

A PROMETHEE II AND WARPED K -MEANS APPROACH TO ORDERED CLUSTERING: APPLICATION TO THE GLOBAL HEALTH SECURITY INDEX

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RESUMO

Vários estudiosos propuseram estratégias de agrupamento para particionar um conjunto de alternativas em agrupamentos ordenados por preferência, com base em métodos de análise de decisão multicritério não compensatória (MCDA). Assim, algumas abordagens usando métodos baseados em superação foram propostas para construir um particionamento, encontrando centróides representativos de clusters e minimizando ex-post as inconsistências de preferência entre alternativas atribuídas a diferentes grupos. Neste estudo, propomos uma abordagem de agrupamento multicritério que primeiro classifica o conjunto de alternativas e, em seguida, executa um algoritmo iterativo para encontrar clusters ordenados, seus centróides de cluster e os limites superior e inferior de cada cluster. É realizada uma aplicação ao Índice de Segurança Sanitária Global, considerando 195 países. Os resultados são comparados com os segmentos definidos pelo índice original. Limitações são discutidas e pesquisas futuras são propostas

PALAVRAS CHAVE. Clustering multi-critério, PROMETHEE II, Global Security Health Index

ABSTRACT

Several scholars have proposed clustering strategies to partition a set of alternatives into preference-ordered clusters, based on non-compensatory multi-criteria decision analysis (MCDA) methods. Thus, some approaches using outranking-based methods have been proposed to build a partitioning, finding representative centroids of clusters and minimizing ex-post the preference inconsistencies among alternatives assigned to different groups. In this study, we propose a multi-criteria clustering approach which first rank the set of alternatives and then performs an iterative algorithm to find ordered clusters, their cluster centroids, and the upper and lower boundaries of each cluster. An application to the Global Health Security Index (GHSI) is performed, considering 195 countries. Results are compared with the GHSI segments, showing the main differences between these approaches. Limitations are discussed and future research is proposed.

KEYWORDS. Ordered clustering, PROMETHEE II, Global Security Health Index

1. Introduction

The problem of grouping alternatives into homogenous groups has been extensively studied in the MCDA literature and has been conceived in two kind of problems [Zopounidis and Doumpos, 2002]: classification and clustering. In MCDA, classification is a supervised grouping process called sorting in which the decision maker looks for the assignment of alternatives to pre-defined ordered categories [Almeida et al., 2008]. Two approaches are often used to pre-define categories [Macary et al., 2014]: 1) definition of the upper and lower limits of each category; 2) definition of one or several central reference alternatives, qualified as good representatives, for each category. Instead, the clustering problem can be stated as an unsupervised MCDA problem in which the categories are unknown a priori. In that case, a discovering process is applied that helps to find information useful to describe categories: representative centroids, category limits, membership functions. Two kind of clustering approaches are commonly recognized in MCDA: relational and ordered clustering. Relational clustering is performed whenever local relations among clusters is discovered. Instead, ordered clustering helps to find clusters that are ordered from the best to the worst, such that preferential consistency properties among alternatives are satisfied.

Most MCDA approaches for ordered clustering focus on partitioning a set of alternatives by applying an iterative procedure that helps to discover the group centroids. Several scholars have proposed ordered clustering strategies to partition a set of alternatives, based on non-compensatory multi-criteria decision analysis (MCDA) methods [De Smet, 2014] that use the outranking preference relation to compare alternatives. Thus, approaches using PROMETHEE and ELECTRE methods for clustering purposes build a partitioning of the alternatives set minimizing inconsistencies among alternatives assigned to different groups [Fernandez et al., 2010; De Smet et al., 2012]. Some other use the internal structure of preference functions to adapt the method to the k -means algorithm [Chen et al., 2018]. Boujelben and De Smet [2016] propose an approach that integrates PROMETHEE and K -means, a popular greedy algorithm, for partitioning a set of elements into a pre-defined number of clusters so as to minimize the distances to the cluster centroids (the cluster centers). The underlying idea of their approach is based on the notion of belief distance between the alternatives and the centroids. Chen et al. [2018] propose a PROMETHEE-based algorithm, which also integrates the K -means rationale to cluster alternatives at hand. De Smet et al. [2012] propose an exact multi-criteria algorithm to find ordered categories, based on valued preference degrees, computed before the inconsistencies are eliminated.

