South Asian Countries are Less Fatal Concerning COVID-19: A Fact-finding Procedure Integrating Machine Learning & Multiple Criteria Decision-Making (MCDM) Technique

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Abstract Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) which caused an outbreak of pneumonia in December 2019 in Wuhan, China, has spread rapidly throughout the world. This ongoing pandemic has resulted over 55.6 million cases of COVID-19 leading to 1.34 million deaths in more than 188 countries. However, it has been observed that the death rate is significantly in the lower side for the SAARC countries compared to the First World Nations. In this paper, the possible factors have been represented that determine this uneven distribution of COVID-19 deaths. The significance of the factors has been presented in this paper after the data analysis of the factors from 165 different countries. Based on the correlation of the factors and their critical impact towards the concerned countries death toll, the risk index of each factor has been labeled using analytical hierarchy process (AHP)-based MCDM, i.e., multiple criteria decision-making technique. The risk index of all the factors has been used to generate the susceptibility of COVID-19 for each of the countries in study, specifically the SAARC Nations. Finally, the hierarchical clustering was applied to visualize the death toll of the countries corresponding to their susceptibility index.

Keywords COVID-19 · Risk factor · Susceptibility index · Hierarchical clustering · AHP · MCDM

Introduction

The World Health Organization declared the outbreak of COVID-19 [1] a Public Health Emergency of International Concern on January 30, 2020, and a pandemic on 11 March. The first confirmed death was in Wuhan on January 9, 2020. The first death outside China occurred on February 1, 2020, in Philippines and the first death outside Asia was in France on 14 February [2]. Since then, more than 188 countries and territories have had at least one case of COVID-19 so far. Containment measures such as quarantines and curfews have been imposed by many countries to restrict the spread of the virus. By late April, around 300 million people were under lockdown in many European countries, while 200 million people were under some form of lockdown in the USA. However, the death toll in USA has been constantly rising with over 2,39,853 deaths as of November 13, 2020. Similarly, the ratio of confirmed cases to deaths is significantly high for the First World Nations in Europe and Asia compared to the SAARC countries. South Asia accounts for approximately 1.5% of the total coronavirus cases worldwide and even a lower percentage of deaths nations.

The South Asian Association for Regional Cooperation (SAARC) includes India, Afghanistan, Bangladesh, Maldives, Nepal, Pakistan, Bhutan and Sri Lanka. One-fifth of the world’s population resides in these nations. However, the death rate has been significantly low in spite of the high population and mediocre health facilities. India has accounted for 83,64,086 confirmed cases and 1,24,354 deaths, which is the highest among the SAARC nations as of November 13, 2020, whereas the USA has 239,853 deaths as of November 13, 2020, and the death toll of France, Italy, Spain, the UK, and Russia is all high in comparison with their population.
Table 1 signifies the vast difference in the conversion rate of confirmed to death between the SAARC nations and the other developed countries. In spite of the fact that India’s population is equivalent to 17.7% of the total world population and Dhaka, the capital of Bangladesh being the sixth most populated city in the world, the death toll is still low.

The paper focuses on the factors which are responsible for such a low death rate in SAARC nations. In spite of the fact that COVID-19 is highly transmissible, the transmission rate in these nations is low given that these countries house one-fifth of the world population. The factors in the study include (1) The Average Temperature; the warmer and more humid weather in the South Asian region can temper the spread of the disease, (2) The Bacillus Calmette-Guerin (BCG) vaccine offered for the protection against tuberculosis in these nations creates a better immune response against the virus, (3) Critical Days, which signifies the minimum number of days taken by the government to take action after the first occurrence of COVID-19 case in that country, (4) Average age of the country; the younger population respond significantly better than the older population which plays a crucial for the death count of the countries, and (5) The Herd Immunity, which is an indirect protection against infectious diseases that occurs when a large percentage of a population has become immune to an infection. Observations and studies have unanimously indicated that these factors have played a significant role in the low death rate of the SAARC nations. We have assigned logical weights to these factors using analytical hierarchy process to calculate the susceptibility risk index of every country. Finally, the hierarchical clustering has been applied to visualize the distribution countries death rate corresponding to their risk index.

### Related Studies

In the recent past, a lot of work in the field of market research, bioinformatics, data processing, image processing, etc., has been done by using the hierarchical clustering algorithm. A brief review is presented here.

