

Capturing the Differential Impacts of Easing COVID-19 Restrictions: Application of a Hybrid Model of Entropy and TOPSIS

Debasis Neogi

Department of Management, Humanities & Social Sciences,
National Institute of Technology Agartala, Agartala, Tripura, India
E-mail: dnecon@gmail.com

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Abstract

The paper aims to carry out the ordinal evaluation of 30 countries of North and South Americas, separately at two different points of time on 30th July 2020 and on 30th November 2020, on the basis of 13 select criteria. It also compares the changes in the relative rankings, if any, between these two points of time of the nations caused by changes in the pandemic mitigation strategy – i.e by easing the restrictions. The study has used the Multi-criteria Decision Analysis (MCDA) approach for evaluation. The data analysis part has two major sections. The first section assigns weights to all of the thirteen criteria using the Entropy method. The second section uses the TOPSIS method of MCDA. The assigned weights indicate that two of the least important criteria are the counts of daily new cases per million population and the daily new deaths per million populations. The rankings of most of the nations differ on 30th November, 2020 over that on 30th July 2020. Changes in the values of these two criteria, in fact, caused the changes in the ordinal rankings of the nations. These two parameters represent the outcome of the COVID-19 mitigation efforts put forth by the nations. It also establishes that the COVID-19 mitigation strategy really matters when it comes to the ordinal ranking and performance appraisal of the nations. The novelty of the paper is that for the first time, the MCDA technique is used to analyse the impact of policy intervention in pandemic mitigation.

Keywords- Pandemic mitigation efforts, Multi-criteria decision analysis, Entropy, TOPSIS, Ideal best.

1. Introduction

The paper aims to evaluate the socio-demographic profiles of the countries of both the North and South Americas. Such profile plays an important role in the achievements on the health front. The key indicators considered to assess the demographic profile include population density, the average age of the population, shares of the population belonging to the above 65 and above 70 years of age categories and life expectancy at birth. The socio-economic profiles can be judged by parameters like gross domestic product per capita and human development index. The health profile can be decided by factors like hospital beds per thousand population, the death rate caused by cardiovascular diseases, the prevalence of diabetes, rates of daily new cases of COVID-19 infection and the rates of daily new deaths caused by COVID-19. The combined impacts of all the three profiles lead to the evaluation of the performances of the countries.

The study has considered thirty countries from the North and the South Americas to evaluate the impact of policy intervention by the respective Governments of the nations. The social impact of COVID-19 has been hugely negative. The measures like curfew, lockdown, etc. have adversely affected the rural enterprises, thereby breaking the backbone of the rural economy in many countries across the globe (Gautam et al., 2020). While re-opening of the economy after months-long lockdown was necessary for the countries, the danger of the pandemic regaining strength could also not be ruled out. The outcome of the study reveals the relative efficacies of the strategies, involving varying degrees of easing of the COVID restrictions, in terms of its impact

on health outcomes and on the overall economies of the respective nations. The policies adopted by better-performing nations can set a benchmark for the other nations across the globe. In this sense, the need of the study can be well justified. The methodology can be used to explore the impact of policy measures to be adopted by these nations at different points of time later on. In that case, the outcome of the present study will serve as the points of reference. However, the study faced limitations in the form of inadequate data availability. Also, for data, the study had to depend on only one or two sources.

The entire time period commencing with December 2019 and continuing even in March 2021 can be termed as the COVID-19 era. In this era two important points of time are the end of July 2020 and end of November 2020. The COVID-19 caused lockdown started in the Americas in March 2020, when the lock down in other parts of the world also commenced. In most parts of the region it continued till end of May 2020 (COVID-19 Restrictions, 2020). However, all the restrictions were not over by May. In fact, as on 19th July, 2020 about 53% of all destinations across the world had its borders completely closed for international travel and movement. About 40% of the destinations started to ease its border restrictions (UNWTO, 2020). Thus, any comparative appraisal of the conditions of the nations as on 30th July, 2020 reveals the relative positions of the countries as restrictions started to ease. Similarly, the comparative evaluation four months later, when restrictions in the form of lockdown and international travel restrictions were almost relaxed, captures the changes in the relative position of the conditions of these nations. The changes in the ordinal ranking over a span of a short period like four months indicate the resilience and preparedness of the nations in its fight against Coronaviruses, which in turn constitute the key elements to devise a generalized strategy to fight any pandemic. Secondly, out of the 13 criteria selected, except the counts of new cases per million population and the counts of new deaths per million populations, the rest of the criteria are not expected to change over four months. Hence any change in the rankings of the countries over a span of four months can be attributed to these two COVID-19 related criteria, after giving due consideration to the other socio-economic, demographic and health profiles of the nations.

