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Research Article

A hybrid multi criteria decision making and clustering approach for evaluating positive peace

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Abstract

This study is based on the indicators presented in the Positive Peace Report, which assesses countries' levels of peace not only through the absence of conflict but also through their institutional and social structures. The positive peace approach measures countries' capacity for sustainable peace through eight key components: a well-functioning government, low levels of corruption, a robust business environment, equitable distribution of resources, respect for the rights of others, the free flow of information, high levels of human capital, and good relations with neighbors. In this context, the aim of the study is to identify the similarity structures of 163 countries within the framework of these components and to cluster the countries. Given the multidimensional nature of positive peace and the differences in the relative importance of the criteria, it becomes necessary to determine the weights of the criteria objectively and to examine the similarities through multivariate analyses. Accordingly, the study employed the CILOS technique in conjunction with hierarchical clustering analysis. In the first stage, objective weights were determined based on eight criteria; in the second stage, similarities between countries were examined using hierarchical clustering analysis based on this framework. The findings reveal that countries are not homogeneous in terms of positive peace and are grouped into four distinct clusters. Consequently, the study contributes to the comparative analysis of the multidimensional structure of positive peace and demonstrates the effectiveness of the proposed methodological framework.

1. Introduction

Although the concept of peace has long been interpreted primarily as the absence of war or direct violence, this perspective has gradually proven insufficient for explaining societal well-being and sustainable stability. In response, the notion of positive peace has gained prominence as a more comprehensive framework. Rather than focusing solely on the absence of conflict, it emphasizes the capacity of societies to build and maintain resilience in the face of crises. This perspective highlights the need to strengthen key structural components such as institutional effectiveness, social inclusion, equitable resource distribution, access to information, and human capital. In this sense, positive peace offers a valuable analytical framework not only for assessing the level of security in countries, but also for evaluating the quality of governance and the resilience of societies [1].

The Positive Peace Index, developed by the Institute for Economics & Peace, examines the structural characteristics that support peace across countries through eight core pillars: well-functioning government, low levels of corruption, a sound business environment, equitable distribution of resources, acceptance of the rights of others, free flow of information, high levels of

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human capital, and good relations with neighbors. These eight pillars are measured using a total of 24 indicators, and the index covers 163 countries and territories. In this respect, the Positive Peace Index provides a comprehensive dataset that enables a comparative analysis of structural similarities and differences among countries [1].

In the analysis of multidimensional data structures, relying solely on descriptive statistics is often insufficient. To uncover latent patterns among observations, group units with similar characteristics, and support data-driven decision-making processes, data mining and multivariate analysis techniques are widely employed. Within this context, cluster analysis stands out as an important method that groups observations based on similarity without requiring a predefined classification structure. In particular, hierarchical clustering analysis offers an effective and interpretable approach for comparative country studies by revealing proximity relationships among observations within a stepwise framework [2, 3]. However, in datasets characterized by multiple criteria, obtaining more meaningful and reliable clusters requires taking into account the relative importance of the criteria used in the analysis. At this point, multi-criteria decision-making (MCDM) methods play a crucial role in determining criterion weights in a systematic and objective manner. The CILOS method is recognized in the literature as an objective weighting approach that calculates the relative importance of criteria based on the loss of impact within the decision matrix. When combined with cluster analysis, this approach allows for more consistent and robust results, particularly in the evaluation of multidimensional socioeconomic indicators [4].

The main objective of this study is to evaluate 163 countries included in the Positive Peace Report within the framework of the eight core components of positive peace and to reveal how these countries cluster according to their structural similarities. To this end, criterion weights are first determined using the CILOS method, followed by the classification of countries based on their positive peace profiles through hierarchical clustering analysis. In doing so, the study aims to provide both a comparative assessment of the multidimensional nature of positive peace and an analytical framework based on the integrated use of MCDM and clustering analysis.

2. Literature Review

Table 1 summarizes studies employing the CILOS method within the MCDM framework, as well as studies applying cluster and hierarchical clustering analyses.