Ying Zhao, George Karypis and Usama Fayyad in [4] applied hierarchical clustering [5] to cluster documents. In order to remove the early-stage error and improve the quality of clustering solutions the authors combined the features from both partitional and agglomerative approaches. They concluded that constrained agglomerative methods result in better solutions than agglomerative methods alone and observed that for significantly high cases outperform partitional methods, as well.

Feng Luo, Kun Tang, and L Khan in [6] proposed to obtain gene expression pattern by using a new hierarchical clustering which constructs a hierarchy from top to bottom and dynamically find the number of clusters at each level. The authors observed that the algorithm can recognize features in complex gene expression data by extracting patterns with different levels of abstraction.

Deng Cai et. al. [7] proposed a hierarchical method to cluster the web image search results into different semantic

| Countries          | Confirmed | Deaths  |
|--------------------|-----------|---------|
| USA                | 9,802,374 | 239,853 |
| Russia             | 1,712,858 | 29,509  |
| Spain              | 1,356,798 | 38,118  |
| UK                 | 1,099,059 | 47,742  |
| Brazil             | 5,590,941 | 161,170 |
| Germany            | 597,453   | 11,035  |
| Turkey             | 384,509   | 10,558  |
| France             | 168,693   | 38,674  |
| India              | 8,364,086 | 124,354 |
| Pakistan           | 338,875   | 6893    |
| Bangladesh         | 416,006   | 6021    |
| Afghanistan        | 41,925    | 1554    |
| Sri Lanka          | 12,187    | 29      |
| Maldives           | 11,822    | 38      |
| Nepal              | 182,923   | 1052    |
| Bhutan             | 358       | 0       |


clusters. The hierarchical clustering method uses textual, visual and link analysis to obtain three kinds of representations. The representations comprise visual feature-based representation, textual feature-based representation and graph-based representation.

Seema Bandhyopadhyay and E.J. Coyle in [8] proposed a distributed, randomized clustering algorithm. The algorithm can organize the sensors in a wireless sensor network into cluster. The authors generated a hierarchy of cluster heads and observed an increase in energy savings with the increase in the level of hierarchy.

Richard Cheng and Glenn W. Milligan in [9] applied hierarchical clustering to map Influence Regions. They presented three-dimensional response surface plots for several hierarchical clustering methods and simulated core group data structures. The relative influence of the corresponding coordinate location is represented by the response surface in the bivariate data space on the clustering of the core groups. Substantial differences between clustering methods are revealed by the substantial plots.

Twinkle Tiwari and Nihar Ranjan Roy in [10] applied hierarchical clustering in heterogeneous wireless sensor networks. Wireless sensor network can sense the physical parameters like pressure, humidity, temperature, motion, etc. It is a network of small battery powered sensing node which collects information from its environment of deployment and finally report it to a central node called base station. These nodes fulfill their task by proper collaboration. The energy source should be used properly since it is constrained in WSNs. Author used clustering to minimize energy dissipation in WSNs.

Michael R. Loken et. al. in [11] proposed a system to investigate the relationship between the presenting immunophenotype by applying hierarchical clustering. This system will response to therapy in a large, controlled study of pediatric AML patients. Patients with similar diagnostic IEPs are grouped which is defined mathematically from the analysis of unsupervised hierarchical clustering. By minimizing within-cluster variation, appropriate number of clusters was accomplished.

Dac-Tu Ho et. al. in [12] proposed Particle Swarm Optimization (PSO) as an optimization method to find the optimal clusters. This system reduces the energy consumption, bit error rate (BER), and UAV travel time. Low Energy Adaptive Clustering Hierarchy (LEACH) is commonly used to conserve energy in conventional wireless sensor networks (WSNs). Conversation of energy is highly challenging for large-scale deployments than many other things.

Andy Podgursky and Charles Yang in [13] presented a new approach to estimate software reliability by reducing the manual labor required. Partition testing methods along with those of stratified sampling are combined to reduce the sample size necessary to estimate reliability with a given degree of precision. Automatic cluster analysis is used to stratify program execution and group them with similar features.

