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Analysis of Mortality-Based Global Health Metrics: A Principle Component Analysis (PCA) – K-Means Approach to Country-Level Data

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Abstract

In this study, principal component analysis and the k-means algorithm were employed for the analysis of Mortality-Based Global Health Metrics. The aim of this study is to create homogeneous clusters of countries in terms of Mortality-Based Global Health Metrics, to identify similar countries within clusters using within-cluster exploratory data analysis methods, and to investigate the common characteristics of these countries. At the country level, a dataset comprising 34 indicators was compiled. However, due to the curse of dimensionality inherent in machine learning, the dataset was reduced to 6 principal components through principal component analysis (PCA). Countries were then clustered into 6 groups using the K-means clustering analysis method. The elbow method and silhouette method were utilized for optimal cluster selection. The cluster information resulting from dimensionality reduction analysis and clustering analysis can serve as a valuable input for policymakers in healthcare, particularly regarding cluster centroids and the countries constituting each cluster. Healthcare policymakers for each country can develop much more rational policies in their decision-making processes by evaluating their own countries, other countries within the same cluster, the characteristic features of their own clusters, and the distances to successful cluster centroids. This enables better examination of positive and negative indicators in country comparisons.

Keywords Health, Mortality, World Development Indicators, Principal Component Analysis, Clustering

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Contents

1. Introduction

In order to holistically improve health and reduce preventable deaths in countries, it may be useful for academics, researchers and decision-makers in governments to subdivide the world into homogeneous groups according to causes of mortality in order to manage the problem in smaller pieces. Investigating the concentration of certain types of mortality in certain regions of the world can help guide the development of macro-scale health policies. One of the most important functions of the health systems of countries is to protect the physical and mental health integrity of their citizens who benefit from this system and to extend their life span by reducing preventable deaths. By facilitating access to hospitals and achievements in the diagnosis and treatment of mental illnesses, it is possible to reduce suicide rates in countries. As the economic development of countries increases, the budget allocated to the health system may increase. This facilitates hospital access and reduces preventable deaths. Mortality rates are among the quality metrics of healthcare services in countries (Kelley & Hurst, 2006). One of the most important criteria used to compare the health levels of countries is the mortality criteria. It is important to know the cause and manner of death of people living in a country in order to provide, evaluate and plan health services (Hayran & Ozbek, 2017). In this context, the situation of the countries of the world can be examined by expanding the mortality dimension, which is among the health services quality metrics, and addressing sub-variables. Survival to age 65, life expectancy at birth, mortality from cardiovascular diseases (CVD), cancer, diabetes, maternal mortality rate or chronic respiratory diseases (CRD) between ages 30 and 70, mortality rate, maternal mortality rate, infant mortality, number of deaths under the age of five, etc., are among the crucial mortality-based indicators of countries' healthcare quality performance. The aim of this study is to identify countries with similar structures in terms of mortality-based global health metrics. In this context, k-means cluster analysis was used to find homogenous country groups. Due to the large number of variables, the efficiency of cluster analysis was increased by applying dimension reduction analysis with a 95% explained variance threshold before cluster analysis. In the relevant years, six main components with values above this threshold were observed. Primary care, cancer care, acute care, end-of-life care, mental health care, patient safety, patient experiences, prescribing in primary care, integrated care are some of the dimensions of health care quality in countries. These dimensions have dozens of subcategories. However, in this article, the rates of mortality types, survival and life expectancy at birth, which are important outputs of all these dimensions, will be discussed and countries will be clustered according to their healthcare levels. Data Compiled from World Development Indicators (WDI) database. World Development Indicators is a compilation of 1,400 time series indicators from 217 countries on global development and poverty reduction. In this study, 34 variables from 196 countries were utilized.

2. Literature Review

According to the World Health Organization (WHO), cancer is the second leading cause of death worldwide, accounting for one in every six deaths and killing an estimated 9.6 million people in 2018. The burden of cancer is increasing worldwide, and it is difficult for health systems, especially in low-and middle-income countries, to manage this increasing burden due to limited access to early diagnosis and treatment. Alcohol consumption causes 2.6 million deaths and worsens the health of billions of people annually and increases the global burden of disease. Alcohol use is a major risk factor for premature death and disability, particularly in people aged 20 to 39 years, accounting for 13% of deaths in this age group. Cardiovascular diseases are the leading cause of death, killing an estimated 17.9 million people worldwide each year. One third of deaths from cardiovascular disease (CVD) occur in people under the age of 70, leading to premature death. In CVDs, especially in primary health care services, identifying people at risk and ensuring their access to treatment is important in terms of preventing early deaths. According to World Health Organization data, the number of deaths of children under 5 years of age has halved between 2000 and 2017 thanks to the initiatives implemented. Despite these positive results, child mortality can be significantly prevented by ensuring access to health services, improving living conditions and reducing environmental risk factors. Especially in developing countries, adverse environmental conditions and pollution cause an increase in child mortality (WHO, 2024).

Hedegaard et al. analyzed deaths from suicide in the USA in their study in 2021. In this academic article, they emphasized that suicide was the second most important cause of death among deaths in the 10-34 age group in the USA for 2019 (Hedegaard, 2021). In the academic study of Bizzego et al. in 2021, the causes of under-5 child mortality in low- and middle-income countries were analyzed with machine learning methods. Among the findings of this study is the necessity to reduce the under-five mortality rate by discouraging "geriatric primiparity," improving the education of household heads, enhancing family welfare, improving housing conditions (focusing on cooking fuels, toilet facilities, refrigeration, and drinking water), and reducing family size and household overcrowding (Bizzego et al., 2021). According to UNICEF reports, under the framework of the Sustainable Development Goals, the aim is to end preventable deaths of newborns and children under 5 years of age by 2030. The goal is for all countries to reduce the neonatal mortality rate to at least 12 deaths per 1,000 live births and the under-5 mortality rate to at least 25 deaths per 1,000 live births (UNICEF, 2023). In their 2020 study, Cheng et al. examined the impact of population aging on mortality rates for 195 countries/regions and 169 causes of death. In this study, it was found that population aging was associated with significant changes in the number of deaths between 1990 and 2017. However, the attributed mortality rate varied substantially across income levels, countries, and causes of death. Additionally, the two largest contributors to disease-specific deaths globally due to population aging between 1990 and 2017 were identified as ischemic heart disease and stroke (Cheng et al., 2020). Victora et al. (2020) conducted a study in which they analyzed the relationship between ethnicity and the mortality rate for children under the age of five using data obtained from demographic surveys across 36 low- and middle-income countries (Victora et al., 2020). In 2023, Liang et al. reviewed academic literature on a wide range of mortality indicators relevant for measuring health system performance in high-income countries. The findings suggest that premature mortality indicators are important variables for measuring both public health and health system performance (Liang et al., 2023). Ward et al. examined cause-based maternal mortality rates across countries in 2023 and built a simulation and forecasting model for the period 1990-2050. According to this study, even if there is a decrease in maternal mortality rates over the years, this decrease does not come close to the Sustainable Development Goal targets (Ward et al., 2023). In 2014, Sartorius et al. conducted a comprehensive analysis of infant mortality rates (IMRs) across 192 countries for the period from 1990 to 2011. The study's findings reveal that Sub-Saharan Africa (SSA) has the highest infant mortality rates globally. Furthermore, the research identifies maternal mortality (survival), insufficient access to water and sanitation, and female education as critical determinants significantly contributing to elevated IMR (Sartorius & Sartorius, 2014). The same region (Sub-Saharan Africa) was also studied by Kayode et al. in 2017. In this study, differences in the quality of health service management, HIV prevalence and socioeconomic deprivation were identified as factors explaining the differences in neonatal mortality rates observed in countries in this region (Kayode et al., 2017). The 2006 study by Kelley and Hurst aims to provide a conceptual framework for the OECD's Health Care Quality Indicator (HCQI) Project. The study examined the concepts and dimensions of health care quality (Kelley & Hurst, 2006). When academic studies are analyzed, it can be seen that the infant mortality rate (IMR) health indicator is one of the important quality metrics of public health (Sartorius & Sartorius, 2014).

3. Methodology

The analysis utilized two unsupervised machine learning algorithms in a hybrid approach. Due to the large number of variables, which posed the curse of dimensionality problem, principal component analysis (PCA) was initially applied to reduce the dimensionality of the variables. Clustering algorithms tend to decrease in performance as the number of dimensions increases. Therefore, PCA, employed as a precursor, positively contributes to the performance of clustering analysis.

There are many advantages of applying principal component analysis before cluster analysis, especially when working with a large number of variables. Some of these advantages include reduction of cluster analysis processing time and computational burden, more homogeneous contribution of transformed variables to cluster analysis, more reliable clustering results, reduction of noise and redundant variables distorting cluster analysis, more distinct clusters and more meaningful cluster centers (Odong et al., 2013; Ros & Riad, 2024; Sanguansat, 2012).

3.1. Dimensionality Reduction

Dimension reduction is one of the algorithms of unsupervised machine learning. It helps to transform the dataset from its complex structure into a simpler form. In this process, a condensed set of new features is created based on the original features of the dataset (Ros & Riad, 2024).

3.1.1. Principle Component Analysis (PCA)

The process of principal component analysis begins with the computation of covariances for all columns (features) and storing these values in a matrix structure. This initial step encapsulates the information about how each variable is related to others. This matrix structure can then be used to find eigenvectors, which represent the directions of data distribution, and eigenvalues, which indicate the magnitude of importance along each eigenvector (Pajankar & Joshi, 2022).

By creating new features with minimal information loss from the original features, we reduce the high-dimensional space to a lower-dimensional space. The new features are called principal components and each principal component is orthogonal to each other. This captures different aspects of the dataset characteristics. The first few principal components often represent a significant proportion of the variance explained, preserving an important part of the information. Principal Component Analysis (PCA) is a powerful technique to help reduce the size of the data (Ros & Riad, 2024).

3.2. Clustering Analysis

Cluster analysis is the process of partitioning a dataset consisting of units (observations) and variables (features) into useful clusters, maximizing the homogeneity within clusters of units with each other and the heterogeneity with other cluster units (Ramasubramanian & Singh, 2019).

3.2.1. K-Means Algorithm

The K-Means algorithm is an algorithm that groups units into k clusters based on their attributes. K is a positive integer that can be found using various methods to determine the most suitable value. While finding the optimal clusters, the sum of the squared distances between the data and the corresponding vector set is minimized. In this way, homogeneous clusters are found, and relatively close units are identified. During the steps of the algorithm, cluster centers are updated in each iteration (Mohbey & Bakariya, 2022).

The steps of the K-Means algorithm are as follows (Vasques, 2024):

1. Determination of the number of clusters
2. K cluster centers are randomly selected
3. Using a specific distance metric (Euclidean, Manhattan, Minkowski, etc.), observations are assigned to the nearest center point.
4. For each cluster, the weight centers are updated according to the average of the observations within the cluster.
5. Repeat steps 3 and 4 until convergence is reached as measured by a threshold for minimum change in cluster center position.

4. Data Set, Application and Findings

4.1. Dataset and Preprocess

Survival to age 65, life expectancy at birth, mortality from CVD, cancer, diabetes or CRD between exact ages 30 and 70 (%), mortality rate attributed to household and ambient air pollution, mortality rate attributed to unintentional poisoning, mortality rate attributed to unsafe water, unsafe sanitation and lack of hygiene, adult mortality rate, infant mortality rate, neonatal mortality rate, under-5 mortality rate, probability of dying among adolescents ages, probability of dying among children ages 5-9 years, probability of dying among youth ages 20-24 years, completeness of infant death reporting, completeness of total death reporting, probability of dying at age 5-14 years and suicide mortality rate are some of the variables in this analysis. The World Development Indicators (Knoema, 2024; World Bank, 2024) database was used to compile the dataset.