The importance of all three profiles and the associated factors are well explained in the literature. Proper planning of health care of a country needs information on the rate at which the population of that country is expected to grow. The growth rate of the population, on the other hand, depends on the fertility and mortality rates. The share of the old-age population not only depends on the fertility rate that the country experienced eight to nine decades before but also on the mortality rate during the last eight to nine decades. The fertility rate, in turn, depends not only on the trend presently existing in the society but also on the exposure of the womenfolk to the risk involved during the reproduction phase (Grundy, 2011).

The impact of the population density on certain health outcomes, like the spread of COVID-19 infections, is not uniform in all instances. In areas characterized by a dense population, the rapid spread of infection may seem obvious due to people's inability to maintain the much-needed social distancing. At the same time, these are the same populous areas that have adequate medical facilities, which play a crucial role in restricting the spread of infections. However, there is the study (Hamidi et al., 2020) that points to the population density as the responsible factor for spreading the infectious disease. The study was conducted on the US metropolitan counties. The study found that the larger metropolitan areas had both higher infection and higher mortality rates. Their findings were interesting once the metropolitan population were controlled. After such control, the county population density was found to be not significantly related to the

infection rate. But, the counties characterized by relatively denser populations, had lower infection rate. If the former could be attributed to the adherence to the social distancing guidelines, the latter was due to the availability of better health infrastructure in areas having dense population.

Historically, the impact of the outbreak of any disease had been devastating, especially on the people in their old age. WHO data by April 2020 revealed that about 95% of the losses of lives occurred among people over 60 years of age. In a country like Sweden, more than 90% of death was recorded among people over 70 years of age. The susceptibility of people in their old ages is such that the care centres set up for nursing the infected people also recorded death in larger proportion among the older people (Sandoiu, 2020). In a report, Centres for Disease Control and Preventions have categorically mentioned that old age is a factor that cause rise in mortality for the persons infected with COVID-19. In the USA 80% of the death caused by COVID-19 occurred among persons belonging to the above 65 years of age categories (Centers for Disease Control and Prevention, 2020). People in their old age were found to possess co-morbidities such as respiratory illness, cardiovascular disease and diabetes etc. that along with their weaker immune system increased the risk of severe COVID-19 infection and the infection related death. Data provided as early as in March 2020 by the Chinese Centres for Disease Control and Prevention pointed to the vulnerability of the older population to COVID-19. The case fatality rate was reported to be 3.6% for people in their 60s. The same rate increased with age to 8% for the adults in their 70s and to 14.8% for those with age 80 and above (Sandoiu, 2020). The volume of global population above 65 years of age was 703 million in 2019. The average mortality rate due to COVID-19 among populations above 76 years of age was 18% (Dhama et al., 2020).

Differences in the life expectancies at birth across the nations can help us interpret the differences in the mortality rates. However, a study from the Spanish region revealed that the life expectancies at birth kept changing during the COVID-19 catastrophe. The weekly estimates were found to be lower during 11th to 20th week of 2020 compared with the same during the same time frame of 2019. The study further noticed that the drop in the weekly estimate was stronger during 13th and 14th weeks – from March 23rd to April 5th. The national decline was in the range of 6.1 to 7.6 years. The most shocking of all was the regional weekly decline by as high as 15 years recorded in Madrid. The annual estimates differed between 2019 and 2020 by an average of 0.9 years across both genders. The fall ranged from 0 years to a high of 2.8 years (Trias-Llimós et al., 2020).

2. Multi-criteria Decision Analysis

Multiple Criteria Decision Analysis/ Making (MCDA/MCDM) is used to find optimum solutions within a complex set-up that includes a number of parameters; a number of objectives, often conflicting in nature and a set of criteria. It is, in fact, a constituent of a specialized branch of mathematics, known as Operation Research (Kumar et al., 2017). Multiple Criteria Decision Making process involves making the ordinal evaluation of the available alternatives based on a certain number of criteria. For this, the first step is to assign weights to the criteria. While the assignment of subjective weights strictly depends on the intuition and experience of the decision-makers, the objective weights are obtained through the complex evaluation of the decision matrix containing information about the criteria and the alternatives (Chen, 2020).