Though the South Asian Countries are less fatal concerning COVID-19, this fact is not revealed in any published work as per the authors’ best knowledge. However, in very few researches, it is considered that the death toll in South Asian countries is less than the rest of the world. Jennifer Beam Dowd and Liliana Andriano et. al. in [14] showcased the impact of demographic structure on the mortality rate by taking the examples of Italy and South Korea. Similarly, authors like Yueling Ma et. Al. in [15] and Abhibhav Sharma et al. in [16] have portrayed the significance of temperature and BCG vaccine in correspondence to the mortality rate due to COVID-19 in their respective publications. However, the authors of this paper claim to have brought upon the different critical factors leading to the lower death count in SAARC nations on the basis of the analysis of the risk factor, which is so far a totally unique work.

**Causes of Less Disaster Concerning COVID-19 in South Asian Countries**

The biggest threat posed by COVID-19 [17, 18] is its spread rate. Despite the high transmission rate, conversion rate of confirmed cases to death is not same everywhere. Significant difference has been noticed for the SAARC countries with respect of confirm cases to death.

In Fig. 1, the statistical visualization has been presented of the death count in eight different countries which includes four SAARC countries depicted with dashed lines. The death count is so low in the SAARC countries that the four different lines are clustered in same space. Though the death count in India is quite high concerning other SAARC countries, at the same time, the total population of India needed to be considered, which is the second highest in the world.

**Fundamental factors responsible for less fatality in South Asian Countries**

The fundamental factors include 1. Bacillus Calmette-Guerin (BCG) vaccine, 2. Average Temperature, 3. Average Age, 4. Critical Days, 5. Herd Immunity and are described below elaborately.
1. Bacillus Calmette-Guerin (BCG) Vaccine: BCG vaccine is mainly used to protect against tuberculosis [19]. Even though this vaccine does not protect against COVID-19, it strengthens the immune systems. Studies [20, 21] have proved that the recovery chances from COVID-19 increasing in persons with a strong immune system (Table 2). The vaccine is taken in every SAARC nation, but none of the countries with high death count takes it (see Table T3).

2. Average Temperature: The major cities with the highest death rates include Zurich, London, Berlin and Paris. During the months of February, March and April all these countries had an average temperature of 5.60 °C to 6.10 °C [22]. For the SAARC nations, the temperature increased to 21.30 °C to 29.80 °C. Studies have shown that every 10 °C increase in Average Temperature leads to a decrease in the cumulative number of cases by 0.86 [23].

Figure 2 gives a clear visualization of dependency of death per million with respect to the Average Temperature. The graph is plotted with respect to the data collected from 165 countries till April 31. The Average Temperature of the whole year has been considered given the fact that the pandemic is up and running. Since three SAARC countries fall in the Average Temperature range of 70 °C to 150 °C and display a bimodal distribution with respect to rest of the countries in the world. The weight given to average

### Table 2 Distribution of BCG vaccine taken by (a) countries with highest deaths and (b) SAARC countries

| Countries | Confirmed | Deaths | BCG taken |
|-----------|-----------|--------|-----------|
| (a) USA   | 9,802,374 | 239,853| No        |
| Russia    | 1,712,858 | 29,509 | No        |
| Spain     | 1,356,798 | 38,118 | No        |
| UK        | 1,099,059 | 47,742 | No        |
| Brazil    | 5,590,941 | 161,170| Yes       |
| Germany   | 597,453  | 11,035 | No        |
| Turkey    | 384,509  | 10,558 | Yes       |
| France    | 168,693  | 38,674 | No        |
| (b) India | 8,364,086 | 124,354| Yes       |
| Pakistan  | 338,875  | 6893   | Yes       |
| Bangladesh| 416,006  | 6021   | Yes       |
| Afghanistan| 41,925  | 1554   | Yes       |
| Sri Lanka | 12,187   | 29     | Yes       |
| Maldives  | 11,822   | 38     | Yes       |
| Nepal     | 182,923  | 1052   | Yes       |
| Bhutan    | 358      | 0      | Yes       |
The temperature during calculation of risk factor (RF) in Eq. (1) will have the least value which makes our prediction more robust and scalable.

3. Critical Days: The Critical Days signify the number of days taken by the government to take action, i.e., localized recommendation, national recommendation, localized lockdown, national lockdown [24] after the appearance of first COVID-19 confirm case in that country. Sri Lanka has taken action even before the country had its first confirm case. India declared the lockdown in March 25, 2020, when the overall death count of the country was below 50. By contrast, most of the states in the USA did not have a proper lockdown [2]. European countries like Sweden did not impose a complete lockdown. When compared to the COVID-19 spread on the scale of population density, the SAARC countries have shown better results. The impact of the Critical Days is relatively high in the case of COVID-19 compared to other infectious diseases is because of its high transmission rate.

