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SIMILARITIES AMONG COUNTRIES DURING THE COVID-19 PANDEMIC

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Abstract

On Jan 30, 2020, The World Health Organization (WHO) declared the current novel coronavirus disease 2019 (COVID-19) epidemic a Public Health Emergency of International Concern. The new type of coronavirus (2019-nCoV) is a new virus among viruses under the name. The novel coronavirus disease 2019 (COVID-19) pandemic has spread from China to 25 countries. This study aims to identify the countries that seem similar to each other by examining their situations during the COVID-19 process. For this purpose, cluster analysis was performed for 30 countries considering the total cases per million, total deaths per million, population over the age of 65, Gross Domestic Product (GDP) per capita, and hospital beds per 100k obtained from the Humanitarian Data Exchange (HDX) website for the dates of 15 May 2020 and 23 January 2021. Partition coefficient, partition entropy, modified partition coefficient, silhouette, fuzzy silhouette, and Xie and Beni index were used to determine the optimal number of clusters the optimal number of clusters was found to be 4. Thus, the countries were grouped into 4 clusters for both datasets. According to the results of the analysis, the similarities among the countries were evaluated by comparing their figures for both dates during the pandemic.

Keywords: *COVID-19, countries, clustering, similarities*

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Introduction

At the beginning of December 2019, the COVID-19 virus that slipped from animals to humans in Wuhan city, China, caused an outbreak of respiratory illness and spread significantly into other countries in Asia. Then, to other continents such as the Pacific region, North America, Europe, and even Africa (1). The World Health Organization (WHO) defined the SARS-CoV-2 virus (initially known as 2019-nCoV) outbreak as a severe global threat.

Similar to other viral respiratory infections, SARS-CoV-2 or COVID-19 can be transmitted through the respiratory tract. It mainly causes respiratory tract infections and develops severe pneumonia in infected patients who may require intensive care. Severe disease may result in death due to progressive respiratory failure (2).

The number of COVID-2019 cases is rising around the world. Everyone is susceptible to this virus, but the elderly and those with underlying diseases are more at risk of adverse outcomes. Current knowledge has shown that the death rate is high in people with chronic underlying diseases. Therefore, special attention should be paid to the elderly and immunocompromised patients. Infections might progress rapidly in these groups and timely clinical decisions are needed (3).

This virus, which kills thousands of people and affects tens of thousands of people, causes people to fear and panic. While a new one is added to the deaths caused by the Coronavirus every day, most people are investigating what it can do to protect it from the virus. Although there is no cure for coronavirus yet, there are points to consider and some precautions that everyone can take. The heaviest losses in the virus spread from China all over the world are in Europe. Life has almost stopped all over the world due to the virus. While the new type of coronavirus (COVID-19) epidemic took 42 thousand lives worldwide, the total number of cases exceeded 860 thousand. Countries around the world struggling with the coronavirus have been struggling with the spread of the outbreak by taking some measures to prevent the spread of the outbreak. The COVID-19 Government Measures were implemented by governments worldwide in response to the Coronavirus pandemic. The researched information available falls into five categories: Social distancing, Movement restrictions, Public health measures, Social and economic measures, Lockdowns. Each category is broken down into several types of measures (ACAPS Government Measures Dataset). The timeline illustrates (Figure 1) when the first case of COVID-19 was reported in each affected country based on when the country first appeared on The Center for Systems Science and Engineering (CSSE) dashboard (on top) relative to when it first appeared in a WHO situation report (on bottom). The countries listed in blue were reported by CSSE before the WHO, and those listed in red were reported after the WHO. While the new type of coronavirus (COVID-19) epidemic, which led to the worldwide public health crisis, faced severe human and material losses, primarily in Europe and North America, countries in different parts of the world have come a long way in combating the outbreak in their way.

There are many studies on COVID-19. Some of them are as follows. Yang et al. (2020) used a purely data-driven statistical method to estimate the case fatality rate (CFR) in the early phase of the COVID-19 outbreak. Daily numbers of laboratory-confirmed COVID-19 cases and deaths were collected from January 10 to February

3, 2020, and divided into three clusters: Wuhan city, other cities of Hubei province, and other provinces of mainland China.