Table 1. Literature Review

CILOS Method					
Author(s)	Objective	Method / Model	Key Findings	Contribution	Reference
Alao et al. (2021)	Selection of waste-to-energy technology for distributed generation	IDOCRIW (Entropy + CILOS)-weighted TOPSIS	Proposes a hybrid approach and ranks waste-to-energy alternatives	One of the earliest and widely cited applications of CILOS within IDOCRIW in energy planning	[5]
Tajik et al. (2023)	Selection of sustainable cathode materials for lithium-ion batteries	CILOS-based hybrid MCDM (SAW, TOPSIS, CoCoSo, MARCOS) + DEA	Hybrid ranking approaches yield flexible and robust results	Strong example of CILOS in multi-ranking decision environments	[6]
Uguz et al. (2023)	Optimization of CO_2 and NH_3 removal in photobioreactors	CILOS weighting + GRA	Identifies dominant criteria and optimal experimental setups	Demonstrates applicability of CILOS in environmental optimization	[7]

Kaur et al. (2025)	Prioritization of components in hybrid renewable systems	Multiple objective weights CILOS + MARCOS	Reduces subjectivity and identifies component priorities	Uses CILOS within integrated objective weighting frameworks	[8]
Linh et al. (2025)	Stability of alternative scores under different weighting methods	Comparative analysis of weighting methods	Shows impact of weighting on ranking stability	Provides evidence of CILOS influence on ranking robustness	[9]
Lei (2026)	Prioritization of labor protection measures in Industry 4.0	Entropy + CRITIC + MEREC + CILOS + MARCOS	PPE ranked as most critical; consistency observed	Highlights CILOS in multi-weight decision frameworks	[10]
Hierarchical Clustering Analysis					
Author(s)	Objective	Method / Model	Key Findings	Contribution	Sources
Bu et al. (2020)	Comparison of hydrochemical classification methods	Hierarchical clustering	Method choice significantly affects results	Provides comparison framework	[11]
Zarikas et al. (2020)	Clustering COVID-19 country data	Time series + Hierarchical clustering	Countries grouped by pandemic patterns	Introduces country-level clustering approach	[12]
Inguanzo et al. (2021)	Subgroup identification in Parkinson's disease	Hierarchical clustering	Reveals data-driven subtypes	Example in clinical applications	[13]
Leite et al. (2021)	Clustering of management practices	Cluster + Hierarchical clustering	Identifies similar practice profiles	Supports profile-based interpretation	[14]
Ogasawara & Kon (2021)	Clustering interval-valued data	Hierarchical clustering (Ward)	Compares two interval-based approaches	Extends Ward method	[15]
Randriamihamison et al. (2021)	Effect of spatial constraints in clustering	Ward hierarchical clustering	Constraints improve interpretability	Provides methodological guidance	[16]
Sadeghi et al. (2021)	COVID-19 preparedness and performance	Hierarchical clustering + scoring	Countries grouped and evaluated	Framework for country comparison	[17]
Altuntas et al. (2022)	Country grouping by suicide profiles	Panel data + Hierarchical clustering	Countries grouped based on patterns	Application in panel data	[18]
Dogan & Birant (2022)	Development of new linkage method	Hierarchical clustering	Improves clustering performance	Introduces new linkage technique	[19]
Maurel et al. (2023)	Biomedical subgroup identification	Hierarchical clustering	Identifies clinical subgroups	Example of subgroup discovery	[20]
Ran et al. (2023)	Review of hierarchical clustering algorithms	Hierarchical clustering	Summarizes recent developments	Key reference for literature	[21]

Moniz et al. (2024)	Clustering Long-COVID symptoms	Hierarchical clustering	Identifies symptom patterns	Highlights heterogeneity	[22]
Contreras et al. (2025)	Comparison of hierarchical methods	PCA + hierarchical clustering	Method choice affects outcomes	Shows distance-linkage impact	[23]
Takemura et al. (2025)	Classification of city profiles	Hierarchical clustering + factor analysis	Identifies urban profiles	Spatial/socioeconomic profiling	[24]
Visbal-Cadavid et al. (2025)	Country profiling using multiple indices	MFA + hierarchical clustering	Countries grouped into profiles	Multi-index clustering framework	[25]
Drastichová & Fišer (2026)	SDG-based country clustering	Hierarchical clustering	Groups countries by SDG similarity	SDG-focused analysis	[26]

3. Methodology

This section first introduces the CILOS technique, an objective weighting method within the multi-criteria decision-making (MCDM) framework, employed to determine the relative importance of the criteria. Subsequently, hierarchical clustering analysis is applied to reveal similarities and differences among countries based on the obtained results.

