1		Cluster-2		Cluster-3	
Countries	**Rank**	**Countries**	**Rank**	**Countries**	**Rank**
Trinidad and Tobago	1	United Arab Emirates	1	Mauritania	1
Ecuador	2	Qatar	2	Congo, Rep.	2
Costa Rica	3	Singapore	3	Kenya	3
El Salvador	4	Kuwait	4	Senegal	4
Bhutan	5	Saudi Arabia	5	Ghana	5
Panama	6	Malaysia	6	Cameroon	6
Dominican Republic	7	Mauritius	7	Zimbabwe	7
Brazil	8	Oman	8	Tajikistan	8
Mexico	9	Brunei Darussalam	9	Niger	9
Bahamas	10	Turkiye	10	Angola	10
Thailand	11	Bahrain	11	Guinea	11
Albania	12			Cote d'Ivoire	12
Venezuela, RB	13	**Cluster-4**		Gabon	13
Cabo Verde	14	**Countries**	**Rank**	Tanzania	14
Colombia	15	Slovak Republic	1	Uganda	15
Paraguay	16	Argentina	2	Liberia	16
Jamaica	17	Poland	3	Zambia	17
Bolivia	18	Czechia	4	Haiti	18
Nicaragua	19	Uruguay	5	Togo	19
Guatemala	20	Lithuania	6	Ethiopia	20
Jordan	21	Belarus	7	Namibia	21
Belize	22	Russian Federation	8	Burkina Faso	22
Peru	23	Latvia	9	Mali	23
Barbados	24	Ukraine	10	Benin	24
Suriname	25	Estonia	11	Malawi	25
Iran, Islamic Rep.	26	Serbia	12	Sudan	26
Algeria	27	Seychelles	13	Congo, Dem. Rep.	27
Sri Lanka	28	Croatia	14	South Africa	28
Tunisia	29	Romania	15	Sierra Leone	29
Honduras	30	Bulgaria	16	Madagascar	30
		Georgia	17	Mozambique	31
		Hungary	18	Afghanistan	32
		Bosnia and Herzegovina	19	Djibouti	33
		Moldova	20	Nigeria	34
				Chad	35
				Lesotho	36

Cluster-2 comprised of 11 countries, a developed (Singapore) and ten developing countries. Turkey was also in this cluster. It had the second-highest the number of COVID-19 vaccinations, the third-highest cases, and the fourth-highest deaths and stringency index. It also had the second-highest GDP per capita and life expectancy and the highest diabetic prevalence values. The United Arab Emirates ranked first, Bahrain last, and Turkey tenth in this cluster.

Cluster 3 consisted of both developing and least developed countries. The overall performance of the cluster is the fourth. It had the least number of COVID-19 cases, deaths, vaccinations, and stringency index. It also had the lowest GDP per capita, life expectancy, percentages of the elderly population, smoking prevalence, and diabetic prevalence values. Mauritania performed best, and Lesotho was the least-performing country in this cluster.

Cluster-4 comprised of both developed and developing countries and ranked as the fifth cluster. It had the highest number of COVID-19 cases and deaths, the third-highest vaccinations, and the second-least stringency index. In addition, it had the highest value in terms of smoking prevalence and alcohol consumption, the third-highest GDP per capita and life expectancy, and the second-highest EPI, sharing health expenditure in GDP and elderly population proportions. The Slovak Republic ranked first, and Moldova last in this cluster.

Cluster-5 consisted of 28 developed and two developing countries (Cuba and Chile). It had the highest number of COVID-19 vaccinations, the second-highest cases, and the third-highest deaths and stringency index. It also had the highest GDP per capita, share health expenditure in GDP, life expectancy, elderly population portion, and EPI values, and the lowest mortality of chronic diseases. Norway, Iceland, and Denmark were this cluster's best-performing countries. United States, Cuba, and Slovenia ranked last, respectively.

Cluster-6 ranked as last overall and comprising both developing and least developed countries. It had the second-least number of COVID-19 cases, deaths, vaccinations, and the highest stringency index value. The countries in this cluster also had the lowest EPI, share health expenditure in GDP, the highest mortality from chronic diseases, the second-least GDP per capita, life expectancy, and alcohol consumption values. Azerbaijan ranked first, and Lebanon ranked last in this cluster.

Clusters were also evaluated using MULTIMOORA. According to study indicators, cluster-5 was the best performance cluster, whereas Cluster-6 was the least favorable cluster.