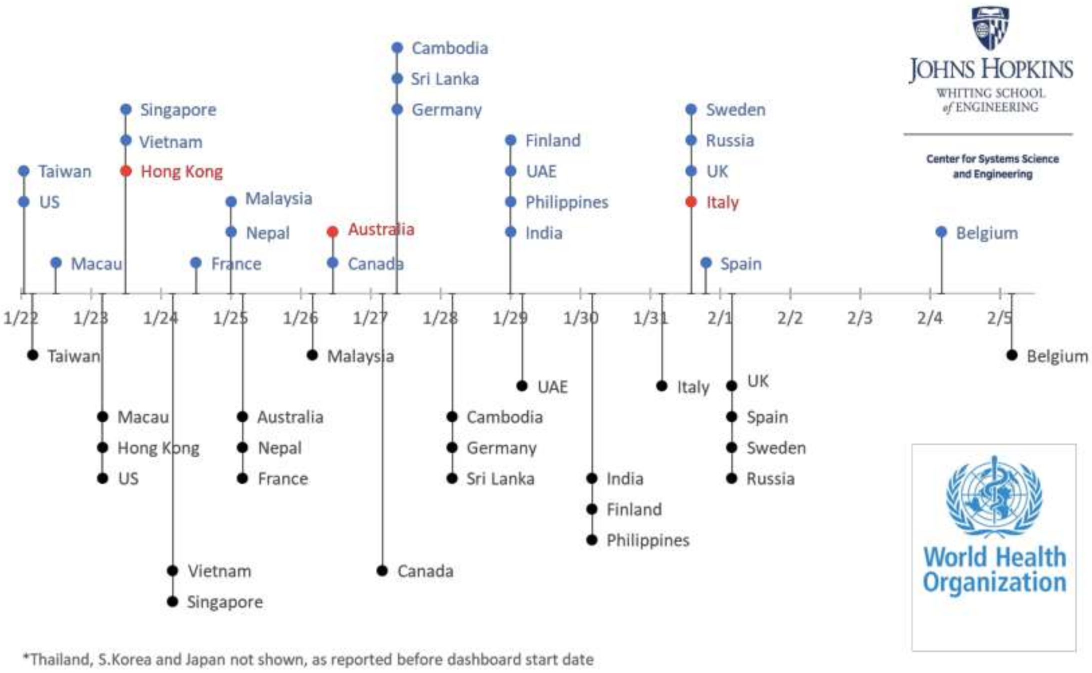

Figure 1. Comparison of COVID-19 case reporting between JHU CSSE, the WHO, and CCDC (4).