3.1. MCDM–CILOS Method

Multi-criteria decision-making (MCDM) methods provide a systematic framework for evaluating multiple alternatives across a set of criteria that are often conflicting in nature [27, 28]. Among the key stages of these methods, the determination of criterion weights plays a crucial role, as it directly influences both the final ranking of alternatives and the overall evaluation outcomes [29]. In the literature, criterion weights are generally derived using either subjective or objective approaches. In recent years, however, there has been a growing preference for objective weighting techniques, primarily due to their ability to minimize decision-maker bias and ensure a more data-driven evaluation process [15]. Within this context, the CILOS (Criterion Impact Loss) method has emerged as a prominent objective weighting approach that determines the relative importance of criteria based on the loss of impact observed within the decision matrix [30]. By focusing on how the exclusion or variation of criteria affects overall performance, CILOS offers a robust and transparent mechanism for weight determination. The procedural steps of the CILOS method are illustrated in Figure 1 [4, 31, 32].

3.2. Cluster Analysis – Hierarchical Clustering Analysis

Cluster analysis is an unsupervised analytical approach that aims to group observations with similar characteristics into the same cluster while assigning dissimilar observations to different clusters, without requiring a predefined classification structure. The primary objective of this method is to uncover the inherent group structure within the dataset, systematically evaluate similarity or distance relationships among units, and produce a meaningful classification in which within-cluster similarity is maximized and between-cluster differences are clearly distinguished [33, 34, 35]. Hierarchical clustering analysis reveals the nested structure of clusters in a stepwise manner and is generally based on two main approaches: agglomerative and divisive techniques. In the agglomerative approach, each observation is initially treated as an individual cluster, and the most similar clusters are progressively merged to form a hierarchical structure. In contrast, the divisive approach starts with all observations grouped into a single cluster, which is then recursively partitioned into smaller sub-clusters. Since the merging or splitting operations performed during hierarchical clustering are irreversible, the cluster structure obtained throughout the process cannot be restructured afterward [36]. The procedural steps followed in hierarchical clustering analysis are illustrated in Figure 2 [33].

Step 1

- A decision matrix A is constructed in which the m alternatives are represented in rows and the n criteria are represented in columns. In this matrix, the element a_{ij} denotes the value of the i-th alternative with respect to the j-th criterion.
- $A = [a_{ij}]_{m*n} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}$

Step 2

- For the CILOS method to be applicable, all criteria must be expressed in a benefit-oriented form. Therefore, if the decision matrix includes cost-type criteria, they are transformed into benefit-type criteria [41].
- $a_{ij} = \frac{\min a_{ij}}{a_{ij}}$
- For cost-type criteria, the minimum value in each column is taken as the reference, and this value is divided by all non-zero entries in the column. In this way, the cost criteria are transformed into benefit-type criteria.

Step 3

- The normalization process is carried out [41].
- $x_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n=1} a_{ij}}$

Step 4

- The newly constructed matrix is denoted as X =‖x_{ij}‖. Subsequently, for each column, the maximum value $maxx_{ij}$ is identified, and the rows containing these values are selected. These rows are then combined to form a new square matrix.

Step 5

- The matrix P=‖pkj‖, which reflects the relative loss values of the criteria, is constructed.
- $p_{kj} = \frac{x_j - r_{kj}}{x_j}$
- In the matrix P, the element pk_j represents the relative loss associated with the j-th criterion when the k-th criterion is considered as the optimal criterion.

Step 6

- The q values representing the relative importance levels of the criteria are obtained.
- $FqT = 0$
- F= $A = \begin{bmatrix} -\sum_{i=1}^{n} p_{k1} & p_{12} & \cdots & p_{1n} \\ p_{21} & -\sum_{i=1}^{n} p_{k2} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & -\sum_{i=1}^{n} p_{kn} \end{bmatrix}$

Step 7

- Only the solutions that satisfy the specified condition are taken into consideration.
- $\sum_{i=1}^{m} q_i = 1$

Fig. 1. Application steps of the CILOS method [4, 31. 32]

Step 1

- Each observation included in the analysis is initially treated as a separate cluster.

Step 2

- The distance values between the formed clusters are calculated.

Step 3

- The two closest clusters are identified and merged to form a new cluster structure. Following this, the distance matrix is updated to reflect the revised cluster configuration.

Step 4

- This process is iteratively continued until all observations are grouped into a single cluster.

Fig. 2. Procedural steps of hierarchical clustering analysis [33]

To quantify the similarity or dissimilarity between observations, an appropriate distance or proximity measure is required. While Euclidean distance is the most commonly used metric for this purpose, alternative measures such as Manhattan, Minkowski, and Hamming distances are also frequently employed. The output of hierarchical clustering is a two-dimensional, tree-like structure known as a dendrogram, which illustrates the sequential process of cluster merging or splitting [37]. This structure also indicates the distance levels at which each merging or division occurs. By cutting the dendrogram at a specific level, distinct cluster structures can be identified [33].