In general, the approaches above lie in four features. First, the definition of an indifference-based metric that measures how indifferent is an alternative to a central alternative, or centroid, representing a category. Thus, an alternative is assigned to the cluster where the most indifferent centroid is found. Second, once all the alternatives have been assigned, the centroids are updated, using the information regarding the alternatives in their respective groups. This process continues until a stop condition is satisfied. Third, most effort is put into minimizing the inconsistencies. An inconsistency exists, for instance, whenever an alternative preferred to another is assigned to a worst group than the latter. Fourth, given that K -means-like procedures are applied by the approaches above, focus is put on discovering the group centroids, neglecting the identification of upper and lower cluster limits.

In this article, we focus on the third and fourth features. We propose an approach

in which: (1) the alternatives are ranked by using the PROMETHEE II multi-criteria method; (2) starting from this ranking, centroids and lower and upper boundaries of clusters are found by an iterative algorithm. The outcome of this process is a set of ordered clusters. In order to assign alternatives to clusters in the iterative algorithm, direct and inverse outranking functions are considered in PROMETHEE to build a membership function, which allows to compare every pair of alternatives and centroids.

The proposed approach is applied to the Global Health Security Index 2019, used to rank nations in terms of their ability to cope with a pandemic, proposed as a means for grouping countries into three categories. The Global Health Security (GHS) Index is the first benchmark metric designed to measure the health capabilities of any countries to cope with biological threats. Because of globalization, infectious diseases and outbreaks such as the COVID-19 pandemic can easily spread and become an international catastrophe. Therefore, the GHS aims to assure all countries have the health capabilities to locally manage infectious disease threats and assume their collective responsibility to secure the worldwide health [GHS, 2019].

This article is organized as follows. In Section 2 basics off the clustering approach are presented. Section 2.4 presents the clustering approach. In Section 3, countries included in the GHS 2019 Report are clustered by following the proposed approach. Results are presented and discussed. Limitations of this approach and future research is proposed in Section 4.

2. Methods

2.1. PROMETHEE II

Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE) [Brans and Vincke, 1985] is a family of non-compensatory methods that have been applied in most decision-making problems and domains [Figueira et al., 2010]. PROMETHEE methods evaluate in which degree an alternative outranks another. Thus, the outranking relation helps to model the global assertion “the alternative b is at least as good as the alternative a ”, based on information collected at the level of each criterion.

Formally, let $A = \{a_1, a_2, \dots, a_n\}$ be a set of actions (e.g., countries); let $F = \{g_1, g_2, \dots, g_m\}$ be a family of criteria used to evaluate each action and $W = \{w_j \mid 0 \leq w_j \leq 1, \sum_{j=1}^m w_j = 1\}$ the criteria weights. The vector of performances of an action $(g_1(a), g_2(a), \dots, g_m(a))$ is called the evaluation profile. For any pair $b, a \in A$, the deviation of evaluations on criterion j , $= g_j(b) - g_j(a)$, can be calculated. On each criterion, PROMETHEE uses this deviation to compute a preference function which allows to evaluate how preferred is an action over another.