The simple linear regression model was applied to estimate the CFR from each cluster (5). Emami et al. (2020) examined all relevant articles that reported clinical characteristics and epidemiological information of hospitalized COVID-19 patients. The data of 76993 patients presented in 10 articles were included in their study. According to the meta-analysis, the pooled prevalence of hypertension, cardiovascular disease, smoking history, and diabetes in people infected with SARS-CoV-2 were estimated as 16.37% (95%CI: 10.15%-23.65%), 12.11% (95%CI 4.40%-22.75%), 7.63% (95%CI 3.83%-12.43%) and 7.87% (95%CI 6.57%-9.28%), respectively.[3] Fontanet et al. (2020) conducted a retrospective closed cohort study among pupils, their parents, and siblings, as well as teachers and non-teaching staff of a high school located in Oise Between 30 March and 4 April 2020. Participants completed a questionnaire that covered the history of fever and/or respiratory symptoms since 13 January 2020 and had blood tested for the presence of anti-SARS-CoV-2 antibodies. The infection attack rate (IAR) was defined as the proportion of participants with confirmed SARS-CoV-2 infection based on antibody detection. Blood samples from two blood donor centers collected between 23 and 27 March 2020 in the Oise department were also tested for the presence of anti-SARS-CoV-2 antibodies (6). Chang et al. (2020) performed a systematic review in PubMed and Embase to find relevant case series. Because some reports were published in Chinese journals, the journals and publications of the Chinese Medical Association related to COVID-19 were completely reviewed. A random-effects model was used to pool clinical data in the meta-analysis (7). Rodriguez-Morales et al. (2020) performed a systematic literature review with meta-analysis, using three databases to assess clinical, laboratory, imaging features, and outcomes of COVID-19 confirmed cases. Observational studies and also case reports were included and analyzed separately. They performed a random-effects model meta-analysis to calculate pooled prevalences and 95% confidence intervals (95%CI) (8). Roosa et al. (2020) used phenomenological models that have been validated during previous outbreaks to generate and assess short-term forecasts of the cumulative number of confirmed reported cases in Hubei province, the epicenter of the epidemic, and for the overall trajectory in China, excluding the province of Hubei. They collected daily reported cumulative confirmed cases for the 2019-nCoV outbreak for each Chinese province from the National Health Commission of China. Here, they provided 5, 10, and 15-day forecasts for five consecutive days, February 5th through February 9th, with quantified uncertainty based on a generalized logistic growth model, the Richards growth model, and a sub-epidemic wave model (9). Jia et al. (2020) collected information on COVID-19 clusters in Qingdao City. The epidemiological characteristics and clinical manifestations were analyzed. Eleven clusters of COVID-19 were reported in Qingdao City between January 29, and February 23, 2020, involving 44 confirmed cases, which accounted for 73.33% of all confirmed cases. From January 19 to February 2, 2020, the cases mainly concentrated in the district that had many designated hospitals. Patients aged 20-59 y old accounted for the largest proportion (68.18%) of cases; the male-to-female sex ratio was 0.52:1. Three cases were infected from exposure to confirmed cases. The average incubation period was 6.28 d. The median number of cases per cluster was 4, and the median duration time was 6 d. The median cumulative number of exposed persons was 53 (10). Gupta and Shankar (2020) gave statistical estimates of the infected population by using counts of fatalities and previously estimated parameters for the progress of the disease. The doubling time, τ, is a crucial unknown input parameter that affects these estimates, and may differ strongly from one geographical location to another. They suggested a method for estimating epidemiological parameters for COVID-19 in different locations within a few days, so adding to the information required for gauging the success of public health interventions (11). Liu et al. (2020) presented a timely and novel methodology that combines disease estimates from mechanistic models with digital traces, via interpretable machine-learning methodologies, to reliably forecast COVID-19 activity in Chinese provinces in real-time. Specifically, their method can produce stable and accurate forecasts 2 days ahead of the current time and uses as inputs (a) official health reports from the Chinese Center Disease for Control and Prevention (China CDC), (b) COVID-19-related internet search activity from Baidu, (c) news media activity reported by Media Cloud, and (d) daily forecasts of COVID-19 activity from GLEAM, an agent-based mechanistic model (12). Jung et al. (2020) studied statistically estimated the confirmed case fatality risk (cCFR) and the basic reproduction number-the average number of secondary cases generated by a single primary case in a naïve population by using the exponential growth rate of the incidence. They modeled epidemic growth either from a single index case with illness onset on 8 December 2019 (Scenario 1), or using the growth rate fitted along with the other parameters (Scenario 2) based on data from 20 exported cases reported by 24 January 2020 (13). Anastassopoulou et al. (2020) provided estimates of the main epidemiological parameters based on the publicly available epidemiological data for Hubei, China from January 11 to February 10, 2020. They provided an estimation of the case fatality and case recovery ratios, along with their 90% confidence intervals as the outbreak evolves. Based on a Susceptible-Infectious-Recovered-Dead (SIDR) model, they provided estimations of the basic reproduction number (R0), and the per-day infection mortality and recovery rates (14). Randhawa et al. (2020) identified an intrinsic COVID-19 virus genomic signature and used it together with a machine learning-based alignment-free approach for an ultra-fast, scalable, and highly accurate classification of whole COVID-19 virus genomes. The proposed method combines supervised machine learning with digital signal processing (MLDSP) for genome analyses, augmented by a decision tree approach to the machine learning component, and a Spearman's rank correlation coefficient analysis for result validation (15). Ghosal et al. (2020) aimed at tracing a trend related to death counts expected at the 5th and 6th week of the COVID-19 in India. A validated database was used to procure global and Indian data related to coronavirus and related outcomes. Multiple regression and linear regression analyses were used interchangeably. Since the week 6 death count data was not correlated significantly with any of the chosen inputs, an auto-regression technique was employed to improve the predictive ability of the regression model (16). Vaishya et al. (2020) aimed to review the role of Artificial Intelligence (AI) as a decisive technology to analyze, prepare us for the prevention and fight against COVID-19 (Coronavirus) and other pandemics. A rapid review of the literature was done on the database of Pubmed, Scopus, and Google Scholar using the keyword of COVID-19 and AI. Collected the latest information regarding AI for COVID-19, then analyzed the same to identify its possible application for this disease (17). Altındağ (2021) determined the effects of fear during the Covid-19 epidemic period on job satisfaction and job performance of bank employees with a proposed model (18).