4. Empirical Analysis

This study aims to examine the relationships among countries by considering the components of positive peace. To achieve this, the dataset used in the analysis is first introduced. Based on this dataset, criterion weights are determined using the CILOS method, and subsequently, hierarchical clustering analysis is performed to obtain and present the findings.

4.1. Dataset

The data used in this study are derived from the 2024 Positive Peace Report published by the Institute for Economics & Peace.

Table 2. Set of criteria used in the dataset [1]

Well-Functioning Government	This dimension reflects a governance structure in which public services are delivered effectively, decision-making processes are transparent, and the legal framework operates in a reliable and trustworthy manner. It captures the institutional capacity of the state, its ability to formulate and implement policies, and its legitimacy in the eyes of citizens.
Low Levels of Corruption	This dimension refers to a governance environment in which the misuse of public power for personal interests is limited, the level of corruption and misuse of public resources remains low, and fragmentation driven by vested interests within political and institutional structures is weak. It reflects both the degree of transparency and accountability in public administration and the capacity of governing elites and state institutions to operate in a cohesive and public-oriented manner.
Sound Business Environment	A sound business environment is characterized by the conduct of economic activities within a predictable, stable, and supportive institutional framework. This dimension reflects whether regulatory quality, the functioning of the financial system, and the overall level of economic prosperity provide a conducive structure for private sector development.
Equitable Distribution of Resources	This dimension represents the balanced distribution of economic and social opportunities across different segments of society. It provides insights into the inclusiveness of social welfare by reflecting the level of equality in access to health, education, income, and opportunities.
Acceptance of the Rights of Others	This dimension captures the degree of tolerance, inclusiveness, and equal treatment toward different identities, groups, and segments within society. It reveals whether individuals have equal opportunities to participate in social and political life and highlights the extent of discrimination or social exclusion.
Free Flow of Information	This dimension reflects a structure in which communication channels function effectively and public information can be accessed without censorship or manipulation. It encompasses press freedom, the quality of information, and the accessibility of communication infrastructure.
High Levels of Human Capital	This dimension represents the strength of a society in terms of education, healthcare, and knowledge production capacity. It reflects the productivity of the young population, research capabilities, and access to healthy living conditions, thereby highlighting the human capital foundation of sustainable development and a peaceful society.
Good Relations with Neighbors	This dimension reflects the presence of peaceful, open, and cooperative relationships both within society and at the international level. It captures the principles of equal treatment, openness, and the capacity for social and cross-border interaction.

In order to statistically analyze the distribution of the 163 alternatives included in the decision-making process, the first step involves determining the relative importance of each criterion. Accordingly, the weighting process is carried out using the CILOS method, one of the objective techniques within the multi-criteria decision-making (MCDM) framework. The calculations are performed in MS Excel environment. Following this stage, the dataset is restructured using the obtained weights and transformed into a normalized weighted dataset, which is then transferred to the RStudio environment.