Brans and Vincke [1985] propose several preference functions to measure in which degree an alternative is preferred to another, in terms of a criterion. In particular, the “Type V” function, $P_j(a, b)$ is defined as follows:

$$P_j(b, a) = \begin{cases} 1 & \text{if } g_j(b) - g_j(a) > p_j, \\ 0 & \text{if } g_j(b) - g_j(a) \leq q_j, \\ \frac{g_j(b) - g_j(a) - q_j}{p_j - q_j} & \text{otherwise,} \end{cases} \quad (1)$$

In (1), p_j, q_j are called the strict-preference and the indifference thresholds, respectively. These thresholds allow to model imprecise evaluations. The strict-preference threshold p_j

is defined as the minimum value $g_j(b) - g_j(a)$ such that b is preferred over a on the criterion j . The indifference threshold q_j is defined as the maximum value $g_j(b) - g_j(a)$ such that b can be considered as indifferent to a . Based on the $c_j(b, a)$ ($j = 1, \dots, m$) functions, the following indices can be computed,

$$\begin{cases} \pi(b, a) = \sum_{j=1}^m w_j P_j(b, a), \\ \pi(a, b) = \sum_{j=1}^m w_j P_j(a, b), \end{cases} \quad (2)$$

where $\pi(b, a)$ expresses with which degree b is preferred to a , over all the criteria. Next, the level in which an element b is preferred to, or it is outranked by, the others elements in A can be expressed in terms of two values:

$$\begin{cases} \phi^+(b) = \frac{1}{n-1} \sum_{a \in A, a \neq b} \pi(b, a), \\ \phi^-(b) = \frac{1}{n-1} \sum_{a \in A, a \neq b} \pi(a, b), \end{cases} \quad (3)$$

where $\phi^+(b)$ is called the positive outranking flow of b and $\phi^-(b)$ is called the negative outranking flow. In PROMETHEE II, a net outranking flow is calculated by the following expression

$$\phi(b) = \phi^+(b) - \phi^-(b). \quad (4)$$

This function satisfies $-1 \leq \phi(b) \leq 1$. When $\phi(b) > 0$, b outranks all other alternatives in all criteria more than it is outranked. When $\phi(b) < 0$, b is outranked by all other alternatives in all criteria more than it outranks them. This function can be used to build a prioritization of the alternatives at hand.

2.2. A membership function based on the outranking relation

Let us define the inverse preference function

$$P_j^{inv}(a, b) = \begin{cases} 0 & \text{if } g_j(a) - g_j(b) > p'_j, \\ 1 & \text{if } g_j(a) - g_j(b) \leq q'_j, \\ \frac{g_j(a) - g_j(b) - q'_j}{p'_j - q'_j} & \text{otherwise.} \end{cases} \quad (5)$$

where p'_j, q'_j are called the inverse thresholds [Roy et al., 2014]. Therefore, we define $\mu_j(a, b_h) = \min\{P_j^{inv}(a, b_h), P_j(b_h, a)\}$ as a membership function [Pereira et al., 2019]. From this relation, we re-define the indexes in (3) as follows:

$$\begin{cases} \Gamma_D(b, a) = \sum_{j=1}^m w_j P_j(b_h, a), \\ \Gamma_I(a, b) = \sum_{j=1}^m w_j P_j^{inv}(a, b_h). \end{cases} \quad (6)$$

Therefore, we define the global membership function, that represents the degree in which a belongs to the category described by the centroid b_h , as follows

$$i(a, b_h) = \min\{\Gamma_D(b_h, a), \Gamma_I(a, b_h)\} \quad (7)$$

Note that $0 \leq i(a, b_h) \leq 1$.

2.3. Warped K-means

Leiva and Vidal [2013] introduced the Warped K-means (WKM) clustering approach, originally proposed for problems in which each evaluation profile is modeled as a real vector, and distances between actions and centroids are computed by metric distances, e.g. the Euclidean distance. WKM is a deterministic approach based on K -means that uses the following procedure: 1) building a permutation $A^{(p)}$ from the set A of actions; 2) setting initial groups and centroids by automatically defining boundaries of clusters [Leiva and Vidal, 2013]; 3) moving boundaries and updating the centroids, until the set of centroids is stable. In Figure 1, an example of permutation is represented, with three clusters (red, green, blue), boundaries L_h and centroids b_h ($h = 1, 2, 3$). The left boundary of a cluster is shown which coincides with the first element in each group. Actions in the set $[L_{h-1}, L_h[$ are assigned into C_h such that centroids can be calculated.