Table 1. Variables and Their Definitions

Series	Series Name
SP.DYN.TO65.FE.ZS	Survival to age 65, female (% of cohort)
SP.DYN.TO65.MA.ZS	Survival to age 65, male (% of cohort)
SP.DYN.LE00.FE.IN	Life expectancy at birth, female (years)
SP.DYN.LE00.MA.IN	Life expectancy at birth, male (years)
SP.DYN.LE00.IN	Life expectancy at birth, total (years)
SH.DYN.NCOM.ZS	Mortality from CVD, cancer, diabetes or CRD between exact ages 30 and 70 (%)
SH.DYN.NCOM.FE.ZS	Mortality from CVD, cancer, diabetes or CRD between exact ages 30 and 70, female (%)
SH.DYN.NCOM.MA.ZS	Mortality from CVD, cancer, diabetes or CRD between exact ages 30 and 70, male (%)
SH.STA.AIRP.P5	Mortality rate attributed to household and ambient air pollution, age-standardized (per 100,000 population)

Series	Series Name
SH.STA.AIRP.FE.P5	Mortality rate attributed to household and ambient air pollution, age-standardized, female (per 100,000 female population)
SH.STA.AIRP.MA.P5	Mortality rate attributed to household and ambient air pollution, age-standardized, male (per 100,000 male population)
SH.STA.POIS.P5	Mortality rate attributed to unintentional poisoning (per 100,000 population)
SH.STA.POIS.P5.FE	Mortality rate attributed to unintentional poisoning, female (per 100,000 female population)
SH.STA.POIS.P5.MA	Mortality rate attributed to unintentional poisoning, male (per 100,000 male population)
SH.STA.WASH.P5	Mortality rate attributed to unsafe water, unsafe sanitation and lack of hygiene (per 100,000 population)
SP.DYN.AMRT.FE	Mortality rate, adult, female (per 1,000 female adults)
SP.DYN.AMRT.MA	Mortality rate, adult, male (per 1,000 male adults)
SP.DYN.IMRT.IN	Mortality rate, infant (per 1,000 live births)
SP.DYN.IMRT.FE.IN	Mortality rate, infant, female (per 1,000 live births)
SP.DYN.IMRT.MA.IN	Mortality rate, infant, male (per 1,000 live births)
SH.DYN.NMRT	Mortality rate, neonatal (per 1,000 live births)
SH.DYN.MORT	Mortality rate, under-5 (per 1,000 live births)
SH.DYN.MORT.FE	Mortality rate, under-5, female (per 1,000 live births)
SH.DYN.MORT.MA	Mortality rate, under-5, male (per 1,000 live births)
SH.DYN.1014	Probability of dying among adolescents ages 10-14 years (per 1,000)
SH.DYN.1519	Probability of dying among adolescents ages 15-19 years (per 1,000)
SH.DYN.0509	Probability of dying among children ages 5-9 years (per 1,000)
SH.DYN.2024	Probability of dying among youth ages 20-24 years (per 1,000)
SP.DTH.INFR.ZS	Completeness of infant death reporting (% of reported infant deaths to estimated infant deaths)
SP.DTH.REPT.ZS	Completeness of total death reporting (% of reported total deaths to estimated total deaths)
SH.DYN.0514	Probability of dying at age 5-14 years (per 1,000 children ages 5)
SH.STA.SUIC.P5	Suicide mortality rate (per 100,000 population)
SH.STA.SUIC.FE.P5	Suicide mortality rate, female (per 100,000 female population)
SH.STA.SUIC.MA.P5	Suicide mortality rate, male (per 100,000 male population)

4.2. Principal Component Analysis

The complex data set was simplified by principal component analysis. The curse of dimensionality is avoided, and the performance of the clustering algorithm is improved. As a result of the principal components analysis, the explained variance values for all years within the scope of the analysis are 0.97007 for 2015, 0.97171 for 2016, 0.96780 for 2017, 0.96698 for 2018 and 0.95751 for 2019 as seen in Table 2.

Table 2. Cumulative Explained Variance in Principal Component Analysis

Principal Components	Explained Variance of Principal Component by Years				
	2015	2016	2017	2018	2019
pc1	0,70401	0,70106	0,70365	0,70080	0,70441
pc2	0,14189	0,14160	0,13336	0,13336	0,11989
pc3	0,05469	0,05652	0,05907	0,05905	0,06162
pc4	0,03419	0,03559	0,03427	0,03671	0,03311
pc5	0,02239	0,02394	0,02438	0,02402	0,02734
pc6	0,01291	0,01300	0,01307	0,01306	0,01116
Cumulative Explained Variance	0,97007	0,97171	0,96780	0,96698	0,95751

When the relationship (loadings) of each principal component (PC) with the original variables is analyzed, it can be observed that the variables that affect PC1 the most are the following. The loadings of the first four variables are positive, meaning that an increase in the value of these variables leads to an increase in the value of PC1. The next four variables have negative loadings. In other words, an increase in the value of these variables leads to a decrease in the value of PC1.

- **SP.DYN.IMRT.MA.IN:** Mortality rate, infant, male (per 1,000 live births)
- **SP.DYN.IMRT.IN:** Mortality rate, infant (per 1,000 live births)
- **SH.DYN.MORT.MA:** Mortality rate, under-5, male (per 1,000 live births)
- **SP.DYN.IMRT.FE.IN:** Mortality rate, infant, female (per 1,000 live births)
- **SP.DYN.LE00.MA.IN:** Life expectancy at birth, male (years)
- **SP.DYN.TO65.FE.ZS:** Survival to age 65, female (% of cohort)
- **SP.DYN.LE00.IN:** Life expectancy at birth, total (years)
- **SP.DYN.LE00.FE.IN:** Life expectancy at birth, female (years)

The variables that affect PC2 the most are listed below. While the first ten variables have positive loadings, the last three variables have negative loadings. In particular, the loadings of suicide-related variables in PC2 are relatively very high.

- **SH.STA.SUIC.MA.P5:** Suicide mortality rate, male (per 100,000 male population)
- **SH.STA.SUIC.P5:** Suicide mortality rate (per 100,000 population)
- **SH.STA.SUIC.FE.P5:** Suicide mortality rate, female (per 100,000 female population)
- **SH.DYN.NCOM.MA.ZS:** Mortality from CVD, cancer, diabetes or CRD between exact ages 30 and 70, male (%)
- **SH.DYN.NCOM.ZS:** Mortality from CVD, cancer, diabetes or CRD between exact ages 30 and 70 (%)
- **SH.STA.POIS.P5.MA:** Mortality rate attributed to unintentional poisoning, male (per 100,000 male population)
- **SH.STA.POIS.P5:** Mortality rate attributed to unintentional poisoning (per 100,000 population)
- **SH.DYN.NCOM.FE.ZS:** Mortality from CVD, cancer, diabetes or CRD between exact ages 30 and 70, female (%)
- **SP.DYN.AMRT.MA:** Mortality rate, adult, male (per 1,000 male adults)
- **SH.STA.POIS.P5.FE:** Mortality rate attributed to unintentional poisoning, female (per 100,000 female population)
- **SH.DYN.0514:** Probability of dying at age 5-14 years (per 1,000 children age 5)
- **SH.DYN.0509:** Probability of dying among children ages 5-9 years (per 1,000)

- **SH.DYN.1014:** Probability of dying among adolescents ages 10-14 years (per 1,000)

4.3. Clustering Algorithm

Elbow and silhouette methods were used to determine the optimal number of clusters. The optimal number of clusters for the years 2015, 2016, 2017, 2018 and 2019 included in the analysis was determined as 6. An interesting result of the clustering analyses conducted separately for the five years is that the sixth cluster consists of only one country in all five analyses. This country is Lesotho.

Table 3. Cumulative Explained Variance in Principal Component Analysis

Years	Clusters					
	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
2015	56	67	19	31	22	1
2016	56	66	18	33	22	1
2017	63	62	18	33	19	1
2018	55	68	18	35	19	1
2019	57	64	21	34	19	1

4.4. Findings

When the findings are analyzed, life expectancy at birth for 2015 is as follows: 80.07 years for cluster 1 (with a standard deviation of 2.36 years), 73.35 years for cluster 2 (with a standard deviation of 2.70 years), 68.69 years for cluster 3 (with a standard deviation of 3.45 years), 63.96 years for cluster 4 (with a standard deviation of 2.07 years), 57.62 years for cluster 5 (with a standard deviation of 2.80 years) and 51.10 years for cluster 6 (standard deviation is zero as it consists of a single country).

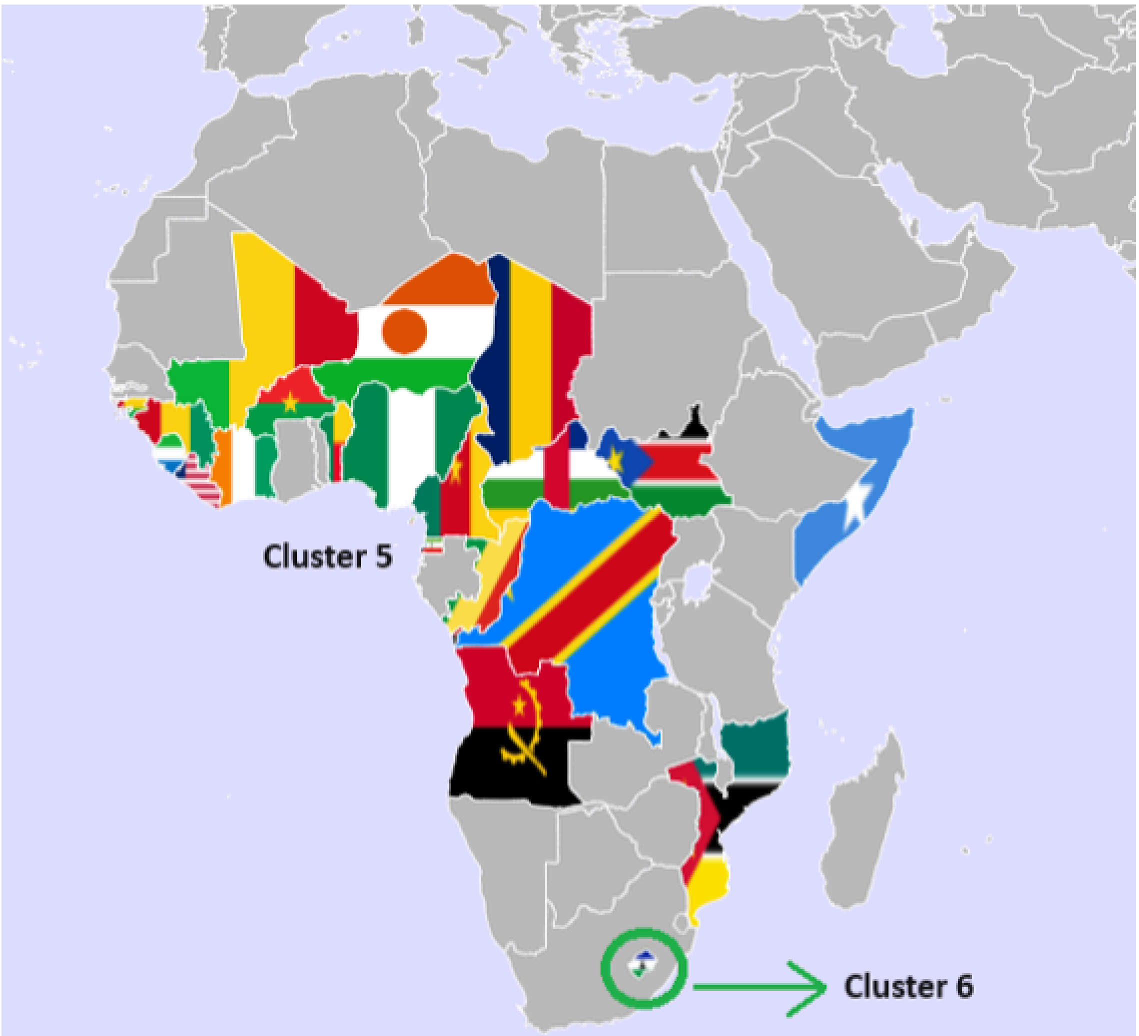
While assigning cluster IDs to the clusters formed as a result of k-means analysis, SP.DYN.LE00.IN (life expectancy at birth, total (years)) was utilized. In each 5-year period, cluster 1 ID was assigned to the cluster with the highest life expectancy at birth and cluster 6 ID was assigned to the cluster with the lowest life expectancy at birth.

For 2015, mortality rates for children under 5 years of age are inversely correlated with life expectancy at birth. Only cluster 5 and cluster 6 are in the opposite order in this context. Under-5 mortality per 1000 live births is 5.40 (st. dev. 2.88) for cluster 1, 19.42 (st. dev. 8.68) for cluster 2, 23.57 (st. dev. 13.96) for cluster 3, 56.42 (st. dev. 10.57) for cluster 4, 100.32 (st. dev. 22.07) for cluster 5 and 82.50 for cluster 6.

There are 54 countries that were in cluster 1 for five years between 2015 and 2019 included in the analysis. These countries are as follows: Albania, Andorra, Australia, Austria, Bahrain, Israel, Uruguay, Belgium, Bosnia and Herzegovina, Canada, United States of America, United Arab Emirates, Chile, Costa Rica, China, Cuba, Croatia, Ecuador, Cyprus, Czechia, Denmark, Turks and Caicos Islands, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Kuwait, Italy, Japan, Malta, Luxembourg, Maldives, Sri Lanka, Qatar, Monaco, Montenegro, Netherlands, New Zealand, Norway, Poland, Portugal, San Marino, Slovakia, Singapore, Slovenia, Spain, South Korea, Sweden, Switzerland, United Kingdom.

There are 19 countries that were in cluster 5 for five years between 2015 and 2019 included in the analysis. These countries are as follows: Angola, Benin, Burkina Faso, Cameroon, Central African

Republic, Chad, Dem. Rep. Congo, Cote d'Ivoire, Eq. Guinea, Guinea, Guinea-Bissau, Liberia, Mali, Mozambique, Niger, Nigeria, Sierra Leone, Somalia, South Sudan. The map of the African continent below illustrates the 19 countries that consistently remained in cluster 5 over a five-year period, as well as Lesotho, which persistently stayed in cluster 6 without any changes during the same timeframe (Figure 1).



Note: The website www.geograf.in was used to create the image (Geograp.IN, 2024).

Figure 1. Representative image of the locations of the countries in Cluster 5 and Cluster 6 with their flags.

There were no countries from outside the African continent in cluster 5 and cluster 6 for the relevant 5 years. Only 9 of the 29 countries in cluster 4 during the relevant 5 years were outside the African continent. These countries can be listed as follows: Lao PDR (Asia), Marshall Islands (Oceania), Myanmar (Asia), Papua New Guinea (Oceania), Timor-Leste (Asia), Haiti (North America - Caribbean), Yemen (Asia), Afghanistan (Asia) and Pakistan (Asia).

Cluster 1 is characterized by the highest survival to age 65 for both men and women, as well as the highest life expectancy at birth for women, men and overall. Cluster 1, which has the lowest value in other mortality-based variables, shows a different structure in suicide variables. Cluster 1 ranks 3rd after Cluster 6 and Cluster 3 in the variables of female, male and overall suicide mortality rate.