Table 3. Alternatives included in the dataset

No	Country	No	Country	No	Country
1	Finland	55	Macedonia	109	Kenya
2	Denmark	56	Mongolia	110	Rwanda
3	Norway	57	Botswana	111	Burkina Faso
4	Sweden	58	Kuwait	112	Sierra Leone
5	Switzerland	59	Serbia	113	Nepal
6	Ireland	60	Moldova	114	Gabon
7	New Zealand	61	Bhutan	115	Cote d'Ivoire
8	Iceland	62	Oman	116	Madagascar
9	Netherlands	63	Tunisia	117	Laos
10	Australia	64	Thailand	118	Togo
11	Germany	65	Ghana	119	Cambodia
12	Canada	66	Ukraine	120	Papua New Guinea
13	Japan	67	China	121	Nicaragua
14	Singapore	68	South Africa	122	Mozambique
15	Belgium	69	Peru	123	Egypt
16	France	70	Bahrain	124	Iran
17	Austria	71	Kazakhstan	125	Bangladesh
18	Portugal	72	Brazil	126	Swaziland
19	South Korea	73	Bosnia and Herzegovina	127	Lebanon
20	United Kingdom	74	Dominican Republic	128	Pakistan
21	Slovenia	75	Namibia	129	Guatemala
22	Estonia	76	Saudi Arabia	130	Uganda
23	Czech Republic	77	Vietnam	131	Tajikistan
24	Lithuania	78	Colombia	132	Turkmenistan
25	Uruguay	79	Jordan	133	Liberia
26	Spain	80	Senegal	134	Niger
27	United States	81	Indonesia	135	Djibouti
28	Italy	82	Guyana	136	Mali
29	Cyprus	83	Belarus	137	North Korea
30	Chile	84	Ecuador	138	Angola
31	Latvia	85	Mexico	139	Ethiopia
32	Taiwan	86	Paraguay	140	Zimbabwe
33	Slovakia	87	India	141	Myanmar
34	Croatia	88	Sri Lanka	142	Mauritania
35	Greece	89	El Salvador	143	Guinea-Bissau
36	Israel	90	Benin	144	Iraq
37	Poland	91	Türkiye	145	Libya
38	Costa Rica	92	Timor-Leste	146	Nigeria
39	Hungary	93	Russia	147	Republic of the Congo
40	United Arab Emirates	94	Bolivia	148	Burundi
41	Mauritius	95	Morocco	149	Cameroon
42	Romania	96	Philippines	150	Guinea
43	Bulgaria	97	Palestine	151	Haiti
44	Trinidad and Tobago	98	Uzbekistan	152	Venezuela
45	Kosovo	99	Cuba	153	Sudan
46	Malaysia	100	Tanzania	154	Equatorial Guinea
47	Qatar	101	Kyrgyz Republic	155	Afghanistan
48	Montenegro	102	Algeria	156	Eritrea
49	Georgia	103	Lesotho	157	Syria
50	Jamaica	104	Azerbaijan	158	Democratic Republic of the Congo
51	Argentina	105	Malawi	159	Chad
52	Albania	106	Zambia	160	Central African Republic
53	Panama	107	Honduras	161	Somalia
54	Armenia	108	The Gambia	162	Yemen
				163	South Sudan

The criteria used in the analysis are selected to reflect the multidimensional nature of positive peace, allowing for a comparative evaluation of countries in terms of institutional structure, social cohesion, and sustainable peace capacity. In line with the relevant literature and the Positive Peace Index framework, a total of eight criteria are considered, and their detailed descriptions are presented in Table 2 [1]. Based on this dataset, hierarchical clustering analysis is applied to group observations according to their similarity structures. This approach enables the classification of decision units into meaningful and homogeneous clusters based on their structural characteristics. The alternatives considered in this study consist of 163 countries included in the Positive Peace Report, as presented in Table 3.

4.2. Results of Criterion Weights Using the CILOS Method

As the first step of the multi-criteria decision-making (MCDM) process, the decision matrix corresponding to the criteria considered in the analysis is constructed using the 2024 dataset. The resulting decision matrix is presented in Table 4.

Table 4. Decision matrix

Criteria No	Well-Functioning Government	Low Levels of Corruption	Sound Business Environment	Equitable Distribution of Resources	Acceptance of the Rights of Others	Free Flow of Information	High Levels of Human Capital	Good Relations with Neighbors
1	1.13	1.22	2.2	1.06	1.05	1.34	1.41	2.26
2	1.16	1.09	2.04	1.07	1.39	1.16	1.38	2.38
3	1.2	1.23	1.84	1.07	1.39	1.26	1.47	2.3
...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...
162	4.75	4.63	4.71	3.98	4.82	4.02	3.77	4.23
163	4.85	4.56	4.79	4.33	4.32	4.18	3.89	4.17

Table 5. CILOS criterion weights

Criteria	Well-Functioning Government	Low Levels of Corruption	Sound Business Environment	Equitable Distribution of Resources	Acceptance of the Rights of Others	Free Flow of Information	High Levels of Human Capital	Good Relations with Neighbors
Wj	0.1284	0.1421	0.1166	0.095	0.0914	0.1314	0.1367	0.1585

Once the decision matrix is constructed, the criterion weights obtained using the CILOS method are presented in detail in Table 5. An examination of the CILOS criterion weights presented in Table 5 indicates that the "Good Relations with Neighbors" criterion has the highest weight (0.1585), whereas the "Acceptance of the Rights of Others" criterion has the lowest weight (0.0914). This finding suggests that the formation of positive peace is shaped not only by countries' internal institutional and social structures but also by their external relations and regional interactions. Indeed, the positive peace literature emphasizes that international cooperation, trade relations, and the level of regional integration play a critical role in sustaining peace [1]. In this context, the relatively high weight assigned to "Good Relations with Neighbors" highlights that peace at the global level is influenced not only by national dynamics but also by international interconnectedness. On the other hand, the relatively low weight assigned to the "Acceptance of the Rights of Others" criterion indicates that, although this dimension is an essential component of positive peace, it exhibits a comparatively lower discriminative power in terms of variability or impact loss within the dataset. By its nature, the CILOS method reflects the relative differentiating capacity of criteria within the dataset rather than their absolute importance [38]. Therefore, the results suggest that certain criteria may receive higher weights not necessarily due to their theoretical significance, but because of the level of variation they exhibit in the data structure. Overall, the findings support the multidimensional nature of positive peace and demonstrate that the interaction between external relations and institutional capacity plays a decisive role in differentiating countries. Subsequently, the decision matrix is weighted using the criterion weights obtained for the given year. The weighted decision matrix is presented in Table 6.