The countries in the left section of Fig. 3 are all SAARC nations who has taken faster action compared to the countries in the right section of Fig. 3. This visualization shows the low margin of Critical Days in the SAARC nations compared to the countries with high death counts [25].

4. Average Age: Reports have shown that older population respond poorly to COVID-19 compared to a younger population (Fig. 4). One of the main reasons could be the strong immune system of the younger people. Another reason is the underlying diseases that the aged person carries tend to weaken their immune system and thus they become more susceptible to get COVID-19 infection. The share of deaths is a low rate of 3.9% for the age range of 18–44 years. The rate jumps to 24.9% for 65–74 years old.
and to 48.7% for above 75 years of age [26]. From these statistics (Table 3), it is clear that the younger population is having a significantly low death rate concerning the aged population. The average age of an Indian is 26.8, while the number is even low for Bangladesh, Nepal and Pakistan. In contrast, countries like Italy, Germany, France and UK [27] all with high death counts have an average age of over 40.

5. Herd Immunity: South Asian countries are exposed to more infectious diseases and germs compared to the western world countries. Since these nations are exposed to more pathogens, the white blood cells develop a broader memory that can trigger an immune response when a virus is recognized. With past history [28] of different infectious diseases like cholera, malaria, dengue, SARS-COV-1 [29, 30], etc., the people tend to possess a greater variation in the leukocyte antigen genes, responsible for immune response. As a result, the immune system fights back in a better way by producing proteins called antibodies. This is a critical factor to observe in our study. The low number of conversions from confirmed to death cases in SAARC countries also signifies that their immune system is churning out more antibodies to fight against COVID-19. Apart from the SAARC nations, it has been observed that the African countries who have also been a victim of lot of past diseases like Ebola, Zika, have a significantly low death count. Their genetic diversity has offered a better protection against COVID-19 compared to the European countries and American countries.

The facts stated and displayed above reflects their significance on the COVID-19 death count. These factors have been applied for each country corresponding to their death count to generate three clusters, namely low risk, moderate risk and high risk. To determine this, we have applied analytical hierarchy process to generate the weights of these five factors based on their individual impact towards COVID-19 deaths. In the paper, a relation has been established between each of these factors and the death rate to generate the risk of COVID-19 for each of the 165 countries. Finally, the hierarchical clustering has been applied to plot the three clusters based on their risk index and death per million counts. The suggested methodology is depicted in Fig. 8.

Enumeration of risk factor (RF)

To investigate the situation holistically with respect to the above attributes, the authors have tried to calculate ‘risk factor (RF)’ associated with individual country. High Average Temperature, usage of BCG and immunity earned or Herd Immunity are all inversely proportional to the death count and high average age and high value of Critical days are directly proportional to the death count. Hence, RF is formulated as follows:

\[
RF = 0.419 \times (\text{Avg. Age}) + 0.263 \times (1/\text{BCG}) + 0.16 \times (1/\text{Herd Immunity}) \\
+ 0.097 \times (\text{Critical Days}) + 0.062 \times (1/\text{Avg. Temperature})
\]

(1)

where the local weights of the five factors, i.e., Avg. Age, BCG given in % of the total population, Immunity earned, Critical Days, and Avg. Temperature of the country, are obtained through MCDM [31–34], i.e., multiple criteria decision-making technique [50–61], particularly analytical hierarchy process (AHP) [35–38], defined as Y, is presented below:
In this paper, the Average Age was recognized as the most significant deciding factor, BCG given in % of the total population is the second, Immunity earned is the third, Critical Days is the fourth, and Average Temperature of the country is the fifth vital deciding factor. Equation 2 shows the relative weight of the deciding factors.

The normalized weights of the factors are calculated by using an online computing software [39] as \( W = \{0.419, 0.263, 0.16, 0.097, 0.062\} \), which shows weights of the Average Age, BCG given in % of the total population, Immunity earned, Critical Days, and Average Temperature of the country, sequentially. The Average Temperature of the country is the least significant and the Average Age is the most important criterion, it is cleared from Fig. 5.

To calculate the risk factor, we have generated a formula based on the weights calculated and the one-to-one relationship between each of the factors and the death rate. High Average Temperature, usage of BCG and Immunity earned or Herd Immunity are all inversely proportional to the death count. High average age and high value of Critical Days are directly proportional to the death count.