Cluster 2 has the second highest survival to age 65 for both men and women, as well as the second highest life expectancy at birth for women, men and men in general. It has the second lowest values for other mortality-based variables. The most characteristic feature of Cluster 2 is that it has the lowest value for female, male and overall suicide mortality variables. Turkey is a country in cluster 2 in 2015, 2016, 2018 and 2019. Turkey was only in cluster 1 in 2017.

Cluster 3 has the third highest survival to age 65 for both men and women, as well as the third highest life expectancy at birth for women, men and overall. The most characteristic feature of cluster 3 is that it is second only to cluster 6 in the mortality rate from cardiovascular diseases, cancer, diabetes or chronic respiratory disease between the ages of 30 and 70, for women, men and overall. In addition, the mortality rate due to unintentional poisoning in men has the second highest value after cluster 6. Cluster 3 has the third lowest values in other mortality rates and the second highest suicide rates after Cluster 6.

Cluster 4 has the fourth highest survival to age 65 for both men and women and the third highest life expectancy at birth for women, men and overall. Cluster 4 has the fourth highest values for other mortality variables.

Cluster 5 and Cluster 6 have the lowest survival to age 65 for both men and women, as well as the lowest life expectancy at birth for women, men and overall. Cluster 6 has higher values than Cluster 5 for most mortality variables, while Cluster 5 averages are higher than Cluster 6 averages for infant mortality rate.

Cluster 6 consists of only one country. This country is Lesotho. Lesotho has by far the highest suicide death rate for both men and women in the world. The other three countries with very high female suicide rates are Guyana, South Korea and the Federated States of Micronesia. The countries with very high male suicide rates are Guyana, Eswatini, Kiribati, Lithuania and the Russian Federation.

The countries with the highest mortality rates from cardiovascular diseases, cancer, diabetes or chronic respiratory diseases in women aged 30-70 years are: Kiribati, Federated States of Micronesia, Lesotho, Afghanistan and Solomon Islands. The countries with the highest mortality rates from cardiovascular diseases, cancer, diabetes or chronic respiratory diseases in men aged 30-70 years are: Kiribati, Federated States of Micronesia, Lesotho, Eswatini and Mongolia. Argentina and Serbia are the countries that have experienced the most displacement between cluster 1 and cluster 2 over the years. Cluster 2 has the lowest suicide rate. Cluster 6 (Lesotho) and cluster 3 have the highest suicide rates.

5. Conclusion and Suggestions

The distribution by continents of the countries forming cluster 1, which have the lowest mortality rates and the highest life expectancy at birth, is as follows: Europe: 59.26%, Asia: 22.22%, North America: 9.26%, South America: 5.56%, Oceania: 3.70%. The countries in cluster 5 and cluster 6, which have the highest mortality rates and the lowest life expectancy at birth, are all in Africa.

Causality analyses can be made in the findings of this study. Lesotho, which constitutes a single cluster, can be scrutinized and its characteristics can be analyzed multidimensionally. Dimensions such as the geographical structure of the country, its economic situation, intensive occupational fields, access to health services, psychological conditions of its citizens, eating habits, genetic structures, etc. can be analyzed. Relationships between countries in clusters and types of diseases can be examined. The findings and causality results can be integrated with the policies of the World Health Organization, thus improving data-driven decision-making processes.

Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

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Appendix

Appendix 1. Clusters and Countries within the Clusters for the Year 2015

CLUSTER_1				
Australia	China	Japan	South Korea	New Zealand
Singapore	Albania	Andorra	Austria	Belgium
Bosnia and Herzegovina	Croatia	Cyprus	Czechia	Denmark
Estonia	Finland	France	Germany	Greece
Hungary	Iceland	Ireland	Italy	Kosovo
Luxembourg	Monaco	Montenegro	Netherlands	Norway
Poland	Portugal	San Marino	Serbia	Slovakia
Slovenia	Spain	Sweden	Switzerland	United Kingdom
Chile	Costa Rica	Cuba	Ecuador	Turks and Caicos Islands
Uruguay	Bahrain	Israel	Kuwait	Malta
Qatar	United Arab Emirates	Canada	United States of America	Maldives
Sri Lanka				
CLUSTER_2				
Brunei	Cambodia	Indonesia	North Korea	Malaysia
Philippines	Samoa	Thailand	Tonga	Vietnam
Armenia	Azerbaijan	Bulgaria	Georgia	Kyrgyzstan
Latvia	North Macedonia	Romania	Tajikistan	Turkey
Turkmenistan	Uzbekistan	Antigua and Barbuda	Argentina	Bahamas
Barbados	Belize	Bolivia	Brazil	British Virgin Islands
Colombia	Dominica	Dominican Rep.	El Salvador	Grenada
Guatemala	Honduras	Jamaica	Mexico	Nicaragua
Panama	Paraguay	Peru	St. Lucia	St. Vincent and the Grenadines
Suriname	Trinidad and Tobago	Venezuela	Algeria	Egypt
Iran	Iraq	Jordan	Lebanon	Libya

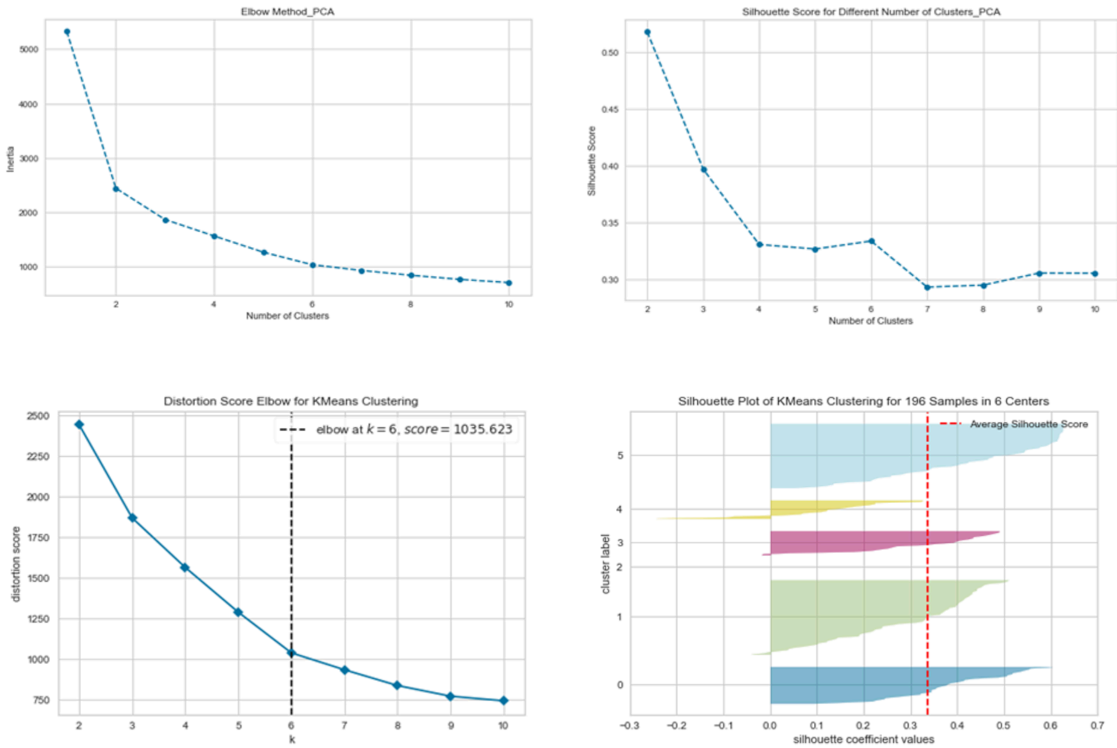
Morocco	Oman	Saudi Arabia	Tunisia	West Bank and Gaza
Bangladesh	Bhutan	India	Cabo Verde	Mauritius
Sao Tome and Principe	Seychelles			
CLUSTER_3				
Fiji	Kiribati	Micronesia, Fed. Sts.	Mongolia	Nauru
Palau	Solomon Islands	Tuvalu	Vanuatu	Belarus
Kazakhstan	Lithuania	Moldova	Russia	Ukraine
Guyana	St. Kitts and Nevis	Botswana	South Africa	
CLUSTER_4				
Lao PDR	Marshall Islands	Myanmar	Papua New Guinea	Timor-Leste
Haiti	Djibouti	Syria	Yemen	Afghanistan
Nepal	Pakistan	Comoros	Congo, Rep.	Eritrea
Ethiopia	Gabon	Gambia	Ghana	Kenya
Madagascar	Malawi	Mauritania	Namibia	Rwanda
Senegal	Sudan	Tanzania	Togo	Uganda
Zambia				
CLUSTER_5				
Angola	Benin	Burkina Faso	Burundi	Cameroon
Central African Republic	Chad	Dem. Rep. Congo	Cote d'Ivoire	Eq. Guinea
Eswatini	Guinea	Guinea-Bissau	Liberia	Mali
Mozambique	Niger	Nigeria	Sierra Leone	Somalia
South Sudan	Zimbabwe			
CLUSTER_6				
Lesotho				

Appendix 2. Mean and Standard Deviation Values of Variables by Clusters for the Year 2015

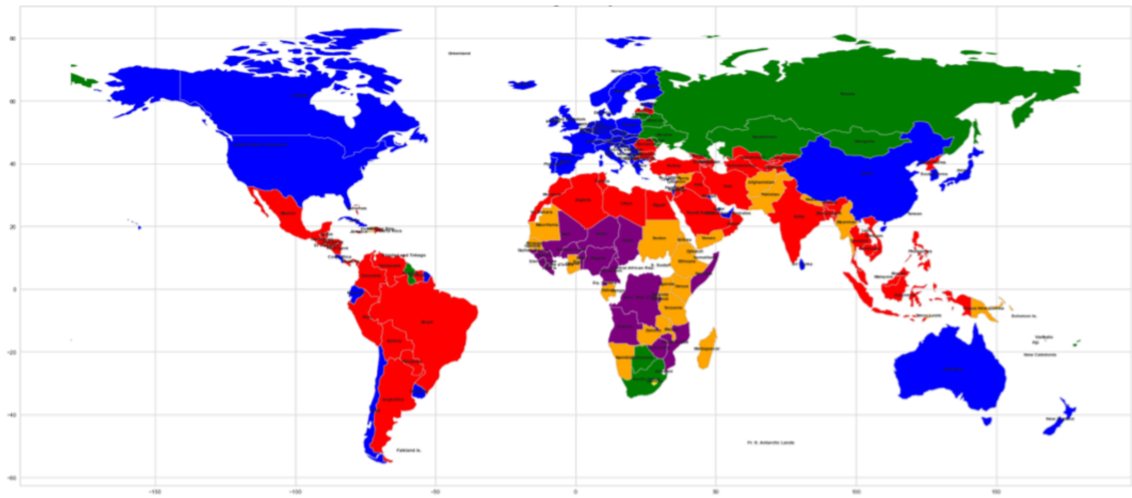
Variable	mean / std. dev.	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
SP.DYN.TO65.FE.ZS	mean	91.45	83.24	75.68	67.02	55.65	38.28
	std. dev.	2.32	4.32	8.53	5.45	5.74	
SP.DYN.TO65.MA.ZS	mean	84.65	72.35	59.24	57.43	48.6	27.53
	std. dev.	5.1	5.8	7.35	5.54	6.26	
SP.DYN.LE00.FE.IN	mean	82.57	76.28	72.36	66.24	59.26	53.86
	std. dev.	2.17	2.9	4.25	2.37	2.94	
SP.DYN.LE00.MA.IN	mean	77.71	70.53	65.22	61.78	55.97	48.48
	std. dev.	2.73	2.79	2.98	2.12	2.76	
SP.DYN.LE00.IN	mean	80.07	73.35	68.69	63.96	57.62	51.1
	std. dev.	2.36	2.7	3.45	2.07	2.8	
SH.DYN.NCOM.ZS	mean	12.98	20.17	31.4	24.3	25.44	47.9
	std. dev.	3.91	5.06	8.24	4.81	5.67	
SH.DYN.NCOM.FE.ZS	mean	9.88	16.8	24.68	22.42	23.7	42.8
	std. dev.	3.04	4.3	9.02	4.67	3.88	
SH.DYN.NCOM.MA.ZS	mean	16.16	23.72	38.8	26.34	27.4	54
	std. dev.	5.34	6.7	7.53	5.7	8.32	
SH.STA.POIS.P5	mean	0.33	0.58	2.44	1.96	3.09	6