Table 6. Weighted decision matrix

Criteria No	Well-Functioning Government	Low Levels of Corruption	Sound Business Environment	Equitable Distribution of Resources	Acceptance of the Rights of Others	Free Flow of Information	High Levels of Human Capital	Good Relations with Neighbors
1	0.145145	0.173309	0.256417	0.1007245	0.09592664	0.17606	0.1927	0.3582155
2	0.148998	0.154842	0.237768	0.1016747	0.1269886	0.15241	0.1886	0.3772358
3	0.154136	0.174729	0.214457	0.1016747	0.1269886	0.16555	0.2009	0.3645556
...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...
162	0.610122	0.657721	0.548964	0.3781921	0.44034896	0.52819	0.51524	0.6704653
163	0.622967	0.647777	0.558289	0.4114501	0.39466961	0.54921	0.53164	0.6609552

4.3. Hierarchical Clustering Analysis

Following the construction of the weighted dataset, the analysis proceeds with cluster analysis. Hierarchical clustering is conducted using the RStudio software environment, with Euclidean distance selected as the distance metric. The choice of Euclidean distance is motivated by its ability to directly and intuitively measure similarities among observations in datasets composed of continuous and numerical variables. Moreover, as it is based on the geometric distance between data points, it is widely used in determining cluster structures and is known to produce consistent results, particularly in hierarchical clustering methods [39]. In this context, the Hopkins statistic is calculated based on Euclidean distance to assess the suitability of the dataset for clustering analysis. The heatmap derived from Euclidean distance is presented in Figure 3.