In the present study, all the parameters have varied significance and weight. Hence, appropriate weights are to be assigned to these parameters before we proceed for ordinal evaluation of the

nations. For this, we resort to the Multi-criteria Decision Analysis (MCDA) approach. Out of a large number of techniques available in MCDA, we have specific interest for the Technique for Order of Preference by Similarity to Ideal Solution (*TOPSIS*). The study has used *TOPSIS* for ordinal evaluation of the nations. We have used the Entropy method to assign weights to the parameters, termed as criteria in MCDA.

The general applications of MCDA techniques are widespread. Poledníková (2014) attempted a quantitative evaluation of the differences among the four Visegrad countries in terms of various socio-economic parameters. The author had used MCDA techniques such as Analytic Hierarchy Process, Simple Additive Weighting and *TOPSIS* to compare the rankings of the countries. The study observed that changes in the ranking of the countries from the year 2000 to 2005 to 2010 actually reflected comparative improvement or deterioration of the nations in terms of those socio-economic indicators. The MCDM methods generally rank the alternatives based on the utility and distance functions. So, the concept of the hierarchy of elements is at the core of such analyses (Poledníková, 2014).

In another study, MCDM approach was used to evaluate and compare 18 European countries on the basis of parameters concerned with children's physical activity and the human development indices. Though the study went on to propose a new approach for determining the priority of the criteria, it used entropy-based methods to assign weights to various criteria as the fundamental method of MCDM (Krylovas et al., 2020).

There is also a study (Safari & Ebrahimi, 2014) that used MCDA Technique to rank countries based on the multiple criteria Human Development Index. The study found that assigning varying weights, rather than the equal weights to all the parameters eventually leads to changes in the ranking of the countries. The varying weights assigned to the criteria point to the differences in the relative importance of the indicators.

3. Objectives

With this backdrop showcasing the popular uses of Multi-Criteria Decision Analysis tools for comparative evaluation of nations, the present study has the following objectives:

- (i) Ordinal evaluation of 30 countries of Americas (which includes both of North and South Americas) at two different points of time: as on 30th July 2020 and on 30th November 2020.
- (ii) To compare and contrast the changes in the relative rankings, if any, of the nations caused by changes in the pandemic mitigation strategy – in the present case by easing COVID-19 restrictions.

4. Novelty of the Study

The study focuses on the changes in ordinal ranking of the nations over a span of four months. This period of four months, in fact, saw changes in the pandemic mitigation strategy, exercised by the nations. However, the relative success of the strategy depends on the background factors. The novelty of the study is that the Multi-Criteria Decision Analysis technique is used in it to capture the influence of these factors on the relative success of the COVID-19 mitigation strategy. All the parameters of the socio-economic, demographic and health profiles of the nations constitute the criteria, based on which the ordinal evaluation of the performances of the nations is done.

5. Implications of the Study

The pandemic mitigation outcome is also influenced by the socio-demographic factors. The present study will help the policy makers to ascertain the relative success of COVID – 19 mitigation strategies adopted by the individual nations, given the diversity existing in the socio-economic profiles across the nations. What happened to such success, once the changes are made in the COVID – 19 mitigation strategy, is of utmost importance to the policymakers. The lesson can help them identify the requirement of incorporating any modification in the strategy in any future pandemic mitigation endeavour. The paper will also indicate the relative success of the nations after the changes are made in their COVID – 19 mitigation strategy.

6. Materials and Method

The study aims to evaluate and rank 30 North and South American nations on the basis of 13 criteria. The countries considered in the present study include 12 nations from South America: Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Guyana, Peru, Paraguay, Suriname, Uruguay and Venezuela. The remaining 18 nations considered from North America are: Antigua & Barbuda, Bahamas, Belize, Barbados, Canada, Costa Rica, Cuba, Dominican Republic, Guatemala, Honduras, Haiti, Jamaica, Mexico, Nicaragua, Panama, El Salvador, Trinidad & Tobago and the United States. The evaluation and the ranking of the nations are done on the basis of 13 criteria which include: New cases per million population, New death per million population, Reproduction rate, Population density, Median age, Aged 65 years and older, Aged 70 years and older, GDP per capita, Cardiovascular death rate, diabetes prevalent, hospital beds per thousand population, Life expectancy and Human Development Index. The study has used the country-wise data available as on 30th July 2020 and as on 30th November 2020. Data has been collected from GitHub and Our World in data (Ritchie, 2020) (COVID-19 data Github, 2020). The data analysis section of the paper has two major parts. In the first part, the weights of all thirteen criteria are computed. This is done using the Entropy method. The second part uses the TOPSIS method of MCDA to judge the performances of 30 nations considered in the study. Shannon's entropy is one of the techniques frequently used for assigning weights to the criteria. Though it was initially developed for information science, subsequent research revealed its usefulness in decision analysis. The weights, computed by this method, eventually become a decisive factor in final ranking of the alternatives, carried out by TOPSIS or any other method of MCDM (Yue, 2017). Kaynak et al. (2015) carried out a study of ordinal evaluation of four of the EU countries in terms of its performances in innovations. They used entropy based TOPSIS approach to evaluate and rank the performances of these countries.