### Clustering countries into different risk regions through hierarchical clustering algorithm

The countries are grouped into three clusters like, high risk, low risk and moderate risk based on the RF calculated using Eq. 1 on the dataset produced. This grouping of countries into different risky zones is done in this correspondence employing hierarchical clustering algorithm.

Hierarchical clustering is the most popular and widely used clustering techniques in Machine Learning [40–45]. Here nodes are compared with one another based on their similarity and instead of producing a single clustering; they produce a hierarchy of clustering. Larger groups are built by joining groups of nodes based on their similarity. A criterion gets introduced to compare nodes based on their relationship. There are mainly two types of hierarchical clustering approaches prevail; namely: Agglomerative approach and Divisive approach. The second one gets utilized in this study. This is a top-down approach in contrast to bottom-up approach of agglomerative method. In Divisive approach initially, all nodes are supposed to belong to the same cluster; gradually, each node forms its own cluster. The hierarchical clustering technique can be visualized using a dendrogram which is basically a tree-like structure that portrays the sequences of merges or splits (Fig. 6).

### Step-by-step procedure of the proposed methodology

Through this paper, the authors want to establish that South Asian countries are less fatal concerning COVID-19. In
Fig. 7, the step-by-step procedure of the proposed methodology is depicted. Firstly, the fundamental factors responsible have been selected for less fatality in south Asian countries, i.e., BCG, Average Temperature, Critical Days, Average Age, Herd Immunity. Secondly, the weights of the individual attributes are calculated through AHP. Thirdly, the attributes are to be labeled with individual weights. Fourthly, the risk factor needs to be formulated combining labeled attributes and also calculated using the dataset for every individual country. Then, countries are clustered into low risk, moderate risk, and high risk through the hierarchical clustering technique and the SAARC countries are analyzed based on the Clustering concerning other countries.

Experimental results and discussion

The objective of our study is based on the fact that in spite of being such a densely populated area, SAARC countries still have a low death count when compared to the first world countries. The dataset used by the authors for this report has been coined from different online sources [19, 25, 46–49]. The authors have framed a dataset containing the attributes – population density (per km²), death/million and whether the country belongs to SAARC or not (see Table 4). The dataset includes eight SAARC countries, countries with high amount of deaths, first world countries along with Singapore and South Korea whose early counter COVID-19 strategy inspired the World.
Figure 8 depicts that even with high population density in SAARC countries like Bangladesh and Maldives, the death count of COVID-19-infected person is low. In the next half of this section, we present the experimental results to showcase how the five factors introduced in section 3 governs the COVID-19 death count and why SAARC enjoys such a low death rate.

The dataset that has been created for the study of the impact of risk factor and death count contains the data of 165 countries have been considered till November 13, 2020. The dendrogram has been plotted (Fig. 9) taking the risk factor (RF) as x-axis and death/million as y-axis. The dendrogram illustrates the arrangement of the clusters produced by the corresponding analyses. A horizontal line is passed though the center of the longest vertical line which in our case is the blue line. Since the horizontal line cuts through three vertical lines, the optimum number of clusters for this particular dataset is three.

The dataset has been feded to the hierarchical clustering model [29] and set the parameter of number of clusters to 3. In Fig. 10, the countries are grouped into three clusters: high risk, low risk and moderate risk. The figure clearly explains that the countries with the low risk factor also have low death count. The countries with high death count that includes UK, USA, France, and Italy are all grouped together in the high-risk cluster. Some of the countries with

| Country     | Density (km²) | Deaths / 1 M | SAARC |
|-------------|---------------|--------------|-------|
| Maldives    | 1802          | 70           | Yes   |
| Bangladesh  | 1265          | 37           | Yes   |
| Sint Maarten| 1261          | 303          | No    |
| Bermuda     | 1246          | 145          | No    |
| Channel Islands | 907   | 275          | No    |
| San Marino  | 566           | 1237         | No    |
| S. Korea    | 527           | 9            | No    |
| India       | 464           | 90           | Yes   |

Figure 8 shows the Step-by-Step Procedure of the Proposed Methodology.
Fig. 8 Distribution of countries on the basis of death/million vs. population density, as of November 13, 2020