Variable	mean / std. dev.	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
	std. dev.	0.28	0.4	1.6	0.72	0.79	
SH.STA.POIS.P5.FE	mean	0.22	0.4	1.3	1.49	2.35	4.8
	std. dev.	0.23	0.31	0.86	0.56	0.62	
SH.STA.POIS.P5.MA	mean	0.44	0.77	3.71	2.42	3.85	7.2
	std. dev.	0.35	0.56	2.56	1.04	1.09	
SP.DYN.AMRT.FE	mean	51.32	101.07	154.89	210.69	289.42	482.66
	std. dev.	14	28.93	61.47	50.01	57.14	
SP.DYN.AMRT.MA	mean	95.58	179.46	277.07	287.03	350.4	593.38
	std. dev.	33.34	45.33	65.72	57.6	70.46	
SP.DYN.IMRT.IN	mean	4.53	16.56	19.52	41.46	66.09	63.2
	std. dev.	2.55	7.17	10.95	8.35	12.7	
SP.DYN.IMRT.FE.IN	mean	4.12	14.91	17.43	37.22	59.99	56.7
	std. dev.	2.3	6.51	9.88	7.87	12.56	
SP.DYN.IMRT.MA.IN	mean	4.93	18.11	21.49	45.5	72.29	69.5
	std. dev.	2.8	7.84	11.99	8.89	13.99	
SH.DYN.NMRT	mean	3.09	11.13	11.52	25.47	32.92	37.9
	std. dev.	1.76	5.28	6.51	6.52	4.48	
SH.DYN.MORT	mean	5.4	19.42	23.57	56.42	100.32	82.5
	std. dev.	2.88	8.68	13.96	10.57	22.07	
SH.DYN.MORT.FE	mean	4.9	17.58	21.19	51.64	93.7	75.2
	std. dev.	2.61	8.02	12.75	10.08	21.76	
SH.DYN.MORT.MA	mean	5.85	21.19	25.83	61	106.6	89.4
	std. dev.	3.13	9.37	15.12	11.14	22.42	
SH.DYN.1014	mean	0.66	1.76	2.24	4.62	8.6	4.4
	std. dev.	0.29	0.72	0.94	1.34	2.4	
SH.DYN.1519	mean	1.65	3.96	4.86	8.47	13.16	11.4
	std. dev.	0.63	1.64	1.79	2.61	3.45	
SH.DYN.0509	mean	0.57	1.65	2.47	6.56	13.8	5.4
	std. dev.	0.28	0.69	1.43	2.1	3.41	
SH.DYN.2024	mean	2.38	5.42	7.64	11.24	17.77	19.7
	std. dev.	0.92	2.5	3.94	3.97	4.64	
SH.DYN.0514	mean	1.23	3.58	4.53	12.04	23.3	9.8
	std. dev.	0.6	1.62	2.17	3.77	6.48	
SH.STA.SUIC.P5	mean	12.12	6.19	22.09	6.4	9.23	92.4
	std. dev.	5.13	4.35	7.44	2.64	6.8	
SH.STA.SUIC.FE.P5	mean	6.11	2.96	8.13	3.39	4.61	39.3
	std. dev.	3.1	2.25	3.19	1.6	2.47	
SH.STA.SUIC.MA.P5	mean	18.19	9.45	37.05	9.47	13.95	147.3
	std. dev.	7.96	7.01	12.83	4.32	12.19	

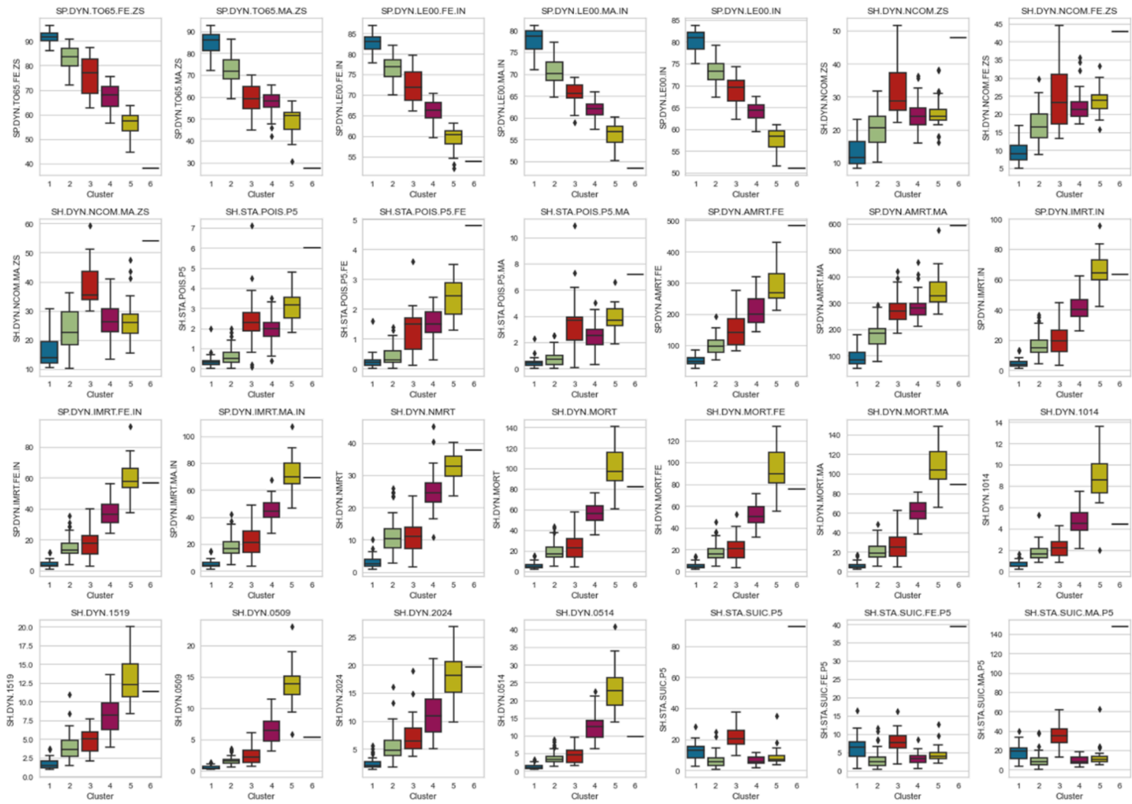
Appendix 3. Determination of the Optimal Number of Clusters for the Year 2015



Appendix 4. Representation of Countries by Clusters on the World Map for the Year 2015



Appendix 5. Box Plots of Clusters by Variables for the Year 2015



Appendix 6. Clusters and Countries within the Clusters for the Year 2016

CLUSTER_1				
Australia	China	Japan	South Korea	New Zealand
Singapore	Albania	Andorra	Austria	Belgium
Bosnia and Herzegovina	Croatia	Cyprus	Czechia	Denmark
Estonia	Finland	France	Germany	Greece
Hungary	Iceland	Ireland	Italy	Kosovo
Luxembourg	Monaco	Montenegro	Netherlands	Norway
Poland	Portugal	San Marino	Serbia	Slovakia
Slovenia	Spain	Sweden	Switzerland	United Kingdom
Chile	Costa Rica	Cuba	Ecuador	Turks and Caicos Islands
Uruguay	Bahrain	Israel	Kuwait	Malta
Qatar	United Arab Emirates	Canada	United States of America	Maldives
Sri Lanka				
CLUSTER_2				
Brunei	Cambodia	Indonesia	North Korea	Malaysia
Philippines	Samoa	Thailand	Tonga	Vietnam
Armenia	Azerbaijan	Bulgaria	Georgia	Kyrgyzstan
North Macedonia	Romania	Tajikistan	Turkey	Uzbekistan
Antigua and Barbuda	Argentina	Bahamas	Barbados	Belize
Bolivia	Brazil	British Virgin Islands	Colombia	Dominica
Dominican Rep.	El Salvador	Grenada	Guatemala	Honduras

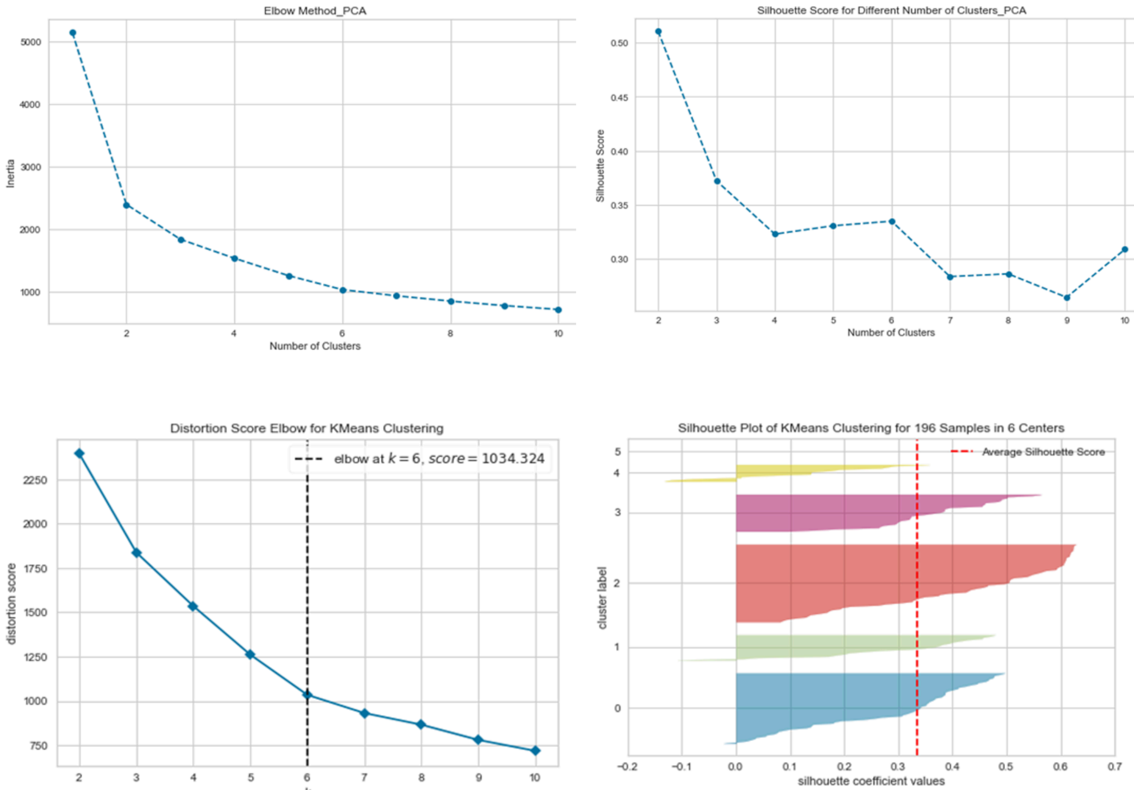
Jamaica	Mexico	Nicaragua	Panama	Paraguay
Peru	St. Kitts and Nevis	St. Lucia	St. Vincent and the Grenadines	Trinidad and Tobago
Venezuela	Algeria	Egypt	Iran	Iraq
Jordan	Lebanon	Libya	Morocco	Oman
Saudi Arabia	Tunisia	West Bank and Gaza	Bangladesh	Bhutan
India	Nepal	Cabo Verde	Mauritius	Sao Tome and Principe
Seychelles				
CLUSTER_3				
Fiji	Kiribati	Micronesia, Fed. Sts.	Mongolia	Palau
Solomon Islands	Tuvalu	Vanuatu	Belarus	Kazakhstan
Latvia	Lithuania	Moldova	Russia	Ukraine
Guyana	Suriname	South Africa		
CLUSTER_4				
Lao PDR	Marshall Islands	Myanmar	Nauru	Papua New Guinea
Timor-Leste	Turkmenistan	Haiti	Djibouti	Syria
Yemen	Afghanistan	Pakistan	Botswana	Comoros
Congo, Rep.	Eritrea	Ethiopia	Gabon	Gambia
Ghana	Kenya	Madagascar	Malawi	Mauritania
Namibia	Rwanda	Senegal	Sudan	Tanzania
Togo	Uganda	Zambia		
CLUSTER_5				
Angola	Benin	Burkina Faso	Burundi	Cameroon
Central African Republic	Chad	Dem. Rep. Congo	Cote d'Ivoire	Eq. Guinea
Eswatini	Guinea	Guinea-Bissau	Liberia	Mali
Mozambique	Niger	Nigeria	Sierra Leone	Somalia
South Sudan	Zimbabwe			
CLUSTER_6				
Lesotho				

Appendix 7. Mean and Standard Deviation Values of Variables by Clusters for the Year 2016

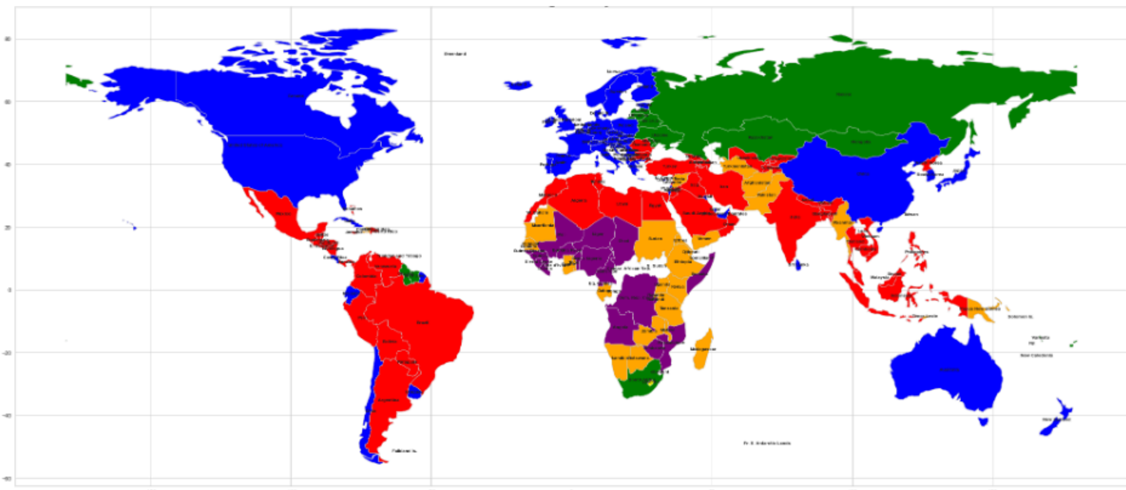
Variable	mean / std. dev.	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
SP.DYN.TO65.FE.ZS	mean	91.63	83.56	77.83	67.94	56.55	40.57
	std. dev.	2.28	4.23	7.86	5.36	5.56	
SP.DYN.TO65.MA.ZS	mean	84.99	72.62	61.66	57.59	49.65	29.66
	std. dev.	4.99	5.8	6.64	5.56	6.11	
SP.DYN.LE00.FE.IN	mean	82.83	76.48	73.74	66.82	59.81	55.1
	std. dev.	2.15	2.87	3.97	2.4	3.01	
SP.DYN.LE00.MA.IN	mean	77.93	70.64	66.42	62.08	56.59	49.56
	std. dev.	2.72	2.79	2.59	2.02	2.81	
SP.DYN.LE00.IN	mean	80.3	73.5	69.99	64.4	58.2	52.26
	std. dev.	2.35	2.67	3.1	2.05	2.85	
SH.DYN.NCOM.ZS	mean	12.73	19.91	30.73	24.5	25.17	46.3
	std. dev.	3.87	4.95	8.9	4.72	5.45	
SH.DYN.NCOM.FE.ZS	mean	9.63	16.7	23.96	22.4	23.44	41.1