7. Results and Discussion

The whole information in the form of data collected is arranged in the form of a matrix called Decision Matrix.

Table 1 mentions 30 Alternatives commencing with A1 to A30. It also mentions 13 Criteria from C1 to C13.

The Alternatives stand for: A1: Argentina; A2: Antigua and Barbuda; A3: Bahamas; A4: Belize; A5: Bolivia; A6: Brazil; A7: Barbados; A8: Canada; A9: Chile; A10: Colombia; A11: Costa Rica; A12: Cuba; A13: Dominican Republic; A14: Ecuador; A15: Guatemala; A16: Guyana; A17: Honduras; A18: Haiti; A19: Jamaica; A20: Mexico; A21: Nicaragua; A22: Panama; A23: Peru; A24: Paraguay; A25: El Salvador; A26: Suriname; A27: Trinidad and Tobago; A28: Uruguay; A29: United States; A30: Venezuela.

Table 1. Decision Matrix of information as on 30th July 2020.

Criteria Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
A1	141.097	3.385	1.17	16.177	31.9	11.198	7.441	18933.91	191.032	5.5	5	76.67	0.825
A2	0.1	0.1	0.26	231.845	32.1	6.933	4.631	21490.94	191.511	13.17	3.8	77.02	0.78
A3	61.03	7.629	1.6	39.497	34.3	8.996	5.2	27717.85	235.954	13.17	2.9	73.92	0.807
A4	0.1	0.1	1.2	16.426	25	3.853	2.279	7824.362	176.957	17.11	1.3	74.62	0.708
A5	145.635	7.367	1.02	10.202	25.4	6.704	4.393	6885.829	204.299	6.89	1.1	71.51	0.693
A6	272.098	5.311	1.06	25.04	33.5	8.552	5.06	14103.45	177.961	8.11	2.2	75.88	0.759
A7	0.1	0.1	0.56	664.463	39.8	14.952	9.473	16978.07	170.05	13.57	5.8	79.19	0.8
A8	8.479	0.318	1.01	4.037	41.4	16.984	10.797	44017.59	105.599	7.37	2.5	82.43	0.926
A9	102.583	5.179	0.91	24.282	35.4	11.087	6.938	22767.04	127.993	8.46	2.11	80.18	0.843
A10	195.842	6.996	1.18	44.223	32.2	7.646	4.312	13254.95	124.24	7.44	1.71	77.29	0.747
A11	96.189	1.374	1.15	96.079	33.6	9.468	5.694	15525	137.973	8.78	1.13	80.28	0.794
A12	0.795	0.1	1.75	110.408	43.1	14.738	9.719	8821.82	190.968	8.27	5.2	78.8	0.777
A13	159.754	2.12	1.03	222.873	27.6	6.981	4.419	14600.86	266.653	8.2	1.6	74.08	0.736
A14	66.712	1.927	1.03	66.939	28.1	7.104	4.458	10581.94	140.448	5.55	1.5	77.01	0.752
A15	68.153	1.786	1.05	157.834	22.9	4.694	3.016	7423.808	155.898	10.18	0.6	74.3	0.65
A16	3.814	0.1	1.29	3.952	26.3	5.305	2.837	7435.047	373.159	11.62	1.6	69.91	0.654
A17	48.664	5.351	1.02	82.805	24.9	4.652	2.883	4541.795	240.208	7.21	0.7	75.27	0.617
A18	2.982	0.175	0.9	398.448	24.3	4.8	2.954	1653.173	430.548	6.65	0.7	64	0.498
A19	2.702	0.1	1.34	266.879	31.4	9.684	6.39	8193.571	206.537	11.28	1.7	74.47	0.732
A20	59.954	4.956	1.02	66.444	29.3	6.857	4.321	17336.47	152.783	13.06	1.38	75.05	0.774
A21	0.1	0.1	0.33	51.667	27.3	5.445	3.519	5321.444	137.016	11.47	0.9	74.48	0.658
A22	213.685	5.331	1	55.133	29.7	7.918	5.03	22267.04	128.346	8.33	2.3	78.51	0.789
A23	0.1	0.1	1.16	25.129	29.1	7.151	4.455	12236.71	85.755	5.95	1.6	76.74	0.75
A24	47.809	0.14	1.26	17.144	26.5	6.378	3.833	8827.01	199.128	8.27	1.3	74.25	0.702
A25	59.973	1.388	1.09	307.811	27.6	8.273	5.417	7292.458	167.295	8.87	1.3	73.32	0.674
A26	0.1	0.1	1.17	3.612	29.6	6.933	4.229	13767.12	258.314	12.54	3.1	71.68	0.72
A27	5.716	0.1	1.94	266.886	36.2	10.014	5.819	28763.07	228.467	10.97	3	73.51	0.784
A28	1.727	0.1	1.09	19.751	35.6	14.655	10.361	20551.41	160.708	6.93	2.8	77.91	0.804
A29	204.225	3.674	0.98	35.608	38.3	15.413	9.732	54225.45	151.089	10.79	2.77	78.86	0.924
A30	24.652	0.07	1.27	36.253	29	6.614	3.915	16745.02	204.85	6.47	0.8	72.06	0.761