The aim of this study is to determine the countries that are similar to each other in the process by examining the states of the countries in the COVID-19 process.

Methods

Fuzzy k-medoids algorithm

Fuzzy clustering analysis is a method that is formed by extending cluster analysis with fuzzy logic and is quite common in terms of application. Fuzzy clustering algorithms have two main stages. The first of these; is to find a suitable function to determine each sample membership degree of each cluster, and the second is to obtain a method that calculates cluster centers.

In the fuzzy k-medoids algorithm, which is the fuzzy version of the k-medoids algorithm, observations are evaluated according to the degree of membership that expresses their level of belonging to the clusters. The fuzzy k-medoids method is based on minimizing the objective function given below.

$$P(i,j) = \sum_{i=1}^{n}\sum_{j=1}^{k} u_{ij}^{m} d_{ij}^{2}$$

$$u_{ij} = \frac{1}{\sum_{q=1}^{k}(\frac{d_{ij}}{d_{qi}})^{2/(m-1)}}$$

Where, m is the fuzzifier parameter, u_{ij}, represents the association degree of membership of the ith object to the jth cluster, and $\sum_{j=1}^{k} u_{ij} = 1$. d_{ij}^{2} , is a dissimilarity measure between the *j*th cluster center and the *i*th object (19-20-21).

Although different methods are used in distance measurement, Euclidean distance measurement is generally taken into consideration. The processing steps of the fuzzy k-medoids algorithm are as follows;

Step 1: Initialize the membership function u_{ij} with random values between 0 and 1.

Step 2: Calculate k fuzzy cluster centers. These centers represent the object selected from the dataset.

Step 3: Compute the objective function.

Step 4: Continue the previous steps until the distance between the cluster centers and the observations is minimal.

Step 5: Calculate final membership values for the observations and generate clustering results.

Data and Results

The present study aims to identify countries that show similarities in terms of coping with the COVID-19 during the pandemic and to evaluate the situations of similar countries. Therefore, cluster analysis was conducted by taking into account the total cases per million, total deaths per million, population over the age of 65, Gross Domestic Product (GDP) per capita, and hospital beds per 100k obtained from the Humanitarian Data Exchange (HDX) website for 30 countries for the dates of 15 May 2020 and 23 January 2021 (22). These countries are Sweden, Singapore, Italy, United Kingdom, Belgium, Spain, United States, Switzerland, Canada, Qatar, Turkey, Vietnam, Philippines, Nepal, Malaysia, Cambodia, India, China, Iran, Sri Lanka, South Korea, Japan, France, Germany, Finland, Russia, Belgium, Norway, Australia, and Austria. The dates were selected randomly. The analysis was carried out using the R statistical software.