Variable	mean / std. dev.	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
	std. dev.	2.94	4.18	9.58	4.53	3.69	
SH.DYN.NCOM.MA.ZS	mean	15.91	23.27	38.15	26.86	27.08	52.7
	std. dev.	5.33	6.58	8.39	5.78	8.13	
SH.STA.POIS.P5	mean	0.34	0.59	2.15	1.88	3.05	5.7
	std. dev.	0.29	0.43	1.58	0.75	0.79	
SH.STA.POIS.P5.FE	mean	0.22	0.38	1.14	1.42	2.34	4.6
	std. dev.	0.23	0.29	0.98	0.57	0.64	
SH.STA.POIS.P5.MA	mean	0.46	0.8	3.23	2.33	3.79	6.9
	std. dev.	0.39	0.64	2.4	1.07	1.1	
SP.DYN.AMRT.FE	mean	50.17	99.12	138.93	204.64	282.59	458.34
	std. dev.	14.07	28.77	52.64	48.52	52.92	
SP.DYN.AMRT.MA	mean	93.21	177.87	254.34	287.02	341.72	568.27
	std. dev.	32.74	46.04	56.3	57.79	67.16	
SP.DYN.IMRT.IN	mean	4.41	16.15	17.03	40	64.39	63
	std. dev.	2.43	6.62	10.53	8.04	12.32	
SP.DYN.IMRT.FE.IN	mean	4	14.59	15.19	35.82	58.18	56.5
	std. dev.	2.18	6.1	9.44	7.62	11.58	
SP.DYN.IMRT.MA.IN	mean	4.79	17.63	18.76	43.97	70.27	69.2
	std. dev.	2.66	7.14	11.55	8.53	13.08	
SH.DYN.NMRT	mean	3.02	10.88	9.74	24.81	32.43	37.7
	std. dev.	1.71	5.02	5.85	6.16	4.49	
SH.DYN.MORT	mean	5.23	18.95	20.4	53.71	97	77.8
	std. dev.	2.72	8.03	13.32	10.48	21.18	
SH.DYN.MORT.FE	mean	4.77	17.19	18.3	48.98	90.46	70.5
	std. dev.	2.47	7.52	12.12	10.13	20.87	
SH.DYN.MORT.MA	mean	5.68	20.62	22.38	58.24	103.21	84.7
	std. dev.	2.97	8.59	14.45	10.94	21.53	
SH.DYN.1014	mean	0.65	1.75	2.04	4.36	8.41	4.3
	std. dev.	0.3	0.71	0.97	1.41	2.4	
SH.DYN.1519	mean	1.63	3.99	4.44	8.12	12.87	11.2
	std. dev.	0.62	1.7	1.85	2.81	3.34	
SH.DYN.0509	mean	0.56	1.62	2.14	6.1	13.37	5.2
	std. dev.	0.27	0.68	1.31	2.22	3.46	
SH.DYN.2024	mean	2.36	5.44	7.06	10.76	17.41	18.8
	std. dev.	0.93	2.57	4.22	3.89	4.59	
SH.STA.SUIC.P5	mean	11.86	5.66	22.44	6.82	8.93	87
	std. dev.	4.91	3.28	7.37	3.38	6.28	
SH.STA.SUIC.FE.P5	mean	5.86	2.67	8.24	3.5	4.35	36
	std. dev.	3.03	1.86	3.29	1.71	2.07	
SH.STA.SUIC.MA.P5	mean	17.88	8.67	37.58	10.18	13.65	139.6
	std. dev.	7.55	5.26	12.71	5.6	11.74	

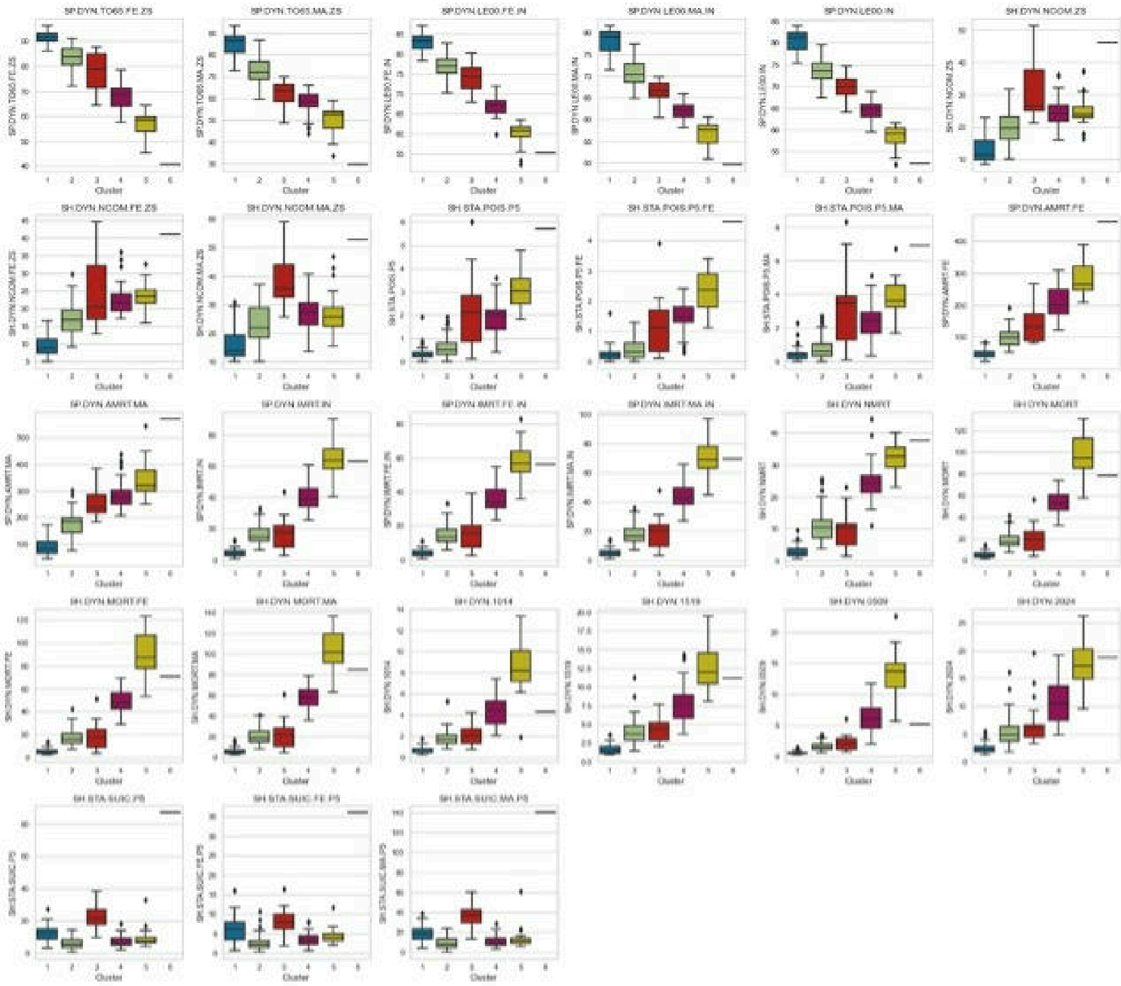
Appendix 8. Determination of the Optimal Number of Clusters for the Year 2016



Appendix 9. Representation of Countries by Clusters on the World Map for the Year 2016



Appendix 10. Box Plots of Clusters by Variables for the Year 2016



Appendix 11. Clusters and Countries within the Clusters for the Year 2017

CLUSTER_1				
Australia	China	Japan	South Korea	New Zealand
Singapore	Thailand	Albania	Andorra	Austria
Belgium	Bosnia and Herzegovina	Croatia	Cyprus	Czechia
Denmark	Estonia	Finland	France	Germany
Greece	Hungary	Iceland	Ireland	Italy
Kosovo	Luxembourg	Monaco	Montenegro	Netherlands
Norway	Poland	Portugal	San Marino	Slovakia
Slovenia	Spain	Sweden	Switzerland	Turkey
United Kingdom	Argentina	Chile	Colombia	Costa Rica
Cuba	Ecuador	Panama	Peru	Turks and Caicos Islands
Uruguay	Bahrain	Israel	Kuwait	Lebanon
Malta	Qatar	United Arab Emirates	Canada	United States of America
Maldives	Sri Lanka	Cabo Verde		
CLUSTER_2				
Brunei	Cambodia	Indonesia	North Korea	Malaysia
Palau	Philippines	Samoa	Tonga	Vietnam

Armenia	Azerbaijan	Bulgaria	Georgia	Kyrgyzstan
North Macedonia	Romania	Serbia	Tajikistan	Turkmenistan
Uzbekistan	Antigua and Barbuda	Bahamas	Barbados	Belize
Bolivia	Brazil	British Virgin Islands	Dominica	Dominican Rep.
El Salvador	Grenada	Guatemala	Honduras	Jamaica
Mexico	Nicaragua	Paraguay	St. Kitts and Nevis	St. Lucia
St. Vincent and the Grenadines	Trinidad and Tobago	Venezuela	Algeria	Egypt
Iran	Iraq	Jordan	Libya	Morocco
Oman	Saudi Arabia	Syria	Tunisia	West Bank and Gaza
Bangladesh	Bhutan	India	Nepal	Mauritius
Sao Tome and Principe	Seychelles			
CLUSTER_3				
Fiji	Kiribati	Micronesia, Fed. Sts.	Mongolia	Solomon Islands
Tuvalu	Vanuatu	Belarus	Kazakhstan	Latvia
Lithuania	Moldova	Russia	Ukraine	Guyana
Suriname	Botswana	South Africa		
CLUSTER_4				
Lao PDR	Marshall Islands	Myanmar	Nauru	Papua New Guinea
Timor-Leste	Haiti	Djibouti	Yemen	Afghanistan
Pakistan	Burundi	Comoros	Congo, Rep.	Eritrea
Eswatini	Ethiopia	Gabon	Gambia	Ghana
Kenya	Madagascar	Malawi	Mauritania	Namibia
Rwanda	Senegal	Sudan	Tanzania	Togo
Uganda	Zambia	Zimbabwe		
CLUSTER_5				
Angola	Benin	Burkina Faso	Cameroon	Central African Republic
Chad	Dem. Rep. Congo	Cote d'Ivoire	Eq. Guinea	Guinea
Guinea-Bissau	Liberia	Mali	Mozambique	Niger
Nigeria	Sierra Leone	Somalia	South Sudan	
CLUSTER_6				
Lesotho				

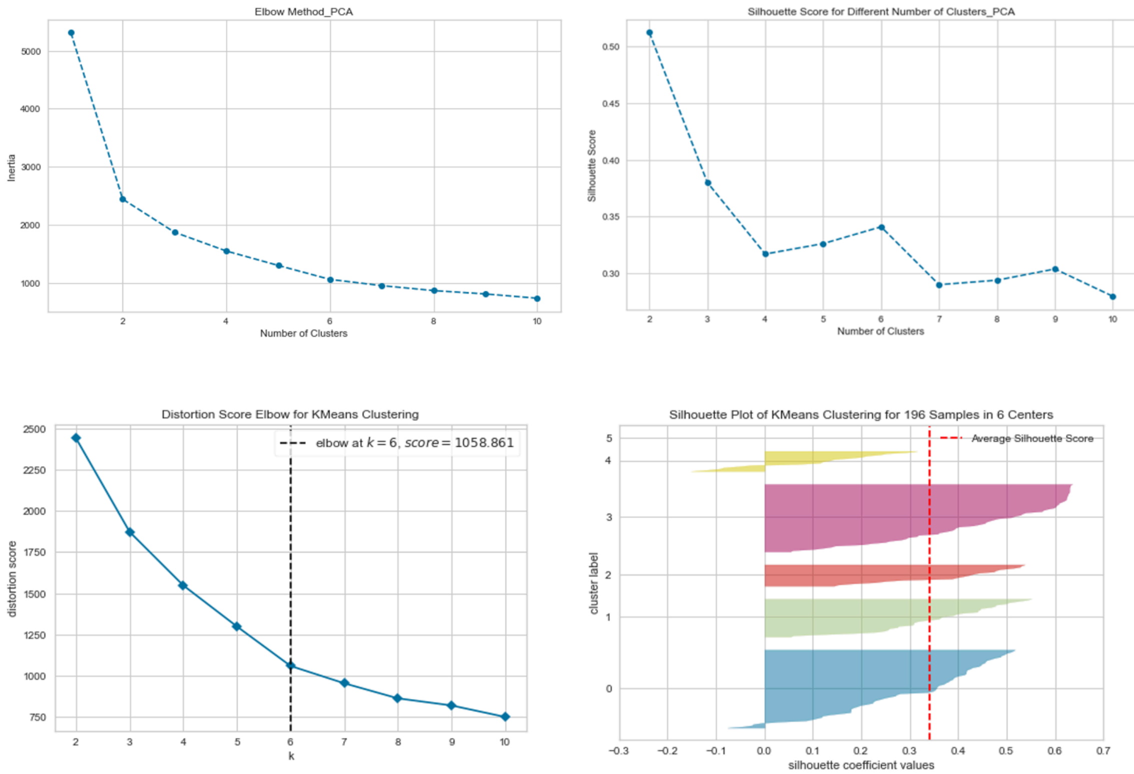
Appendix 12. Mean and Standard Deviation Values of Variables by Clusters for the Year 2017