Table 5 Dataset-2 Snapshot

| Country     | BCG | Avg_temp | CriticalStage | Avg_Age | Immunity Earned | Deaths / 1 M |
|-------------|-----|----------|---------------|---------|-----------------|--------------|
| San Marino  | No  | 14.33    | 17.0          | 44.4    | No              | 1237         |
| Belgium     | No  | 11.55    | 11.55         | 41.4    | No              | 1079         |
| Andorra     | No  | 9.6      | 8.0           | 44.3    | No              | 970          |
| Spain       | No  | 15.3     | 38.0          | 45.5    | Yes             | 823          |
| Italy       | No  | 15.45    | 20.0          | 45.5    | Yes             | 665          |
| UK          | No  | 10.55    | 51.0          | 40.5    | Yes             | 708          |
| France      | No  | 12.7     | 44.0          | 41.4    | Yes             | 598          |
| Sint Maarten| No  | 26.0     | 18.0          | 41.0    | No              | 303          |

Fig. 9 Dendrogram
high risk factor have low deaths which is mainly due to their low population. To have a clear view where the SAARC countries stand with respect to Fig. 10, an extra filter has been applied to label the SAARC countries only.

The distribution of the SAARC countries (labeled and colored blue) is depicted in Fig. 11. It is clearly observable that the SAARC countries enjoy a low risk factor for which the death count is also low. The results prove the impact of the factors that the authors have taken into consideration. Apart from the SAARC countries, the countries that satisfy the ideal conditions of the five governing factors also display a low death count as shown in Fig. 10.

Concluding remarks

COVID-19 virus is mutating and evolving day-by-day. The number of infected cases is increasing at a very high rate. Many of the countries like USA, France, and Italy have reached the stage of community spread. In contrast, India, Pakistan, and Bangladesh with such high population density are in the local transmission stage. Other SAARC countries have a very low infected case. This paper has tried to establish the factors that segregate the SAARC countries from the countries with high infected cases and high death counts. The factors have been considered based on their individual impact on 165 different countries. Each of the factors has been weighted after studying their interrelation with death count. The risk index calculated using AHP shows the proper result when mapped with the real data. The objective of the study has been justified with cluster graphs which helps us to visualize where the SAARC countries stand with regard to the COVID-19 death count when compared to the other developed nations with superior medical facilities.

Appendix

Analytical hierarchy process (AHP)

The algorithm of AHP mainly having four steps as follows [31–39]:

Table T1 1 to 9 AHP scale (Saaty proposed)

| Saaty’s rating | Description                      |
|----------------|----------------------------------|
| 1              | Equal significance               |
| 3              | Moderate significance            |
| 5              | Essential or strong significance |
| 7              | Very strong significance         |
| 9              | Extreme significance             |
| 2, 4, 6, 8     | Intermediate values of the two adjacent judgments |
Table T2  Values of RI

| Average | Random | Index (RI) |
|---------|--------|------------|
| a       | 1      | 2          |
| RI      | 0.58   | 0.90       |
|         | 1.12   | 1.24       |
|         | 1.32   | 1.41       |
|         | 1.45   | 1.49       |

Table T3  Distribution of BCG vaccine taken worldwide

| Country         | BCG |
|-----------------|-----|
| USA             | No  |
| Spain           | No  |
| Italy           | No  |
| UK              | No  |
| France          | No  |
| Germany         | No  |
| Russia          | Yes |
| Turkey          | Yes |
| Brazil          | Yes |
| Iran            | Yes |
| China           | Yes |
| Canada          | No  |
| Belgium         | No  |
| Peru            | Yes |
| India           | Yes |
| Netherlands     | No  |
| Switzerland     | No  |
| Ecuador         | No  |
| Saudi Arabia    | Yes |
| Portugal        | Yes |
| Mexico          | Yes |
| Sweden          | No  |
| Ireland         | Yes |
| Pakistan        | Yes |
| Chile           | Yes |
| Singapore       | Yes |
| Belarus         | Yes |
| Israel          | No  |
| Qatar           | Yes |
| Austria         | No  |
| Japan           | Yes |
| UAE             | Yes |
| Poland          | Yes |
| Romania         | Yes |
| Ukraine         | Yes |
| Indonesia       | Yes |
| S. Korea        | Yes |
| Bangladesh      | Yes |
| Denmark         | No  |
| Serbia          | No  |
Step 1 Based on the given problem, the decision hierarchy needs to be formed with the sub-problems or the independent factors.