Table 6: Clustered Countries According to K-Means and Their MULTIMOORA ranking results (Clusters 5-6 and clustered ranking)

Cluster-5		Cluster-6	
Countries	**Rank**	**Countries**	**Rank**
Norway	1	Azerbaijan	1
Iceland	2	Iraq	2
Denmark	3	Morocco	3
Australia	4	Philippines	4
Canada	5	Kazakhstan	5
Korea, Rep.	6	Vietnam	6
New Zealand	7	Indonesia	7
Israel	8	Timor-Leste	8
Japan	9	Egypt, Arab Rep.	9

Clustered Ranking	
Clusters	**Rank**
Cluster-5	1
Cluster-2	2
Cluster-1	3
Cluster-3	4
Cluster-4	5
Cluster-6	6

Ireland	10	India	10
Luxembourg	11	Uzbekistan	11
Finland	12	Fiji	12
United Kingdom	13	Bangladesh	13
Austria	14	Cambodia	14
Malta	15	Papua New Guinea	15
France	16	China	16
Belgium	17	Kyrgyz Republic	17
Spain	18	Pakistan	18
Italy	19	Myanmar	19
Germany	20	Mongolia	20
Portugal	21	Lebanon	21
Sweden	22		
Greece	23		
Switzerland	24		
Chile	25		
Netherlands	26		
Cyprus	27		
United States	28		
Cuba	29		
Slovenia	30		

4. DISCUSSION

Examining the results of the study, there are some points to consider. Initially, developed countries had a higher proportion of elderly population and the number of COVID-19 cases but a relatively lower number of COVID-19 deaths due to their higher GDP per capita and higher number of vaccinations. Also, developing and least-developed countries had lower GDP per capita and number of vaccinations, but their number of COVID-19 cases and deaths vary; some are higher, and some are lower. Hossain et al. (Moyazzem Hossain, Abdulla, & Rahman, 2022, p. 1) found that low and middle-income countries did not have enough resources in hospitals and COVID-19 vaccinations, so their number of COVID-19 deaths were higher compared to higher income nations. In this study, the least favorable cluster comprises developing and undeveloped countries, whereas the most favorable cluster comprises developed and developing countries.

In addition to this, there are several works of literature pointed out that lower and middle-wealth countries report their COVID-19 cases and deaths less than actual values, so they had lower values compared to higher-income countries (Levin et al., 2022, p. 1; Valero & Valero-Gil, 2021, p. 1229). For this reason, the countries had the lowest GDP per capita and life expectancy and the lowest COVID-19 cases and deaths due to a lack of reporting about the pandemic. These countries are a priority in expanding their health systems to measure health outcomes better.

Furthermore, it is found that the countries with the highest number of COVID-19 deaths and cases are the countries with the highest smoking prevalence and alcohol consumption. There are several studies to find the relations between smoking prevalence and COVID-19 severity and mortality (Dai et al., 2020, p. 1; Dorjee, Kim, Bonomo, & Dolma, 2020, p. 1; Kumru et al., 2022, p. 945; Zhang & Baranova, 2022, p. 1). On the other hand, the studies did not find a direct relationship between alcohol consumption and COVID-19 mortality and severity.

Moreover, one of the crucial indicators of COVID-19 transmission and severity is environmental factors, which are air pollution, climate changes, chemical exposures…etc (Weaver, Head, Gould, Carlton, & Remais, 2022, p. 271). In this study, higher income countries had higher environmental performance index. However, the association between environmental performance index values and COVID-19 cases and deaths might change due to the low reported COVID-19 outcomes. It is also valid for diabetic prevalence and mortality from chronic diseases indicators like several studies(Aydin & Yurdakul, 2020; Kumru et al., 2022; Rizvi et al., 2021).

CONCLUSION

This study aimed to find factors related to the COVID-19 pandemic in countries and rank their performance. A two-stage model was used for it. First, clustering analysis was used to find hidden structures of countries dealing with COVID-19. Secondly, the MULTIMOORA approach ranked countries for each cluster and clusters.