Variable	mean / std. dev.	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
SP.DYN.TO65.FE.ZS	mean	91.38	82.76	78.78	67.02	57.42	42.38
	std. dev.	2.47	4.63	7.26	5.59	5.64	
SP.DYN.TO65.MA.ZS	mean	84.47	71.58	62.98	56.75	50.84	31.45
	std. dev.	5.26	6.34	5.94	6.86	5.33	
SP.DYN.LE00.FE.IN	mean	82.63	75.9	73.95	66.48	59.94	55.9
	std. dev.	2.15	2.64	4.07	2.33	3.14	
SP.DYN.LE00.MA.IN	mean	77.62	70.15	66.75	61.79	56.84	50.35
	std. dev.	2.9	2.84	2.71	2.45	2.99	
SP.DYN.LE00.IN	mean	80.06	72.96	70.28	64.09	58.39	53.06
	std. dev.	2.43	2.58	3.23	2.27	3.02	

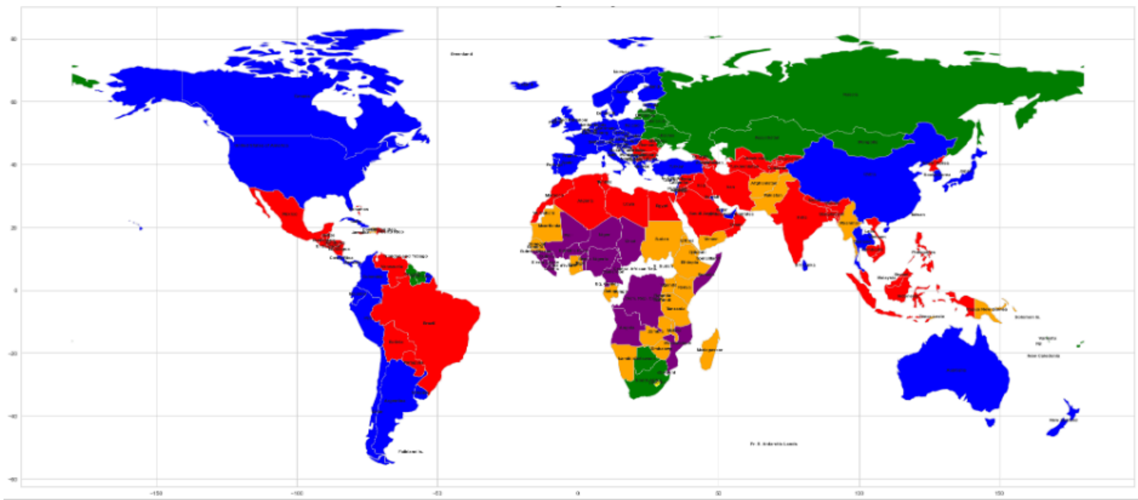
Variable	mean / std. dev.	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
SH.DYN.NCOM.ZS	mean	12.62	20.85	30.27	24.57	23.94	44.2
	std. dev.	3.76	4.3	9.16	5.07	4.93	
SH.DYN.NCOM.FE.ZS	mean	9.66	17.46	23.57	22.46	22.67	38.5
	std. dev.	2.85	3.66	9.8	4.6	3.6	
SH.DYN.NCOM.MA.ZS	mean	15.64	24.4	37.72	26.89	25.41	51
	std. dev.	5.15	5.94	8.49	6.44	7.18	
SH.STA.POIS.P5	mean	0.35	0.63	2.08	2.04	2.84	5.3
	std. dev.	0.27	0.45	1.37	0.8	0.71	
SH.STA.POIS.P5.FE	mean	0.22	0.38	1.14	1.55	2.17	4.2
	std. dev.	0.22	0.31	0.84	0.62	0.59	
SH.STA.POIS.P5.MA	mean	0.47	0.87	3.13	2.55	3.55	6.4
	std. dev.	0.35	0.69	2.13	1.1	1.05	
SP.DYN.AMRT.FE	mean	51.31	103.13	135.2	213.66	271.64	436.91
	std. dev.	15.58	28.52	51.56	52.31	48.7	
SP.DYN.AMRT.MA	mean	97.23	183.84	247.22	296.53	327.13	546.7
	std. dev.	35.71	49.48	55.04	71.28	51.77	
SP.DYN.IMRT.IN	mean	5.12	16.5	17.41	40.02	66.06	62
	std. dev.	3.26	7.06	10.99	7.54	9.84	
SP.DYN.IMRT.FE.IN	mean	4.65	14.86	15.54	35.83	59.77	55.7
	std. dev.	2.92	6.41	9.86	7.17	9.27	
SP.DYN.IMRT.MA.IN	mean	5.57	18.04	19.16	43.97	72.04	68.1
	std. dev.	3.58	7.74	12.05	7.95	10.44	
SH.DYN.NMRT	mean	3.49	11.07	10.11	24.88	33.05	37.4
	std. dev.	2.22	5.26	6.3	5.48	3.65	
SH.DYN.MORT	mean	6.07	19.32	20.99	53.77	99.95	75.5
	std. dev.	3.76	8.5	13.85	9.91	16.51	
SH.DYN.MORT.FE	mean	5.52	17.47	18.88	49.02	93.39	68.3
	std. dev.	3.39	7.8	12.6	9.56	16.59	
SH.DYN.MORT.MA	mean	6.59	21.06	23.03	58.3	106.22	82.3
	std. dev.	4.09	9.22	15.05	10.31	16.55	
SH.DYN.1014	mean	0.73	1.75	2.05	4.48	8.66	4.2
	std. dev.	0.4	0.72	0.99	1.68	2.02	
SH.DYN.1519	mean	1.85	4.11	4.22	8.25	13.14	11
	std. dev.	0.98	1.9	1.67	2.79	3.21	
SH.DYN.0509	mean	0.62	1.64	2.19	6.3	13.6	5.1
	std. dev.	0.36	0.7	1.4	2.48	3.17	
SH.DYN.2024	mean	2.65	5.9	6.2	10.88	17.92	18.2
	std. dev.	1.35	3.78	2.82	3.68	4.82	
SH.DYN.0514	mean	1.32	3.45	4.06	11.38	22.08	13.2
	std. dev.	0.78	1.41	2.14	3.96	5.91	
SH.STA.SUIC.P5	mean	11.06	5.51	22.25	7.47	7.28	78.3
	std. dev.	5.29	3.17	6.9	5.08	2.85	
SH.STA.SUIC.FE.P5	mean	5.36	2.63	8.35	3.57	3.79	30.8

Variable	mean / std. dev.	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
	std. dev.	3.04	1.91	3.39	1.81	1.15	
SH.STA.SUIC.MA.P5	mean	16.82	8.42	37.05	11.47	10.79	127.2
	std. dev.	8.21	4.98	11.24	9.53	5.08	

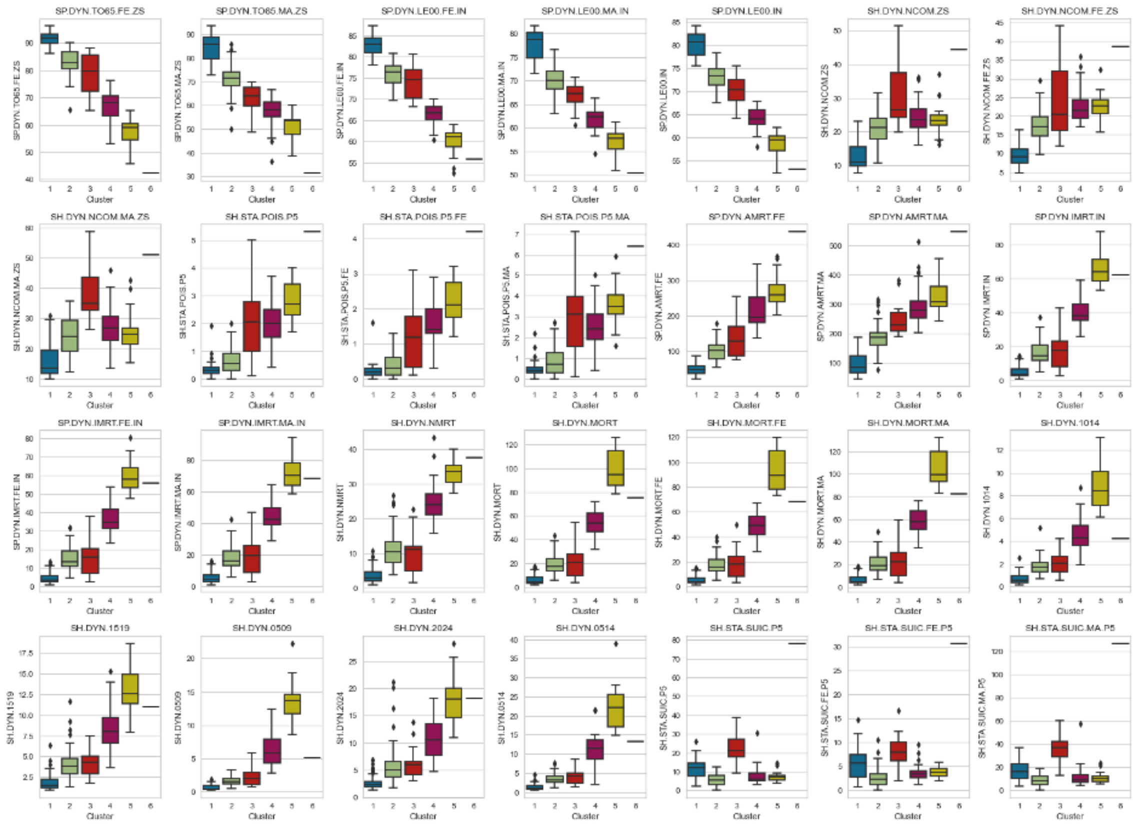
Appendix 13. Determination of the Optimal Number of Clusters for the Year 2017



Appendix 14. Representation of Countries by Clusters on the World Map for the Year 2017



Appendix 15. Box Plots of Clusters by Variables for the Year 2017



Appendix 16. Clusters and Countries within the Clusters for the Year 2018

CLUSTER_1				
Australia	China	Japan	South Korea	New Zealand
Singapore	Albania	Andorra	Austria	Belgium
Bosnia and Herzegovina	Croatia	Cyprus	Czechia	Denmark
Estonia	Finland	France	Germany	Greece
Hungary	Iceland	Ireland	Italy	Kosovo
Luxembourg	Monaco	Montenegro	Netherlands	Norway
Poland	Portugal	San Marino	Slovakia	Slovenia
Spain	Sweden	Switzerland	United Kingdom	Chile
Costa Rica	Cuba	Ecuador	Turks and Caicos Islands	Uruguay
Bahrain	Israel	Kuwait	Malta	Qatar
United Arab Emirates	Canada	United States of America	Maldives	Sri Lanka
CLUSTER_2				
Brunei	Cambodia	Indonesia	North Korea	Malaysia
Philippines	Samoa	Thailand	Tonga	Vietnam
Armenia	Azerbaijan	Bulgaria	Georgia	Kyrgyzstan
North Macedonia	Romania	Serbia	Tajikistan	Turkey
Uzbekistan	Antigua and Barbuda	Argentina	Bahamas	Barbados
Belize	Bolivia	Brazil	British Virgin Islands	Colombia
Dominica	Dominican Rep.	El Salvador	Grenada	Guatemala
Honduras	Jamaica	Mexico	Nicaragua	Panama