Note the action a in Figure 1. Let $i(a, b)$ be an indifference relation between alternatives a and b . Thus, if $i(a, b_1) < i(a, b_2)$ then a should be better assigned to C_2 . Thus, re-assignment of this action means that L_1 should be moved to the left, centroids should be updated and the process repeated. Several rounds can be applied, in left (or descending) and right (or ascending) directions, until the centroids are stable or a number of iterations is reached. Leiva and Vidal [2013] provides a detailed explanation of this method.

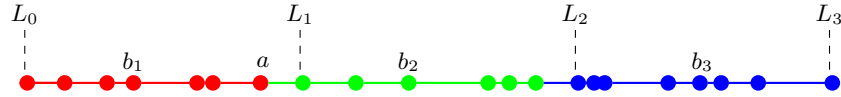


Figura 1: Example of three clusters boundaries L_h and three centroids b_h ($h = 1, 2, 3$)

2.4. Clustering process O-WKM

The clustering process proposed in this article is presented in Figure 2. Firstly, the set of alternatives, the family of criteria, the number of clusters and parameters w, p, q for each criterion are defined. Secondly, the PROMETHEE II method is applied which generates a complete pre-order of alternatives in A . Third, the O-WKM algorithm is applied to find a set of ordered clusters.

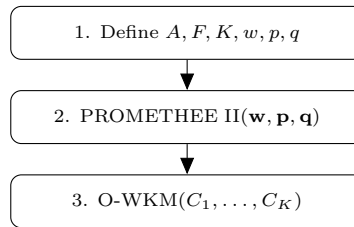


Figura 2: Approach for the ordered clustering

O-WKM is an adaptation of WKM to cases in which similarity between an action and a centroid is replaced by the relation (7), presented in Section 2.1. Thus, by using the PROMETHEE II method, a permutation p of A , i.e. $A^{(p)} = \{a_{i_1}, a_{i_2}, \dots, a_{i_n}\}$, may be obtained in which, for all $v \leq u$, it follows $a_{i_v} \preceq a_{i_u}$, which means that a_{i_u} outranks (it is

preferred or indifferent to) a_{i_v} . By using O-WKM, a partition $C_k \succ C_{k-1} \succ \dots \succ C_1$ with centroids $b_k, b_{k-1}, \dots, b_1$, respectively, of $A^{(p)}$ satisfies two conditions defining an ordered clustering process Cailloux et al. [2007]: 1) For any C_i, C_j ($i > j$) an element $a_i \in C_i$ is not outranked by none element $a_j \in C_j$; 2) For any $l > p$, the centroid b_l outranks b_p .

Given $A^{(p)}$, boundaries L_h can be computed by the Algorithm 1 [Leiva and Vidal, 2013]). WKM bases the improvement of the k -means global similarity function as a corner step of its process. We propose do not use such a function and use instead two assignment rules. Therefore, we define an outranking-based clustering process, which we call the O-WKM algorithm, identified in the Algorithm 2. In this algorithm, the expression $\overleftarrow{C}_h$ means that this set is explored from right to left. Similarly, $\overrightarrow{C}_h$ means that the set is explored from left to right. This allows to implement the descending and ascending rules. These rules were introduced by Almeida et al. [2008] in the context of supervised multi-criteria sorting processes, but these can be adapted to the clustering process.

Note that in the Algorithm 2, the Repeat-Until loop mimics the iterative k -means algorithm. Although we propose to control it by a maximum number of iterations, *MaxIt*, it could continue until another stop condition is fulfilled.