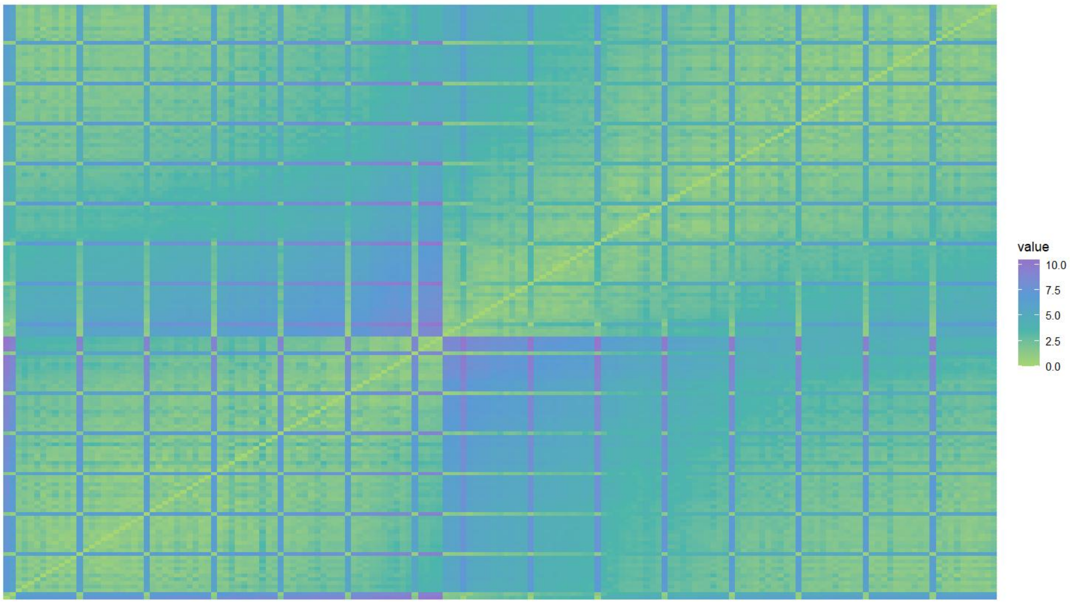

Fig. 3. Euclidean distance heatmap

The Hopkins statistic calculated for the weighted dataset is 0.9999424. The clustering tendency of the data is assessed using this statistic, which compares the nearest-neighbor distance distribution of randomly generated points with that of randomly selected observations from the dataset. Under the null hypothesis, the distances from randomly generated points to their nearest neighbors are expected to be similar to the average nearest-neighbor distances among the actual observations, indicating a random data structure and yielding a Hopkins value of approximately 0.5. In contrast, when a clear clustering structure is present, the distances between randomly generated points and the nearest observations tend to be larger, resulting in a Hopkins value greater than 0.5 [40]. According to the widely accepted interpretation in the literature, a Hopkins statistic exceeding 0.5 indicates that the data are not randomly distributed and are suitable for clustering analysis [41, 42]. The Hopkins statistic plot is presented in Figure 4. First, the optimal number of clusters and the clustering algorithm were determined for the dataset. Based on the Dunn index, a four-cluster solution was selected, and hierarchical clustering analysis was applied. The cluster validation results are presented in Figure 5.