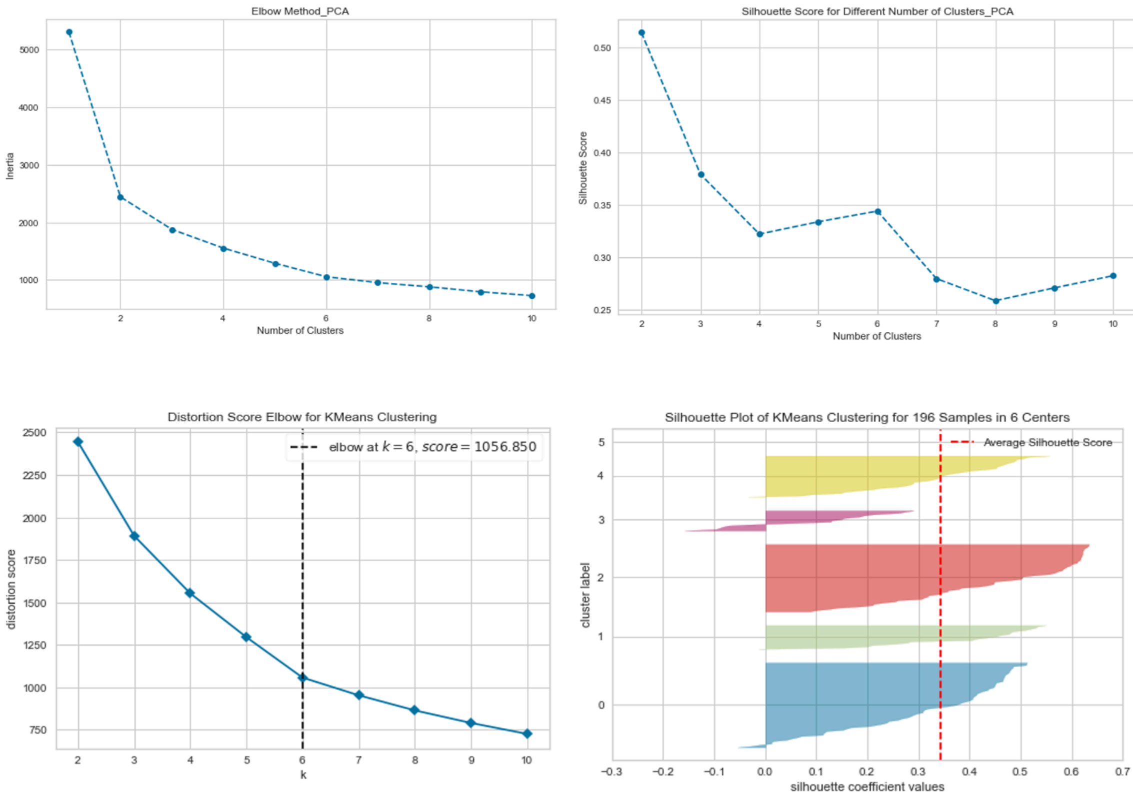
Paraguay	Peru	St. Kitts and Nevis	St. Lucia	St. Vincent and the Grenadines
Trinidad and Tobago	Venezuela	Algeria	Egypt	Iran
Iraq	Jordan	Lebanon	Libya	Morocco
Oman	Saudi Arabia	Syria	Tunisia	West Bank and Gaza
Bangladesh	Bhutan	India	Nepal	Cabo Verde
Mauritius	Sao Tome and Principe	Seychelles		
CLUSTER_3				
Fiji	Kiribati	Micronesia, Fed. Sts.	Mongolia	Palau
Solomon Islands	Tuvalu	Vanuatu	Belarus	Kazakhstan
Latvia	Lithuania	Moldova	Russia	Ukraine
Guyana	Suriname	South Africa		
CLUSTER_4				
Lao PDR	Marshall Islands	Myanmar	Nauru	Papua New Guinea
Timor-Leste	Turkmenistan	Haiti	Djibouti	Yemen
Afghanistan	Pakistan	Botswana	Burundi	Comoros
Congo, Rep.	Eritrea	Eswatini	Ethiopia	Gabon
Gambia	Ghana	Kenya	Madagascar	Malawi
Mauritania	Namibia	Rwanda	Senegal	Sudan
Tanzania	Togo	Uganda	Zambia	Zimbabwe
CLUSTER_5				
Angola	Benin	Burkina Faso	Cameroon	Central African Republic
Chad	Dem. Rep. Congo	Cote d'Ivoire	Eq. Guinea	Guinea
Guinea-Bissau	Liberia	Mali	Mozambique	Niger
Nigeria	Sierra Leone	Somalia	South Sudan	
CLUSTER_6				
Lesotho				

Appendix 17. Mean and Standard Deviation Values of Variables by Clusters for the Year 2018

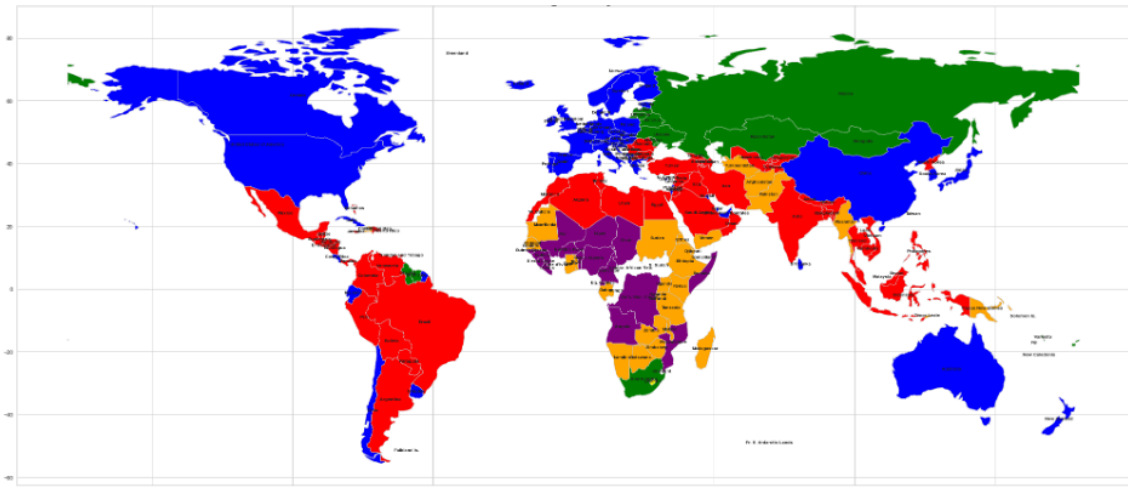
Variable	mean / std. dev.	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
SP.DYN.TO65.FE.ZS	mean	91.87	84.09	78.82	67.83	58.25	43.98
	std. dev.	2.3	4.14	7.65	5.49	5.8	
SP.DYN.TO65.MA.ZS	mean	85.49	73.32	62.71	57.33	51.55	32.92
	std. dev.	4.92	5.72	6.61	6.51	5.15	
SP.DYN.LE00.FE.IN	mean	83.03	76.79	74.41	66.95	60.44	56.59
	std. dev.	2.09	2.72	3.91	2.36	3.19	
SP.DYN.LE00.MA.IN	mean	78.24	71.02	66.94	62.15	57.3	50.99
	std. dev.	2.71	2.72	2.63	2.39	2.89	
SP.DYN.LE00.IN	mean	80.57	73.85	70.59	64.51	58.87	53.73
	std. dev.	2.32	2.57	3.11	2.23	2.99	
SH.DYN.NCOM.ZS	mean	12.19	19.57	30.11	24.55	23.83	43.4
	std. dev.	3.73	4.55	9.16	4.92	4.79	
SH.DYN.NCOM.FE.ZS	mean	9.25	16.34	23.39	22.25	22.55	37.8
	std. dev.	2.85	3.94	9.75	4.47	3.53	

Variable	mean / std. dev.	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
SH.DYN.NCOM.MA.ZS	mean	15.18	22.95	37.5	27.09	25.28	50.4
	std. dev.	5.08	6.05	8.61	6.36	6.94	
SH.STA.POIS.P5	mean	0.34	0.55	2.03	1.94	2.79	5.3
	std. dev.	0.27	0.4	1.49	0.8	0.69	
SH.STA.POIS.P5.FE	mean	0.22	0.36	1.03	1.47	2.11	4.3
	std. dev.	0.24	0.28	0.85	0.62	0.56	
SH.STA.POIS.P5.MA	mean	0.48	0.76	3.14	2.44	3.47	6.4
	std. dev.	0.33	0.58	2.34	1.11	1.03	
SP.DYN.AMRT.FE	mean	48.67	96.03	131.88	207.79	265.45	419.45
	std. dev.	13.88	28.29	49.61	50.17	49.88	
SP.DYN.AMRT.MA	mean	90.08	172.87	247.82	292.28	321.59	529.3
	std. dev.	32.29	46.01	53.79	66.96	49.19	
SP.DYN.IMRT.IN	mean	4.14	15.09	16.14	38.6	64.59	60.8
	std. dev.	2.24	6.39	10.18	7.26	9.68	
SP.DYN.IMRT.FE.IN	mean	3.77	13.62	14.4	34.51	58.42	54.6
	std. dev.	2.01	5.87	9.13	6.91	9.09	
SP.DYN.IMRT.MA.IN	mean	4.49	16.48	17.77	42.49	70.45	66.8
	std. dev.	2.43	6.91	11.15	7.68	10.3	
SH.DYN.NMRT	mean	2.87	10.15	9.32	24.23	32.57	37
	std. dev.	1.63	4.86	5.68	5.25	3.68	
SH.DYN.MORT	mean	4.92	17.68	19.28	51.43	97.29	76.4
	std. dev.	2.5	7.67	12.77	9.86	16.38	
SH.DYN.MORT.FE	mean	4.49	16.02	17.28	46.76	90.84	69.4
	std. dev.	2.28	7.12	11.6	9.56	16.47	
SH.DYN.MORT.MA	mean	5.34	19.25	21.13	55.86	103.46	83.1
	std. dev.	2.71	8.24	13.88	10.24	16.43	
SH.DYN.1014	mean	0.61	1.69	1.96	4.3	8.54	4.1
	std. dev.	0.27	0.71	0.94	1.7	2.01	
SH.DYN.1519	mean	1.59	3.86	4.31	7.95	12.81	10.7
	std. dev.	0.61	1.72	1.86	2.9	3.13	
SH.DYN.0509	mean	0.51	1.52	1.98	5.96	13.25	5
	std. dev.	0.25	0.65	1.26	2.52	3.17	
SH.DYN.2024	mean	2.3	5.41	6.84	10.61	17.48	17.8
	std. dev.	0.99	2.79	4.47	3.89	4.4	
SH.DYN.0514	mean	1.11	3.43	3.81	10.61	22.32	9.1
	std. dev.	0.53	1.81	1.97	4.06	5.89	
SH.STA.SUIC.P5	mean	11.75	5.51	21.43	7.61	7.22	76.6
	std. dev.	5	3.24	7.27	4.9	2.67	
SH.STA.SUIC.FE.P5	mean	5.82	2.61	7.86	3.56	3.74	29.9
	std. dev.	3	1.87	3.63	1.78	1.15	
SH.STA.SUIC.MA.P5	mean	17.68	8.43	35.85	11.76	10.71	124.6
	std. dev.	7.7	5.15	11.67	9.17	4.66	

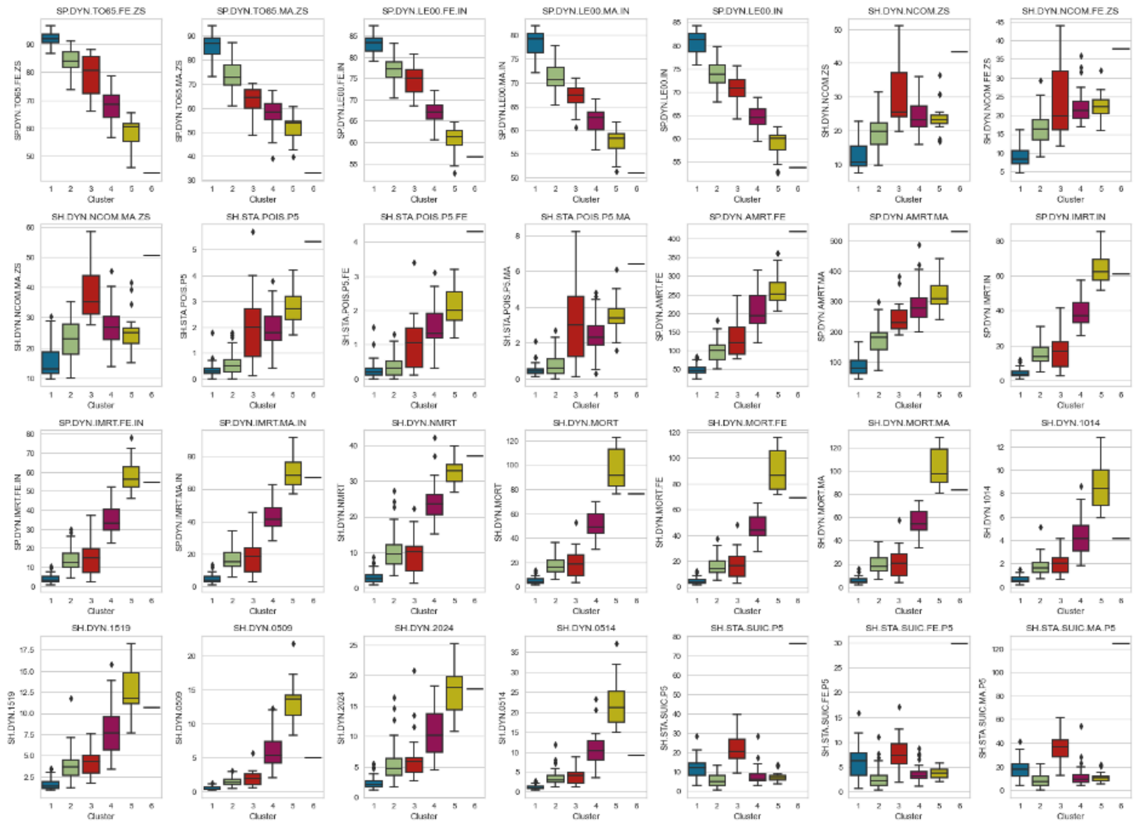
Appendix 18. Determination of the Optimal Number of Clusters for the Year 2018



Appendix 19. Representation of Countries by Clusters on the World Map for the Year 2018