Algorithm 1: Boundaries

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Input:  $k, \Gamma_D$ 
Result: boundaries  $L_h, h = 0, \dots, k$ 
 $L_0 = a_1$ ;
for  $i = 2$  to  $n$  do
    |  $L_i = L_{i-1} + \Gamma_D(a_i, a_{i-1})$ 
end
 $S = L_n/k$ ;
 $j = 1$ ;
for  $h = 1$  to  $k$  do
    | while  $S * (h - 1) > L_j$  do
    | |  $j = j + 1$ ;
    | |  $L_h = a_j$ 
    | end
end
end

```

If the ascending rule is adopted, the clusters' centroids are updated as follows. For $a_i \in \overrightarrow{C}_h$ compute $\psi_h(a_i) = \psi_h(a_{i-1}) + \sigma_D(a_i, a_{i-1})$. A centroid in C_h is defined as the first action $a_t \in \overrightarrow{C}_h$ satisfying $\psi_h(a_t) > \lfloor \psi_h(a_h)/2 \rfloor$, where a_h is the last action at the right side of C_h . Thus, we define $b_h = a_t$. Note that this procedure computes the median of a cluster, in the sense of the outranking relation. Moreover, b_h becomes a medoid since it is a member of the alternatives set. It allows to update the centroids each time that the clusters boundaries change. A similar procedure is applied in the case of the descending rule.

3. Application

The Global Health Security Index (GHSI) is the first comprehensive framework designed to measure the proven health capabilities across the 195 countries that make up the States Parties to the International Health Regulations. GHSI includes 34 indicators and 85 sub-indicators organized across six categories covering prevention, detection, and response to health global risks. Questions, indicators, and sub-indicators were selected based on the extant literature, the opinions of an International Panel of Experts, practitioners, and academics. The index includes qualitative and quantitative questions to be answered using open-source data. Priorities are assigned to the countries' health system resilience, compliance with international norms, and capability for managing biological risks that may cause national and global instability, economic consequences, morbidity, and mortality

Algorithm 2: Clustering algorithm O-WKM

Input: $A^{(p)}, L_h (h = 0, \dots, K-1), b_h (h = 1, \dots, K)$
 Result: Clusters $C_1, \dots, C_k$
 $It = 0$;
 repeat
 1. Descending Rule. Decrease h from $K-1$ until 1:
 For $a \in \underline{C_h}$:
 • if $\min\{\Gamma_I(a, b_h), \Gamma_D(b_h, a)\} > \min\{\Gamma_I(a, b_{h+1}), \Gamma_D(b_{h+1}, a)\}$ then:
 – Assign a to C_h ; otherwise, assign a to C_{h+1} .
 – Update $L_h (h = 0, \dots, K-1), b_h (h = 1, \dots, K)$.
 2. Ascending Rule. Increase h from 1 until K :
 For $a \in \underline{C_h}$:
 • if $\min\{\Gamma_I(a, b_h), \Gamma_D(b_h, a)\} > \min\{\Gamma_I(a, b_{h-1}), \Gamma_D(b_{h-1}, a)\}$ then:
 – Assign a to C_h ; otherwise, assign a to C_{h-1} .
 – Update $L_h (h = 0, \dots, K-1), b_h (h = 1, \dots, K)$.
 3. $It = It + 1$.
 Until $It = MaxIt$

(www.ghsindex.org). GHSI allows ranking countries to track their progress toward public health and define collaborative projects to increase the global resilience toward infectious diseases [Razavi et al., 2020]. In which follows, we analyze the the Global Health Security Index (www.ghsindex.org), based on the Report 2019.

3.1. Clustering the Global Health Security Index