Table 2. Decision Matrix for information as on 30th November 2020.

Criteria Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
A1	126.693	5.686	0.95	16.177	31.9	11.198	7.441	18933.91	191.032	5.5	5	76.67	0.825
A2	0.1	0.1	0.3	231.845	32.1	6.933	4.631	21490.94	191.511	13.17	3.8	77.02	0.78
A3	61.03	0.1	0.77	39.497	34.3	8.996	5.2	27717.85	235.954	13.17	2.9	73.92	0.807
A4	279.16	2.515	1.15	16.426	25	3.853	2.279	7824.362	176.957	17.11	1.3	74.62	0.708
A5	7.367	0.428	0.93	10.202	25.4	6.704	4.393	6885.829	204.299	6.89	1.1	71.51	0.693
A6	99.445	1.35	1.17	25.04	33.5	8.552	5.06	14103.45	177.961	8.11	2.2	75.88	0.759
A7	3.48	0.1	0.66	664.463	39.8	14.952	9.473	16978.07	170.05	13.57	5.8	79.19	0.8
A8	209.183	2.676	1.14	4.037	41.4	16.984	10.797	44017.59	105.599	7.37	2.5	82.43	0.926
A9	68.685	2.825	0.99	24.282	35.4	11.087	6.938	22767.04	127.993	8.46	2.11	80.18	0.843
A10	165.675	3.577	0.95	44.223	32.2	7.646	4.312	13254.95	124.24	7.44	1.71	77.29	0.747
A11	499.596	7.067	1.06	96.079	33.6	9.468	5.694	15525	137.973	8.78	1.13	80.28	0.794
A12	4.503	0.088	0.83	110.408	43.1	14.738	9.719	8821.82	190.968	8.27	5.2	78.8	0.777
A13	47.475	0.092	1.18	222.873	27.6	6.981	4.419	14600.86	266.653	8.2	1.6	74.08	0.736
A14	32.194	2.154	0.95	66.939	28.1	7.104	4.458	10581.94	140.448	5.55	1.5	77.01	0.752
A15	5.079	0.279	1.05	157.834	22.9	4.694	3.016	7423.808	155.898	10.18	0.6	74.3	0.65
A16	38.141	1.271	1.03	3.952	26.3	5.305	2.837	7435.047	373.159	11.62	1.6	69.91	0.654
A17	36.852	0.909	0.8	82.805	24.9	4.652	2.883	4541.795	240.208	7.21	0.7	75.27	0.617
A18	1.929	0.088	0.87	398.448	24.3	4.8	2.954	1653.173	430.548	6.65	0.7	64	0.498
A19	18.236	0.338	1	266.879	31.4	9.684	6.39	8193.571	206.537	11.28	1.7	74.47	0.732
A20	50.197	2.21	0.95	66.444	29.3	6.857	4.321	17336.47	152.783	13.06	1.38	75.05	0.774
A21	0.1	0.1	0.48	51.667	27.3	5.445	3.519	5321.444	137.016	11.47	0.9	74.48	0.658
A22	249.608	4.403	1.17	55.133	29.7	7.918	5.03	22267.04	128.346	8.33	2.3	78.51	0.789
A23	0.1	0.1	0.96	25.129	29.1	7.151	4.455	12236.71	85.755	5.95	1.6	76.74	0.75
A24	72.625	1.823	1.09	17.144	26.5	6.378	3.833	8827.01	199.128	8.27	1.3	74.25	0.702
A25	0.1	0.463	1.12	307.811	27.6	8.273	5.417	7292.458	167.295	8.87	1.3	73.32	0.674
A26	0.1	0.1	0.82	3.612	29.6	6.933	4.229	13767.12	258.314	12.54	3.1	71.68	0.72
A27	6.431	0.1	1.21	266.886	36.2	10.014	5.819	28763.07	228.467	10.97	3	73.51	0.784
A28	40.59	0.288	1.18	19.751	35.6	14.655	10.361	20551.41	160.708	6.93	2.8	77.91	0.804
A29	477.038	3.541	1.25	35.608	38.3	15.413	9.732	54225.45	151.089	10.79	2.77	78.86	0.924
A30	12.449	0.106	0.95	36.253	29	6.614	3.915	16745.02	204.85	6.47	0.8	72.06	0.761