In the first stage, the K-means algorithm was used to cluster 148 countries according to COVID-19, expenditures, socioeconomic, health risk, and disease mortality and prevalence indicators. Silhouette index was used to find optimal clusters, and clustering results were validated with Discriminant analysis. In the second stage, the MULTIMOORA method was used to rank the countries for each cluster using the same study indicators to understand clusters and the state of the countries efficiently. Then, six clusters were found as optimal clusters. As a result, Cluster-5 with developed countries was seen as the best-performing cluster; also, Norway, Iceland, and Denmark were the best-performing countries in this cluster, according to study indicators. Turkey was in the second cluster, performing as the second-best cluster. Cluster-6 consisted of developing and least-developed countries, which were found to be the least-performing countries. According to study results, COVID-19 cases, deaths, and vaccinations were related to GDP per capita, environmental index, life expectancy, and diabetes prevalence. In addition, the countries had the lowest GDP per capita and life expectancy and the lowest COVID-19 cases and deaths due to a lack of reporting about the pandemic. In addition, the stringency index was not associated with COVID-19 indicators in clusters in the study.

The study has some limitations. Firstly, it was restricted to 148 countries and 13 indicators. Some countries cannot used in that study due to lack of data. It might be planned to study more countries and indicators comparing other clustering methods and deeply investigate countries with low and high performance. Several confounding factors affect COVID-19 outcomes. In future studies, causal analysis can be carried out by adding confounding variables. Moreover, k-means clustering has some disadvantages. It is sensitive to initial conditions and outliers, and it is challenging to guess the optimal number of clusters. It is still easy to implement and an efficient and flexible clustering tool. In future studies, it might use more than one clustering method to compare the results and explain the advantages and disadvantages of the methods.

Overall, the study uses machine learning and MCDM methods to objectively compare and determine the countries' needs. As a result, policymakers can develop pandemic policies for country groups separately, and assistance can be provided in this regard according to the countries' priority order.

Authors have to prepare their work according to the rules of the Journal of Administrative Sciences. Editors or referees should not be expected to make necessary corrections. After the necessary corrections are determined, the authors are required to upload the corrected version of the articles to the system via Dergipark within two weeks at the latest.

Ülkelerin COVID-19 ve İlişkili Faktörlere göre Kümelenmesi ve Değerlendirilmesi: Kümeleme ve MULTIMOORA Analizleri

1. GİRİŞ

COVİD-19 salgını insanlığın en zorlu zamanlarından biri olmuştur. İlk vakalar ilk olarak Aralık 2019'da Çin'in Wuhan kentinde belgelenmiş; Dünya Sağlık Örgütü (WHO) Mart 2020'de salgını pandemi ilan etmiştir. Bunun sonucunda, COVID-19 pandemisi global olarak bütün dünyayı ve Mart 2020'den itibaren ülkemizi de etkilemiştir. Üç yıldan fazla bir süre sonra 5 Mayıs 2023'de COVID-19'un WHO salgın özelliğini kaldırmıştır fakat yine de her ülkede hastalığın etkisinin aynı olmadığını, hala ülkelere sağlık politikaları konusunda destek vereceğini açıklamıştır. Global olarak COVID-19 2021 ve 2022'de en çok öldüren üçüncü hastalık, aynı dönemde ülkemizde ise beşinci hastalık olarak raporlanmıştır.

COVID-19 pandemisi dünya genelinde insan sağlığını ve sağlık sektörüne verdiği ciddi zararların yanı sıra kapanmaların etkisiyle ülke geliri, işsizlilk, eğitim, ve sonuç olarak sosyal yaşamı her yönüyle etkilemiştir. Pandemi bütün ülkeleri etkilese de, farklı sosyal, ekonomik ve çevresel yapıya sahip oldukları için hepsini aynı derecede etkilememiştir. Bu nedenle ülkelerin sosyoekonomik yapısına göre COVID-19 pandemi etkisinin bilinmesi ile ülkelere özgü sağlık politikaları üretilmesi yöneticiler için önem arz etmektedir. Bu çalışmanın amacı, ülkelerin COVID-19 vaka sayısı, ölüm sayısı, aşılama sayısı ile sosyoekonomik ve çevresel faktörlere göre benzer özellikli ülkeler kümeleme analizi ile bulunmuş, bu ülkeler araştırma değişkenlerine göre sıralanarak öncelikli yardım gereken ülkelerin belirlenmesi amaçlanmıştır.

2. YÖNTEM

. Çalışmanın verileri halka açık kaynaklardan elde edilmiştir. Bu amaçla ülkelerin için en son ulaşılabilir verisi 2021 yılıdır. Araştırmada 13 değişken ve 148 ülke bulunmaktadır. Çalışmanın değişkenleri, kümülatif COVID-19 vaka sayısı (her 1.000.000 kişide), ölüm sayısı (her 1.000.000 kişide), toplam aşı sayısı (her 100 kişide), politika sıklığı indeksi, doğumda beklenen yaşam süresi, yaşlı nüfus oranı, kişi başına düşen GSYH, sigara içme sıklığı, alkol tüketimi, çevresel performans indeksi, diyabet prevelansı, kalp hastalığı, kanser ,diyabet ve KOAH'dan ölümlülük oranı.