Step 2 Decision-maker needs to calculate and decide the weights to the judgment factors. Pairwise comparison executed on each decision factor.

Step 3 It is very essential to confirm that the consistency ratio is maintained based on the calculation.

Step 4 The final ranking of each alternative is obtained considering the synthesized overall result.

Considering the pairwise comparison of each judgment factor, an evaluation matrix $Y$ is to be formed. Experts will choose the value of the weight factors from the Saaty’s 1 to 9 fundamental scale (Table T1). Now, square matrix $Y$ can be written as,

$$Y = \begin{pmatrix}
    y_{11} & y_{12} & y_{13} \\
    y_{21} & y_{22} & y_{23} \\
    y_{31} & y_{32} & y_{33}
\end{pmatrix}$$

where $p$th and the $q$th judgment factor is expressed by $y_{pq}$ and here, a number of decision factors is considered. Each entry of the matrix can be written as the pairwise ratio, i.e., $y_{pq} = \frac{w_p}{w_q}$ where $p, q = 1, 2, ..., a$. In AHP, each entry of the matrix maintains the reciprocal property $y_{pq} = \frac{1}{y_{qp}}$. The following condition needs to meet for becoming matrix $Y$ as a consistent matrix;

$$y_{pr}y_{rq} = y_{pq}, \quad p, q, r = 1, 2, ..., a$$

The equation $Y_{AHP} = \lambda_{max} w_{AHP}$ provides the eigenvalue $\lambda_{max}$ and eigenvector $w_{AHP}$. Priority vector $w_{AHP} = \{w_1, w_2, ..., w_m\}$ expresses the local weights of the criteria. Due to the inconsistency of the matrices, it is necessary to find out the decision error, which is can be measured by the consistency ratio (C.R.). C.R. is simply a ratio of consistency index (C.I.) to random index (R.I.), viz, $C.R. = \frac{C.I.}{R.I.}$. Table T2 shows all the R.I. values corresponding to the various number of decision factors. Again, C.I. can be described as $C.I. = \frac{\lambda_{max} - a}{(a - 1)}$.

Where,

$$\lambda_{max} = \frac{1}{a} \sum_{p=1}^{a} \left( \frac{Y_{AHP}}{w_{AHP}} \right)_p$$

Normally, $C.I. = 0$ is expected for consistent matrix and the accepted value of the $C.R. \leq 0.1$, otherwise when $C.R. > 0.1$, adjustment is required pairwise comparison. Using Saaty’s AHP, the final ranking of the alternatives is expressed by global ranking $w_{AHP\text{,global}}$ where $w_{AHP\text{,q}}$ are the local weights,

$$w_{AHP\text{,global}} = w_{AHP\text{,intermediate}} q \cdot w_{AHP\text{,q}}$$

| Table T3 |
|----------|
| Maldives | Yes  |
| Kenya    | Yes  |
| Malta    | Yes  |
| Jamaica  | Yes  |
| Jordan   | Yes  |
| Taiwan   | Yes  |
| Paraguay | Yes  |
| Venezuela| Yes  |
| Palestine| No   |
| Mauritius| Yes  |
| Montenegro| No |
| Isle of Man | No |
| Equatorial Guinea | Yes |
| Vietnam  | Yes  |
| Guinea-Bissau | Yes |
| Faeroe Islands | No |
| Cabo Verde | Yes |
| Myanmar  | Yes  |
| Madagascar| Yes |
| Gibraltar| Yes  |
| Ethiopia | Yes  |
| Brunei   | No   |
| Zambia   | Yes  |
| Togo     | Yes  |
| Trinidad and Tobago | No |
| Bermuda  | No   |
| Botswana | No   |
| Egypt    | No   |
| Libya    | Yes  |
| French Polynesia | No |
| South Sudan | No |
| Malawi   | Yes  |
| Mongolia | Yes  |
| Angola   | Yes  |
| Zimbabwe | Yes  |
| Antigua and Barbuda | No |
| Timor-Leste | Yes |
| Botswana | Yes  |
| Belize   | Yes  |
| New Caledonia | No |
| Gambia   | Yes  |
| Curaçao  | No   |
| Sao Tome and Principe | Yes |
| Burundi  | Yes  |
| Turks and Caicos | No |
| Montserrat | No |
| Greenland | Yes |
| Suriname | No   |
| Mauritania | Yes |
| Bhutan   | Yes  |
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