The Criteria stand for: C1: New cases per million population; C2: New death per million population; C3: Reproduction rate; C4: Population density; C5: Median age; C6: Aged 65 years and older; C7: Aged 70 years and older; C8: GDP per capita; C9: Cardiovascular death rate; C10: Diabetes prevalent; C11: Hospital beds per thousand population; C12: Life expectancy and C13: Human Development Index.

The analysis is based on TOPSIS method of MCDA. A pre-requisite in this case is assignment of weights to the criteria. The present study has used the Entropy method of weight determination. Before we proceed with the Entropy method, normalization of the decision matrix is required. The normalization is done in the following way:

$$k_{ij} = \frac{\beta_{ij}}{\sum_{i=1}^{20} \beta_{ij}} \tag{1}$$

i = countries; j = criteria; k_{ij} = normalized element; β_{ij} = element of i th row (country) and j th column $i = 1, 2, \dots, 30$; $j = 1, 2, \dots, 13$. Normalized data is obtained separately for Table 1 and Table 2 – that is for the decision matrices at the two points of time. Using the normalized matrix we find Entropy (σ_j) for every criterion:

$$\sigma = -\phi \sum_{i=0}^{20} k_{ij} \cdot \ln(k_{ij}) \tag{2}$$

$i = 1, 2, \dots, 30$; $j = 1, 2, \dots, 13$. ϕ is a constant and is calculated as:

$$\phi = \frac{1}{\ln(n)} \dots \tag{3}$$

n = number of alternatives (countries in the present case) = 30. So, $\phi = \frac{1}{\ln(30)}$.

Once entropy is known, in the next step weight vectors are calculated. The weight vector of any criterion is the ratio of the diversification of that criterion and the sum of the values of diversification with respect to all the criteria. The quantum of diversification actually signifies the freedom of the decision-maker to utilize the available information to make the optimum decision. (Jozi et al., 2012).

$$D_j = \frac{1 - \sigma_j}{\sum_{j=1}^{13} (1 - \sigma_j)} \tag{4}$$

D_j = Degree of Diversification

Table 3. Weight Vectors for the criteria.

Weight Vectors for the criteria as on 30 th July 2020													
Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
Weight Vector	0.071400	0.071200	0.078800	0.071900	0.079200	0.078500	0.078400	0.077000	0.078700	0.078900	0.077400	0.079400	0.079300
Rank	12	13	5	11	3	7	8	10	6	4	9	1	2
Weight Vectors for the criteria as on 30 th November 2020													
Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
Weight Vector	0.069400	0.071700	0.079200	0.072000	0.079300	0.078600	0.078500	0.077100	0.078800	0.079000	0.077500	0.079500	0.079400
Rank	13	12	4	11	3	7	8	10	6	5	9	1	2

The weight vectors computed for the criteria as on 30th July, 2021 indicate that in terms of importance, the criteria are marginally different from one another. However, life expectancy (C12) turns out to be the most significant criterion, followed by human development index (C13), median age of the population (C5), diabetes prevalent (C10), reproduction rate (C3), Cardiovascular death rate (C9) and share of the population with age 65 years or more (C6) comprising the top half hierarchy of the criteria. The other half comprising of the six least important criteria are new death per million population (C2), new cases of COVID-19 per million population (C1), population density (C4), GDP per capita (C8) and hospital beds per thousand population (C11) and share of the population with age 70 years or more (C7) respectively.