Çalışmada K-Means kümeleme analizi ve MULTIMOORA yöntemleri iki aşamalı olarak uygulanmıştır. Bunun için öncelikle, K-Means kümeleme analizi ile ülke grupları belirlenmiş. Ardından bir çok kriterli karar verme tekniği olan MULTIMOORA yöntemi ilke kümelerin ve kümelerdeki ülkelerin sıralaması belirlenmiştir.

Analizler R studio 2022.07.2 kullanılarak gerçekleştirilmiştir.

3. BULGULAR

Çalışmada Silhouette and Dunn Index kullanılarak en uygun küme sayısı altı olarak bulunmuştur. Birinci kümede 30 ülke (%20), ikinci kümede 11 ülke (%7), üçüncü kümede 36 (%24), dördüncü kümede 20 (%14), beşinci kümede 30 (%20), altıncı kümede 21 (%14) ülke bulunmaktadır.

Çoğunlukla gelişmiş ülkelerden (28/30) oluşan beşinci küme en yüksek performansa sahip küme olarak bulunmuştur. Bu kümedeki ülkeler, en yüksek COVID-19 aşılama oranı, kişi başına düşen GSYH, sağlık harcamasının GSYH oranı, doğumda beklenen yaşam süresi ve çevre performans indeksine, en düşük kronik hastalıklardan ölüm oranın sahiptir. Bunun yanında, Norveç, İzlanda ve Danimarka bu kümedeki en iyi performansa sahip ülkeler olarak belirlenmiştir. Türkiye ise ikinci en iyi performansa sahip kümede yer almaktadır. Bu kümedeki ülkeler ise ikinci sırada en yüksek aşılama sayısına, kişi başına düşen GSYH'ye, doğumda beklenen yaşam süresine ve en yüksek diyabet oranına sahiptir. Bu kümede Birleşmiş Arap Emirlikleri ilk sırada, Türkiye 10. Sırada yer almaktadır. Bunun yanında, altıncı küme en düşük performansa sahip küme olarak belirlenmiş ve bu kümedeki en yüksek sıralamaya sahip ülke Azerbaycan, en düşük ise Lübnan olarak belirlenmiştir.

4. TARTIŞMA

Çalışmada, COVID-19 ve ilişkili sosyoekonomik değişenler kullanılarak benzer ülkeler gruplandırılmış ve ülkelerin öncelik sıralamaları belirlenmiştir. Böylece, ülke grupları ve ülke özelinde salgın hastalıklar için politikalar geliştirilebilir. Bunun yanında, gelişmiş ülkelerin daha COVID-19 yüksek vaka ve ölüm sayısına sahip olmasının ülkelerin sağlık sistemlerinin gelişmişliği ile ilişkili olduğu bu çalışma ile de doğrulanmış, COVID-19 vaka ve ölüm sayılarını olduğundan az raporlayan ülke grupları da belirlenmiştir. Bunun yanında, en yüksek ortalama sigara içme sıklığı ve alkol tüketimine sahip olan ülke grubu, en yüksek COVID-19 vaka ve ölüm sayısına sahiptir.

SONUÇ

Bu çalışma, ülkelerin COVID-19 salgını ile ilişkili sosyoekonomik faktörlerini belirleyerek ülkeleri önem sırasına göre sıralamak amaçlanmıştır. Bu nedenle iki aşamalı bir model kullanılarak K-Means kümeleme analizi ve MULTIMOORA algoritması kullanılmıştır.

Gelişmiş ülkelerden oluşan grup en yüksek performansa sahip küme olarak bulunmuştur. Norveç, İzlanda ve Danimarka bu kümedeki en yüksek performansa sahip ülkeler olarak bulunmuştur. Türkiye ise ikinci en iyi performansa sahip kümede yer almaktadır. COVID-19 değişkenleri (vaka sayısı, ölüm sayısı, aşılama sayısı) kişi başına düşen GSYH, çevresel performans indeksi ve doğumda beklenen yaşam süresi ile ilişkili bulunmuştur.

Çalışmanın literatüre katkısı, politika yapıcılar ülke gruplarına yönelik ayrı ayrı COVİD-19 politikaları geliştirebilir ve ülkelerin öncelik sırasına göre pandemi konusunda yardımlar sağlanabilir.

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