Since the observations that take enormous value within the data set can change the center point and average of the cluster to be included in the analysis, clustering is performed by using the observation positioned closest to the middle point in the cluster, instead of calculating the average of the observations in the cluster. The k-medoids algorithm is less sensitive to outliers compared to k-means clustering, as it relies on the most centrally positioned object in a cluster. In clustering problems, the use of the k-medoids algorithm is recommended in terms of the relative ease of use, computing performance, and use in large data sets (23). If clusters do not differ distinctly from each other, or if some objects are unstable in cluster membership, it would be useful to prefer fuzzy clustering methods instead of classical clustering methods. For this reason, cluster analysis was performed with the fuzzy k-medoids method. A total of six clustering validation indices were widely used to choose the optimal number of clusters. The indices include partition coefficient (PC), partition entropy (PE), modified partition coefficient (MPC), silhouette (SIL), fuzzy silhouette (SIL.F), and Xie and Beni index (XB). It should be noted that the optimal number of clusters was observed at the maximum value of each of these indices except for PE, where the optimal number of clusters was found at its minimum value (24-25). The cluster validity indices obtained for both dates examined are given in Table 1 and Table 2, respectively.

Table 1. The cluster validity indices according to the number of clusters for the date of 15 May 2020

The number of clusters	PC	PE	MPC	SIL	SIL.F	XB
2	**0.84**	**0.26**	**0.69**	0.45	0.50	0.36
3	0.79	0.38	0.68	0.49	0.57	0.43
4	0.77	0.45	**0.69**	**0.53**	**0.64**	0.78
5	0.72	0.56	0.65	0.44	0.53	**1.75**
6	0.63	0.76	0.56	0.19	0.36	1.27

Table 2. The cluster validity indices according to the number of clusters for the date of 23 January 2021

The number of clusters	PC	PE	MPC	SIL	SIL.F	XB
2	0.70	0.46	0.40	0.44	0.49	**1.37**
3	**0.84**	**0.32**	0.75	0.56	0.65	0.37
4	0.83	0.35	**0.77**	**0.63**	**0.66**	0.32
5	0.78	0.46	0.72	0.50	0.54	0.52
6	0.75	0.54	0.70	0.44	0.47	0.75

As seen in Table 1, the clustering validation index values of the PC (0.84) and PE (0.26) suggested 2 clusters while the index values of the SIL (0.53) and SIL.F (0.64) suggested 4 clusters. On the other hand, the clustering validation index value of the MPC (0.69) suggested 2 or 4 clusters. Moreover, the clustering validation index of XB (1.75) suggested 5 clusters. In the study, k=4 was selected as the optimum number of clusters since it was suggested by the majority of indices. Also, since it was envisaged that the number of clusters for the study would be 4, the number of appropriate clusters was taken as 4. According to this result, Singapore, the United States, Norway, Switzerland, Canada, Portugal, and Qatar are in Cluster 1. Cluster 2 includes Sweden, Italy, the United Kingdom, France, Belgium, and Spain. Cluster 3 includes Turkey, Vietnam, Philippines, Nepal, Malaysia, Cambodia, India, China, Iran, and Sri Lanka. Cluster 4 includes South Korea, Japan, Germany, Finland, Russia, Australia, and Austria.

Table 2 reveals that 3 clusters were suggested according to the index values of the PC (0.84) and PE (0.32), while the number of clusters suggested was 4 according to the index values of the MPC (0.77), SIL (0.63), and SIL.F (0.66) values. On the other hand, the index value of XB (1.37) suggested 2 clusters. Similarly, since it was suggested by the majority of indices and it was thought that the number of clusters for the study would be 4, k=4 was selected as the optimum number of clusters. Accordingly, Australia, Canada, Norway, Qatar, Singapore, and Finland are in Cluster 1. Cluster 2 includes Sweden, Italy, the United Kingdom, France, Belgium, Spain, Portugal, Switzerland, and United States. Cluster 3 includes Turkey, Vietnam, Philippines, Nepal, Malaysia, Cambodia, India, China, Iran, and Sri Lanka. Cluster 4 includes South Korea, Japan, Germany, Russia, and Austria. Table 3 presents the countries in the clusters obtained by conducting cluster analysis using the data for the dates of 15 May 2020 and 23 January 2021.