The GHS Index assesses countries' health security and capabilities across six aggregated criteria: g_1 , preventing the emergence or release of pathogens; g_2 , early detection and reporting epidemics of potential international concern; g_3 , rapidly responding to and mitigating the spread of an epidemic; g_4 , sufficient & robust health sector to treat the sick & protect health workers; g_5 , commitments to improving national capacity, financing and adherence to norms; g_6 , risk environment and vulnerability to biological threats. Three groups of countries are defined in GHS: most prepared, more prepared and least prepared. Each criterion is evaluated in the scale $[0, 100]$.

In this case, to setting the threshold values, we have computed the standard deviation σ_j for every criterion j and defined the interval $[\sigma_j - \bar{g}_j, \sigma_j + \bar{g}_j]$, where $\bar{g}_j$ is the average score of the whole set of nations, restricted to the criterion j . To propose an initial number of clusters, we define $K = 3$ which parallels the number of groups defined in the GHS Report. For sake of presentation, in Table 1 results of clustering are shown in three parts: Part 1, Part 2 and Part 3.

In GHSI, three groups of nations are defined according to their GHS score, evaluated in the scale $[0, 100]$: Most Prepared ($[66.7, 100]$); More Prepared ($[33.4, 66.6]$); Least Prepared ($[0, 33.3]$). In Table 1, these categories correspond to nations identified with yellow, orange and dark-orange background, respectively. Column h shows the cluster C_h in which every nation is assigned by the O-WKM algorithm. Note that numbers 1, 2, 3 in these columns indicate just the number of cluster where a country is assigned by the algorithm.

Tabela 1: Ordered clustering GHS 2019, $K = 3$

Part 1		Part 2		Part 3	
Country	h	Country	h	Country	h
Albania	3	Bolivia	2	Brunei	1
Argentina	3	Bosnia and Herzegovina	2	Burkina Faso	1
Armenia	3	Cambodia	2	Burundi	1
Australia	3	Cameroon	2	Cabo Verde	1
Austria	3	Colombia	2	Central African Republic	1
Belgium	3	Costa Rica	2	Chad	1
Brazil	3	Côte d'Ivoire	2	Comoros	1
Bulgaria	3	Cuba	2	Congo (Brazzaville)	1
Canada	3	Cyprus	2	Congo (D.R.)	1
Chile	3	Dominican Republic	2	Cook Islands	1
China	3	Egypt	2	Djibouti	1
Croatia	3	El Salvador	2	Dominica	1
Czech Republic	3	Ethiopia	2	Equatorial Guinea	1
Denmark	3	Ghana	2	Eritrea	1
Ecuador	3	Iran	2	eSwatini (Swaziland)	1
Estonia	3	Jordan	2	Fiji	1
Finland	3	Kazakhstan	2	Gabon	1
France	3	Kenya	2	Gambia	1
Georgia	3	Laos	2	Grenada	1
Germany	3	Lebanon	2	Guatemala	1
Greece	3	Liberia	2	Guinea	1
Hungary	3	Luxembourg	2	Guinea-Bissau	1
Iceland	3	Madagascar	2	Guyana	1
India	3	Maldives	2	Haiti	1
Indonesia	3	Malta	2	Honduras	1
Ireland	3	Mauritius	2	Iraq	1
Israel	3	Moldova	2	Jamaica	1
Italy	3	Montenegro	2	Kiribati	1
Japan	3	Morocco	2	Lesotho	1
Kuwait	3	Myanmar	2	Libya	1
Kyrgyz Republic	3	Namibia	2	Malawi	1
Latvia	3	Nepal	2	Mali	1
Liechtenstein	3	Nicaragua	2	Marshall Islands	1
Lithuania	3	Nigeria	2	Mauritania	1
Malaysia	3	North Macedonia	2	Micronesia	1
Mexico	3	Oman	2	Monaco	1
Mongolia	3	Pakistan	2	Mozambique	1
Netherlands	3	Panama	2	Nauru	1
New Zealand	3	Paraguay	2	Niger	1
Norway	3	Qatar	2	Niue	1
Peru	3	Senegal	2	North Korea	1
Philippines	3	Sierra Leone	2	Palau	1
Poland	3	St Lucia	2	Papua New Guinea	1
Portugal	3	St Vincent and The Grenadines	2	Rwanda	1
Romania	3	Suriname	2	Samoa	1
Russia	3	Tanzania	2	San Marino	1
Saudi Arabia	3	Trinidad and Tobago	2	São Tomé and Príncipe	1
Serbia	3	Tunisia	2	Seychelles	1
Singapore	3	Uganda	2	Solomon Islands	1
Slovakia	3	Ukraine	2	Somalia	1