The weight vectors computed for the same set of criteria 4 months later also highlight similar relative importance attached to the criteria as was found 4 months earlier, except that the reproduction rate (C3) is now 4th important criterion while the prevalence of diabetes (C10) is 5th important one as against the attached importance being 5th and 4th respectively 4 months earlier. Negligible changes in relative importance attached to the criteria also point to the fact that over a span of 4 months, the selected criteria remained compatible to carry out the comparative analysis.

The weight vectors obtained from entropy for the criteria are used in the TOPSIS analysis. We begin TOPSIS with the normalization of the decision matrix given in Table 1 and Table 2. The normalization is done in the following way:

$$Z_{ij} = \frac{N_{ij}}{\sqrt{\sum_{i=1}^{30} N^2_{ij}}} \tag{5}$$

i = countries; j = criteria N_{ij}= element of the decision matrix.

The Weighted Normalized Matrix is obtained by multiplying the weights of each criterion with the normalized elements of the decision matrix.

$$R_{ij} = Z_{ij} * W_j \tag{6}$$

where, $\sum W_j = 1$.

To proceed further with TOPSIS, the next task is to ideal best R_j^+ and ideal worst R_j^- of each criterion. The ideal best alternative, that maximizes the benefit criteria and minimizes the cost criteria, indicates extreme performance on each criterion and the ideal worst alternative, that maximizes the cost criteria and minimizes the benefit criteria, implies reverse extreme performance on each criterion (Roszkowska, 2011).

Table 4. Ideal Best and Ideal Worst of Criteria.

Ideal Best and Ideal Worst of Criteria as on 30 th July, 2020													
Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
Ideal Best	0.034800	0.029540	0.024400	0.047320	0.019810	0.026050	0.026020	0.039040	0.030360	0.025100	0.032430	0.015820	0.017820
Ideal Worst	0.000010	0.000270	0.003270	0.000260	0.010530	0.005910	0.005490	0.001190	0.006050	0.008070	0.003360	0.012280	0.009580
Ideal Best and Ideal Worst of Criteria as on 30 th November, 2020													
Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
Ideal Best	0.040350	0.039300	0.018290	0.047390	0.019840	0.026090	0.026060	0.039140	0.030410	0.025130	0.032480	0.015840	0.017840
Ideal Worst	0.000010	0.000490	0.004390	0.000260	0.010540	0.005920	0.005500	0.001190	0.006060	0.008080	0.003360	0.012300	0.009590

Once the ideal best and the ideal worst are found, the Euclidian distance of the elements of the weighted normalized matrix separately from the ideal best and from the ideal worst are calculated for each of the 30 nations considered in the study.

$$M_i^+ = [\sum_{j=1}^{13} (R_{ij} - R_j^+)^2]^{0.5} \tag{7}$$

$$M_i^- = [\sum_{j=1}^{13} (V_{ij} - V_j^-)^2]^{0.5} \tag{8}$$

The same exercise is done for the decision matrices at the two-time points considered in the study. The TOPSIS model is based on the notion of ‘displaced ideal point’ that creates minimum distance with the non-ideal solution. For the comparative assessment of the alternatives, all the alternatives are assigned with ordinal preferences – i.e ranks. According to Hwang and Yoon, this ranking is done on the basis of the minimum possible distance from the Ideal best and maximum possible distance from the Ideal worst solutions. The merit of TOPSIS lies in the fact that it considers the distances to both of the Ideal best and Ideal worst. The ranking of the preference order is done by simultaneously considering both the distances. The relative closeness of the distances and an amalgamation of both the distances are used (Shih et al., 2007; Hwang & Yoon, 1981; Belenson & Kapur, 1973; Zelany, 1974).

The final step is to compute the performance score X_i in respect of every nation.

$$X_i = M_i^- / (M_i^- + M_i^+) \tag{9}$$

This is done for the alternative nations separately as on 30th July, 2021 and 30th November, 2021. The performance scores are then ranked to judge the relative performances of each of the countries.

Table 5. Performance Scores and Corresponding Ranks of the nations as on 30th July, 2020 and 30th November 2020.