Appendix 20. Box Plots of Clusters by Variables for the Year 2018



Appendix 21. Clusters and Countries within the Clusters for the Year 2019

CLUSTER_1				
Australia	China	Japan	South Korea	New Zealand
Singapore	Albania	Andorra	Austria	Belgium
Bosnia and Herzegovina	Croatia	Cyprus	Czechia	Denmark
Estonia	Finland	France	Germany	Greece
Hungary	Iceland	Ireland	Italy	Latvia
Lithuania	Luxembourg	Monaco	Montenegro	Netherlands
Norway	Poland	Portugal	San Marino	Slovakia
Slovenia	Spain	Sweden	Switzerland	United Kingdom
Argentina	Chile	Costa Rica	Cuba	Ecuador
Turks and Caicos Islands	Uruguay	Bahrain	Israel	Kuwait
Malta	Qatar	United Arab Emirates	Canada	United States of America
Maldives	Sri Lanka			
CLUSTER_2				
Brunei	Cambodia	Indonesia	Malaysia	Philippines
Thailand	Tonga	Vietnam	Armenia	Azerbaijan
Bulgaria	Georgia	Kosovo	Kyrgyzstan	North Macedonia
Romania	Serbia	Tajikistan	Turkey	Turkmenistan
Uzbekistan	Antigua and Barbuda	Bahamas	Barbados	Belize
Bolivia	Brazil	British Virgin Islands	Colombia	Dominica
Dominican Rep.	El Salvador	Grenada	Guatemala	Honduras

Jamaica	Mexico	Nicaragua	Panama	Paraguay
Peru	St. Lucia	St. Vincent and the Grenadines	Trinidad and Tobago	Venezuela
Algeria	Egypt	Iran	Iraq	Jordan
Lebanon	Libya	Morocco	Oman	Saudi Arabia
Syria	Tunisia	West Bank and Gaza	Bangladesh	Bhutan
Cabo Verde	Mauritius	Sao Tome and Principe	Seychelles	
CLUSTER_3				
Fiji	Kiribati	North Korea	Micronesia, Fed. Sts.	Mongolia
Palau	Samoa	Solomon Islands	Tuvalu	Vanuatu
Belarus	Kazakhstan	Moldova	Russia	Ukraine
Guyana	St. Kitts and Nevis	Suriname	India	Nepal
South Africa				
CLUSTER_4				
Lao PDR	Marshall Islands	Myanmar	Nauru	Papua New Guinea
Timor-Leste	Haiti	Djibouti	Yemen	Afghanistan
Pakistan	Botswana	Burundi	Comoros	Congo, Rep.
Eritrea	Eswatini	Ethiopia	Gabon	Gambia
Ghana	Kenya	Madagascar	Malawi	Mauritania
Namibia	Rwanda	Senegal	Sudan	Tanzania
Togo	Uganda	Zambia	Zimbabwe	
CLUSTER_5				
Angola	Benin	Burkina Faso	Cameroon	Central African Republic
Chad	Dem. Rep. Congo	Cote d'Ivoire	Eq. Guinea	Guinea
Guinea-Bissau	Liberia	Mali	Mozambique	Niger
Nigeria	Sierra Leone	Somalia	South Sudan	
CLUSTER_6				
Lesotho				

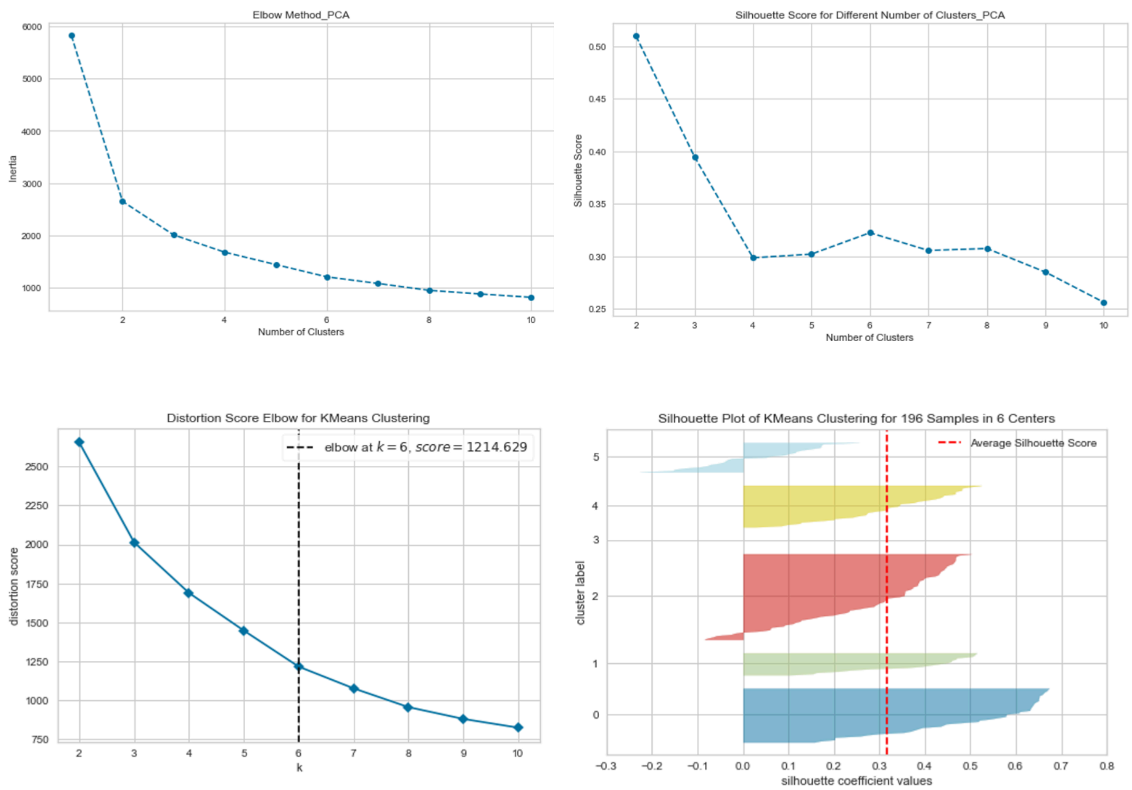
Appendix 22. Mean and Standard Deviation Values of Variables by Clusters for the Year 2019

Variable	mean / std. dev.	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
SP.DYN.TO65.FE.ZS	mean	91.81	84.51	78.59	68.22	58.85	45.12
	std. dev.	2.41	4.19	6.54	5.12	5.77	
SP.DYN.TO65.MA.ZS	mean	85.11	73.83	64.09	57.64	52.1	33.98
	std. dev.	5.66	5.84	6.51	6.39	5.06	
SP.DYN.LE00.FE.IN	mean	83.14	77.04	73.84	67.18	60.83	57.05
	std. dev.	2.2	2.71	3.15	2.17	3.18	
SP.DYN.LE00.MA.IN	mean	78.15	71.28	67.3	62.34	57.67	51.41
	std. dev.	3.11	2.78	2.35	2.27	2.85	
SP.DYN.LE00.IN	mean	80.57	74.11	70.49	64.72	59.24	54.17
	std. dev.	2.57	2.62	2.51	2.09	2.97	
SH.DYN.NCOM.ZS	mean	12.29	19.28	29.39	24.27	23.59	42.7
	std. dev.	3.95	4.39	8.63	4.94	4.69	
SH.DYN.NCOM.FE.ZS	mean	9.19	16.08	23.35	22.04	22.44	37.5
	std. dev.	2.86	3.64	8.89	4.57	3.46	

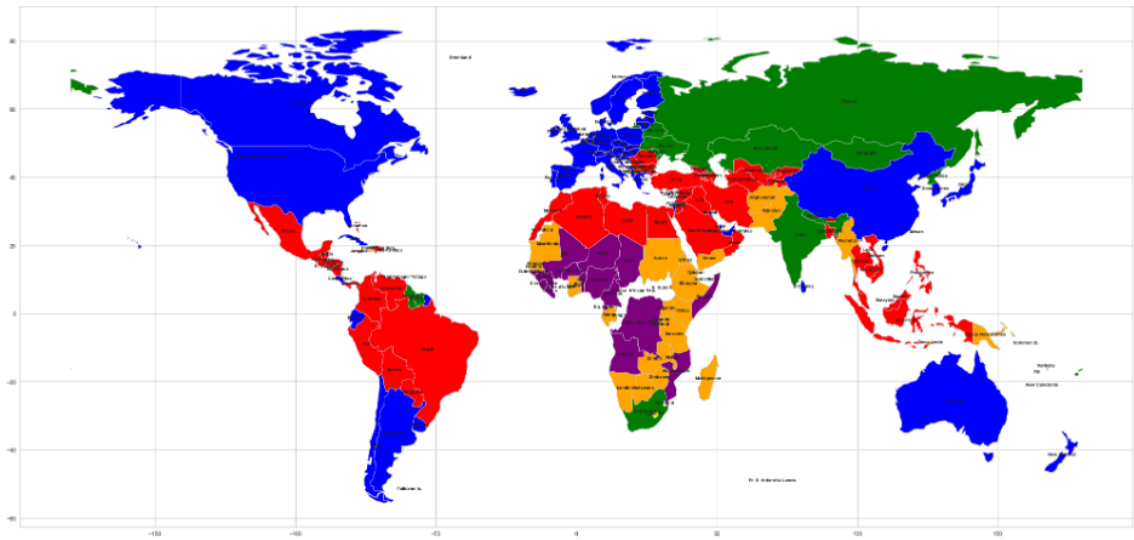
Variable	mean / std. dev.	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
SH.DYN.NCOM.MA.ZS	mean	15.47	22.64	36.01	26.73	24.96	49.4
	std. dev.	5.67	6.01	8.83	6.26	6.78	
SH.STA.AIRP.P5	mean	30.14	73.62	140.77	172.78	202.74	288.3
	std. dev.	28.22	46.18	74.79	37.66	41.81	
SH.STA.AIRP.FE.P5	mean	24.26	62.68	114.61	151.58	180.78	242.2
	std. dev.	25.25	41.51	63.12	38.25	35.07	
SH.STA.AIRP.MA.P5	mean	36.91	86.9	174.02	198.78	230.01	351.9
	std. dev.	32.74	53.53	87.86	42.4	58.03	
SH.STA.POIS.P5	mean	0.39	0.51	1.88	1.93	2.75	5.2
	std. dev.	0.34	0.36	1.36	0.75	0.79	
SH.STA.POIS.P5.FE	mean	0.22	0.34	0.98	1.46	2.1	4.3
	std. dev.	0.22	0.25	0.78	0.58	0.6	
SH.STA.POIS.P5.MA	mean	0.56	0.69	2.83	2.41	3.41	6.2
	std. dev.	0.52	0.51	2.12	1.04	1.13	
SH.STA.WASH.P5	mean	3.61	6.35	12.83	30.96	61.83	108.1
	std. dev.	2.27	4.67	11.91	11.46	20.02	
SP.DYN.AMRT.FE	mean	49.11	93.13	133.43	205.15	261.73	406.66
	std. dev.	15.17	29.05	43.25	47.18	49.32	
SP.DYN.AMRT.MA	mean	92.99	168.55	229.05	290.1	317.67	516.42
	std. dev.	38.61	45.84	56.78	65.31	47.7	
SP.DYN.IMRT.IN	mean	3.95	14.77	17.66	37.66	63.09	60
	std. dev.	2	6.69	8.81	7.23	9.49	
SP.DYN.IMRT.FE.IN	mean	3.58	13.27	15.9	33.68	57.04	53.8
	std. dev.	1.79	5.92	8.16	6.84	8.95	
SP.DYN.IMRT.MA.IN	mean	4.29	16.18	19.31	41.43	68.85	65.9
	std. dev.	2.21	7.42	9.5	7.67	10.05	
SH.DYN.NMRT	mean	2.74	9.87	10.71	23.71	32.07	36.5
	std. dev.	1.45	4.92	5.51	5.22	3.74	
SH.DYN.MORT	mean	4.7	17.29	21.12	50.22	94.6	77.2
	std. dev.	2.25	7.92	11.1	9.77	16.3	
SH.DYN.MORT.FE	mean	4.27	15.59	19.18	45.68	88.26	70.2
	std. dev.	2.04	7.06	10.4	9.42	16.36	
SH.DYN.MORT.MA	mean	5.11	18.9	22.98	54.54	100.65	83.7
	std. dev.	2.47	8.75	11.82	10.2	16.28	
SH.DYN.1014	mean	0.6	1.69	2.01	4.34	8.39	4
	std. dev.	0.25	0.82	0.79	1.69	2	
SH.DYN.1519	mean	1.6	3.71	4.46	7.89	12.53	10.4
	std. dev.	0.63	1.66	1.63	2.81	3.06	
SH.DYN.0509	mean	0.5	1.56	2.03	5.97	12.92	4.8
	std. dev.	0.23	1.04	1.07	2.45	3.17	
SH.DYN.2024	mean	2.34	5.19	6.92	10.57	17.25	17.5
	std. dev.	1.04	2.56	4.18	3.76	4.36	
SH.STA.SUIC.P5	mean	12.19	5.01	19	7.69	7.16	72.4

Variable	mean / std. dev.	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
	std. dev.	5.38	2.81	7.72	5.03	2.6	
SH.STA.SUIC.FE.P5	mean	5.92	2.25	7.67	3.6	3.74	30.1
	std. dev.	3.09	1.27	3.54	1.76	1.21	
SH.STA.SUIC.MA.P5	mean	18.55	7.75	30.87	11.89	10.59	116
	std. dev.	8.64	4.69	13.08	9.34	4.55	

Appendix 23. Determination of the Optimal Number of Clusters for the Year 2019



Appendix 24. Representation of Countries by Clusters on the World Map for the Year 2019



Appendix 25. Box Plots of Clusters by Variables for the Year 2019