Slovenia	3	Uruguay	2	South Sudan	1
South Africa	3	Uzbekistan	2	Sri Lanka	1
South Korea	3	Zimbabwe	2	St Kitts and Nevis	1
Spain	3	Afghanistan	1	Sudan	1
Sweden	3	Algeria	1	Syria	1
Switzerland	3	Andorra	1	Tajikistan	1
Thailand	3	Angola	1	Timor-Leste	1
Turkey	3	Antigua and Barbuda	1	Togo	1
United Arab Emirates	3	Azerbaijan	1	Tonga	1
United Kingdom	3	Bahamas	1	Turkmenistan	1
United States	3	Bangladesh	1	Tuvalu	1
Vietnam	3	Barbados	1	Vanuatu	1
Bahrain	2	Belize	1	Venezuela	1
Belarus	2	Benin	1	Yemen	1
Bhutan	2	Botswana	1	Zambia	1

By applying O-WKM, centroids of groups, (b_1, b_2, b_3) , and upper boundaries of categories C_1 and C_2 are found. In addition, centroids found by using the K -means algorithm, (k_1, k_2, k_3) , are also shown:

$$\begin{aligned} b_1 &= (24.50, 21.90, 28.60, 20.30, 38.00, 44.20), \\ b_2 &= (36.00, 45.80, 43.20, 27.70, 27.80, 57.80), \\ b_3 &= (55.00, 36.70, 58.10, 45.20, 59.40, 77.20). \end{aligned}$$

$$\begin{aligned} L_1 &= (8.2, 8.8, 24.5, 11.5, 32.0, 56.2), \\ L_2 &= (34.9, 47.4, 52.4, 42.7, 47.7, 54.4). \end{aligned}$$

(8)

It is easy to verify that $b_3 S b_2$ and $b_2 S b_1$, where S is the outranking preference relation. In addition, it is straightforward to show that $L_2 P L_1$, where P is the strict preference relation. Note that the C_1 lower bound and the C_3 upper bound are obvious: these correspond to the last and first nation, respectively, found in the ranking step of the clustering process.

Nations in the first GHSI segment, identified with yellow background in the Table, are all in the third group ($h = 3$). However, most of nations classified in C_3 by O-WKM are in the second GHSI segment. This suggests that O-WKM correctly assign the top GHSI countries in the same group. The same could be observed for nations in the last GHSI segment, which are almost all in the C_1 cluster.

A limitation of this approach is that parameters in O-WKM (weights, thresholds) could be uncertain in which case a stochastic approach should be considered. In such case, centroids and category boundaries should not be precise and a specific method needs to be defined to estimate these parameters in a context of uncertainty.

4. Conclusions

In this paper, we have applied a multi-criteria ordered clustering process based on the PROMETHEE II which also performs an iterative algorithm to find ordered clusters, their cluster centroids, and the upper and lower boundaries of each cluster. As a result, an ordered set of clusters is found. The application of this approach to the GHSI shows that the deterministic clustering highly explain the three segments of nations defined in GHSI. However, some new information is provided showing that some countries could be considered in the same group of top nations.

A limitation of this study is that O-WKM needs to be compared with other multi-criteria ordering clustering approaches. Future research considers that comparison. Another future work concerns the cross-validation of GHSI and COVID-19. Although it has been proposed that nor GHS neither Universal Health Coverage (UHC) strategies were able to predict how nations would deal with this disease [Abbey et al., 2020; Lal et al., 2021], we have the intention to analyze the clustering results and some of GHSI variables to know if some countries were indeed more prepared than others to cope with COVID-19.

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