Countries	Score as on 30.07.2020	Score as on 30.11.2020	Rank as on 30.07.2020	Rank as on 30.11.2020
Argentina	0.338683	0.298160	5	6
Antigua and Barbuda	0.157917	0.179006	12	15
Bahamas	0.144789	0.352643	14	3
Belize	0.168521	0.067848	10	25
Bolivia	0.029864	0.203003	29	13
Brazil	0.093677	0.322521	20	4
Barbados	0.487647	0.539273	2	1
Canada	0.373801	0.281793	4	8
Chile	0.15569	0.222157	13	12
Colombia	0.135575	0.267957	15	9
Costa Rica	0.477345	0.118994	3	20
Cuba	0.203834	0.267685	8	10
Dominican Republic	0.117075	0.230207	17	11
Ecuador	0.058067	0.064573	24	26
Guatemala	0.043765	0.07017	26	24
Guyana	0.091627	0.095947	21	23
Honduras	0.032767	0.106762	28	21
Haiti	0.175697	0.198142	9	14
Jamaica	0.12914	0.157539	16	17
Mexico	0.094871	0.151896	19	19
Nicaragua	0.017742	0.018751	30	30
Panama	0.266137	0.295561	6	7
Peru	0.033129	0.042138	27	29
Paraguay	0.059037	0.052896	23	28
El Salvador	0.116157	0.155016	18	18
Suriname	0.083873	0.105781	22	22
Trinidad and Tobago	0.228589	0.30771	7	5
Uruguay	0.166733	0.173618	11	16
United States	0.58506	0.511018	1	2
Venezuela	0.044705	0.062917	25	27

The results shown in Table 5 exhibits some of the interesting changes occurred over a span of four months. While the USA and Barbados retained the top two positions with the USA moving down to 2nd position in November, allowing Barbados to become the top performer; at the bottom level of the hierarchy, Nicaragua's position remained 30 in both July and November. Some of the significant improvement was found in the case of Bahamas from a rank of 14 to a rank of 3; Bolivia from 29 to 13; Dominican Republic from 17 to 11 and Brazil from a low of 20 to a high of 4. Some of the significant deterioration in the relative position was noticed in the case of Belize from 10 to 25; Costa Rica from 3 to 20; Paraguay from 23 to 28 and Haiti from 9 to 14. Mexico maintained the same rank in both July and November.

A curious inquiry into the relative changes in the ordinal ranking of the nations reveals some interesting facts. Though the Bahamas experienced a drastic improvement in ranking from 14 to 3, in respect of all the criteria, Bahamas' performance remained the same in July-end and November-end. It was the performance deterioration of the other nations that caused the Bahamas to experience improvement in relative position.

In the case of Brazil, the improvement in ordinal ranking by November end over that of July end could also be attributed to deteriorating performances of some other nations. At the same time, Brazil recorded significant improvement in the number of new cases per million population, when it dropped from 272 to nearly 100, and also in the number of new deaths per million population, that faced drop from 5.3 to 1.35.

One of the countries that faced deterioration in performances is Belize. Belize saw a tremendous surge in the number of new cases and in the new number of deaths. The number of new cases per million population increased from 0.1 to 279.16, while the count of new deaths per million population increased from 0.1 to 2.5. Similarly for Costa Rica also drastic changes occurred in the case of these two criteria that caused significant deterioration in the ranking of the country.

The present study aims to judge the pandemic mitigation strategy alongside the efforts to come out of the economic impasse, put forth by these 30 nations of the Americas. Among the selected criteria, except for the two i.e the number of new cases and the number of new deaths, the rest of the criteria are not supposed to change in the short run and accordingly these other criteria have not recorded any change in its values. So, the pressing issue is to see how the changes recorded in both the criteria of COVID-19 mitigation efforts alter the ordinal positions of the nations. The changes in performance scores and the ranks of the nations over 4 months period, as depicted in Table 5, well establishes the fact that the differential efforts of the nations really matter in the performance appraisal of the nations.

8. Conclusions

To come out of the economic impasse caused by months-long lockdown, the nations started to ease the COVID restrictions once the infection started subsiding. However, depending on the prevailing situations, the degree of easing had not been uniform across the nations. The varying impacts of such policy interventions by the nations could be well ascertained when the performance evaluation of these select nations was carried out at the end of the first four months of easing COVID restrictions. Using MCDA techniques for performance evaluation of the nations at two points of time, the study has captured the differential impacts of easing COVID restrictions. Besides ordinal evaluation, the paper points to the fact that the socio-demographic

factors also influence the pandemic mitigation outcomes.

Conflict of Interest

The author confirms that there is no conflict of interest to declare for this publication.

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