The countries that best manage the COVID-19 crisis on a global scale are included in Cluster 4. These countries have tried to prevent the spread of the virus in society by isolation and social distancing measures they have implemented since the early days of the pandemic. Schools, businesses, public institutions, and borders of these countries were closed. Firstly, they tested the people who traveled abroad and those who were in contact with them. Secondly, everyone who showed symptoms of the disease was tested. Then, they began to conduct widespread tests for the people living in urban areas where the outbreak could spread. The countries in Cluster 3 rank second in terms of their performance during the pandemic. If these countries continue to take measures, they will manage the process well. The countries that have been worst affected by the pandemic are those in Cluster 1. In these countries, the virus has been on the stage of spreading across the country. Moreover, they delayed acting against it. To manage the process, they need to hire more people, train them, and increase their capacity. If sufficient precautions are not taken, the number of cases will continue to increase.

Table 3. Countries in the clusters were obtained by conducting cluster analysis using data for the dates of 15 May 2020 and 23 January 2021.

Cluster	**1**	**2**	**3**	**4**
Clustering according to data on 15 May 2020	Singapore **United States** Norway **Switzerland** Canada **Portugal** Qatar	Sweden Italy United Kingdom France Belgium Spain	Turkey Vietnam Philippines Nepal Malaysia Cambodia India China Iran Sri Lanka	South Korea Japan Germany **Finland** Russia **Australia** Austria.
Clustering according to data on 23 January 2021	**Australia** Canada Norway Qatar Singapore **Finland**	Sweden Italy United Kingdom France Belgium Spain **Portugal** **Switzerland** **United States**	Turkey Vietnam Philippines Nepal Malaysia Cambodia India China Iran Sri Lanka	South Korea Japan Germany Russia Austria

As can be seen in Table 3, which shows the results of the analysis conducted using the data for 15 May 2020, the United States, Switzerland, and Portugal are in Cluster 1. However, these countries were included in Cluster 2 according to the results of the analysis using data for 23 January 2021. These countries have begun to manage the process well, albeit partially. Finland and Australia are in Cluster 4 according to the analysis performed using the data for 15 May 2020. However, these countries were found to be in Cluster 1 according to the analysis conducted using the data for 23 January 2021. In this case, it can be interpreted that these countries could not manage the process well.

Discussion and Conclusions

The coronavirus, which appeared in Wuhan, China in December 2019, has caused thousands of people to die. With each passing day, the number of both those who died and those who got the virus is increasing. While several countries have taken strong measures to prevent the spread of the virus during the pandemic others have managed the process poorly. In the present study, the situations of the countries during the COVID-19 pandemic were examined and evaluated. In this context, two datasets were created for 30 countries by taking into account the data (total cases per million, total deaths per million, population over the age of 65, Gross Domestic Product (GDP) per capita, and hospital beds per 100k) obtained from the Humanitarian Data Exchange (HDX) website for the dates of 15 May 2020 and 23 January 2021. The fuzzy k-medoids clustering algorithm was applied to the obtained datasets. Six indices (partition coefficient, partition entropy, modified partition coefficient, silhouette, fuzzy silhouette, and Xie and Beni index) were used to determine the optimal number of clusters. According to these index values, the optimal number of clusters was found to be 4. Thus, the countries were grouped into 4 clusters for both datasets. While Cluster 4 included the countries that have managed the COVID-19 pandemic well, Cluster 1 included the countries that have been worst affected. United States, Switzerland, and Portugal were in Cluster 1 according to the analysis of the data for the date of 15 May 2020, while these countries were in Cluster 2 according to the results of the analysis using the data for 23 January 2021. It can be interpreted that these countries have begun to manage the process well, albeit partially. Moreover, Finland and Australia were included in Cluster 4 according to the analysis of the data for 15 May 2020, while these countries were in Cluster 1 according to the analysis of the data obtained for 23 January 2021. It is suggested that these countries need to take more serious measures by reviewing their decisions taken in this process. Countries in Cluster 1 need to take serious measures and implement them as soon as possible, while countries in other clusters should continue to apply their measures without compromise.

Besides, the vaccines developed by some companies against COVID-19 have begun to be shot by countries considering the order of priority. It is thought that these vaccines will bring an end to the pandemic.

Since the data about the numbers of vaccines have not been found for some countries included in this study yet, the variable of the number of vaccines was not involved in the dataset for the date of 23 January 2021.

Conflict of interest

The authors declare that they have no conflict of interest.

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