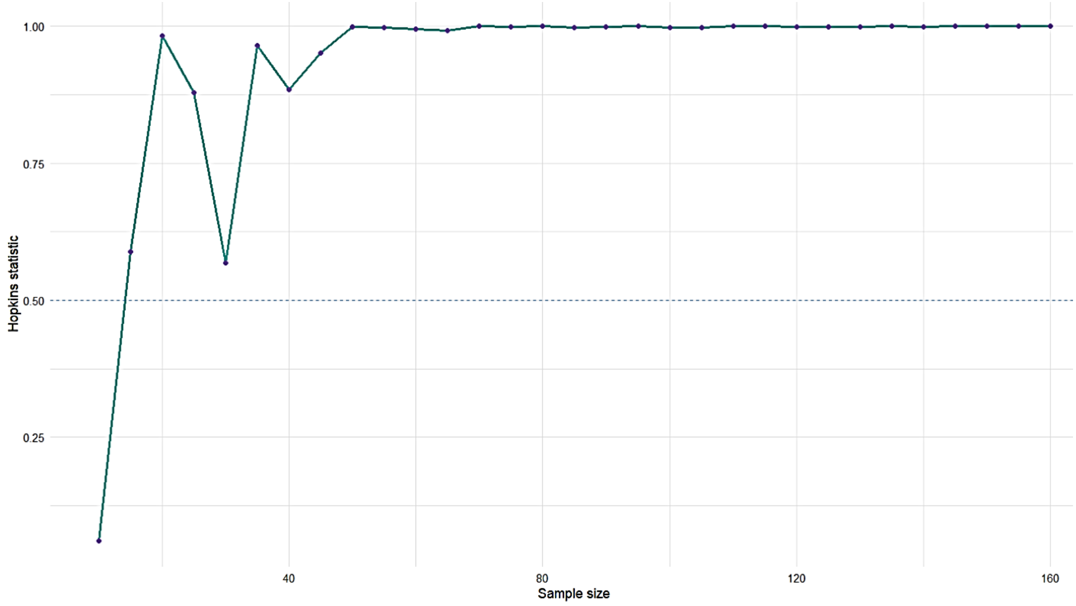

Fig. 4. Plot of the Hopkins statistic

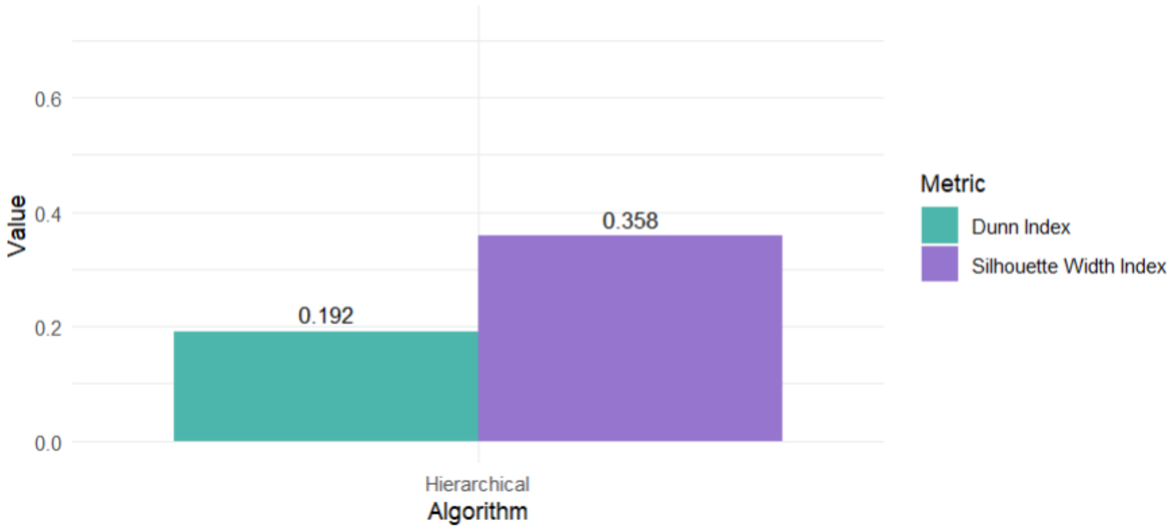

Fig. 5. Cluster validation metrics

The values indicating the selection of the clustering method and the optimal number of clusters based on the Dunn index and Silhouette index are presented in Table 7.

Table 7. Cluster Number and Clustering Method Selection Criteria

Index	Index Value	Clustering Method	Number of Clusters
Dunn Index	0.1920	Hierarchical Clustering	4
Silhouette Index	0.3583	K-means Clustering	3

An examination of the cluster validity indices presented in Table 7 shows that the Dunn index suggests a four-cluster solution, whereas the Silhouette index recommends a three-cluster structure. This discrepancy stems from the different evaluation criteria employed by these indices in assessing clustering quality. In general, cluster validity indices evaluate clustering performance based on within-cluster similarity and between-cluster separation. The Dunn index considers both inter-cluster distance and intra-cluster dispersion, thereby favoring more compact and well-separated clusters [35]. In contrast, the Silhouette index measures the average cohesion and separation of observations by assessing their relative positioning within their assigned cluster compared to other clusters [43]. It is also well documented that different validity indices may suggest different optimal numbers of clusters for the same dataset [35]. In this study, taking into account the multidimensional structure of the dataset and the pronounced differences among positive peace components, the four-cluster solution suggested by the Dunn index is preferred, as it provides a stronger representation of inter-cluster separation. This choice is further supported by the dendrogram obtained from hierarchical clustering analysis, which also indicates a four-cluster structure. In this context, the four-cluster solution enables a more detailed and meaningful interpretation of structural differences among countries. Within the scope of the analysis, four clusters are generated using the hierarchical clustering algorithm for a dataset consisting of 163 countries and 8 criteria. The distribution of these four clusters is illustrated in Figure 6.

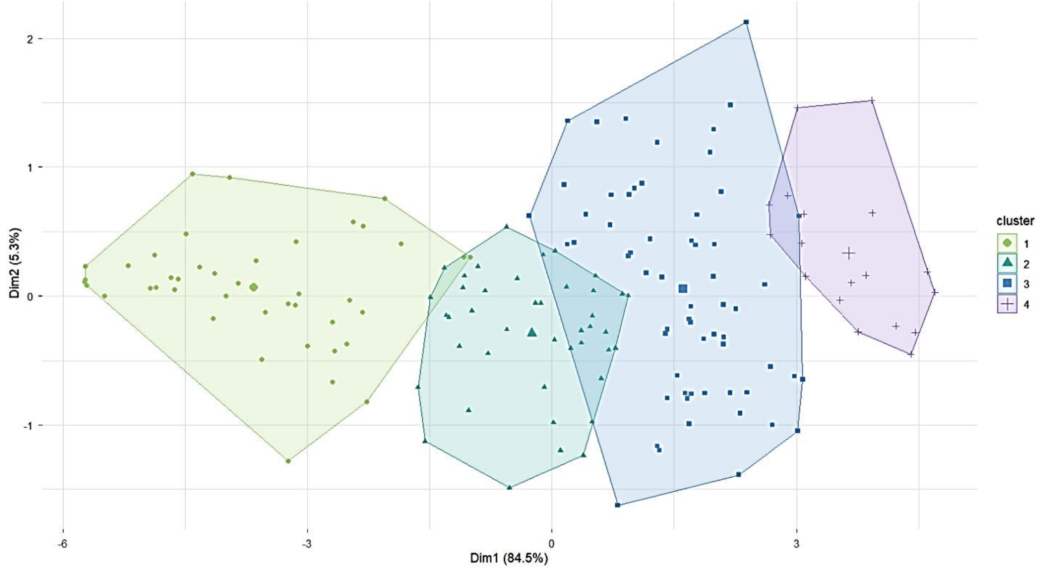

Fig. 6. Cluster distribution based on hierarchical clustering analysis

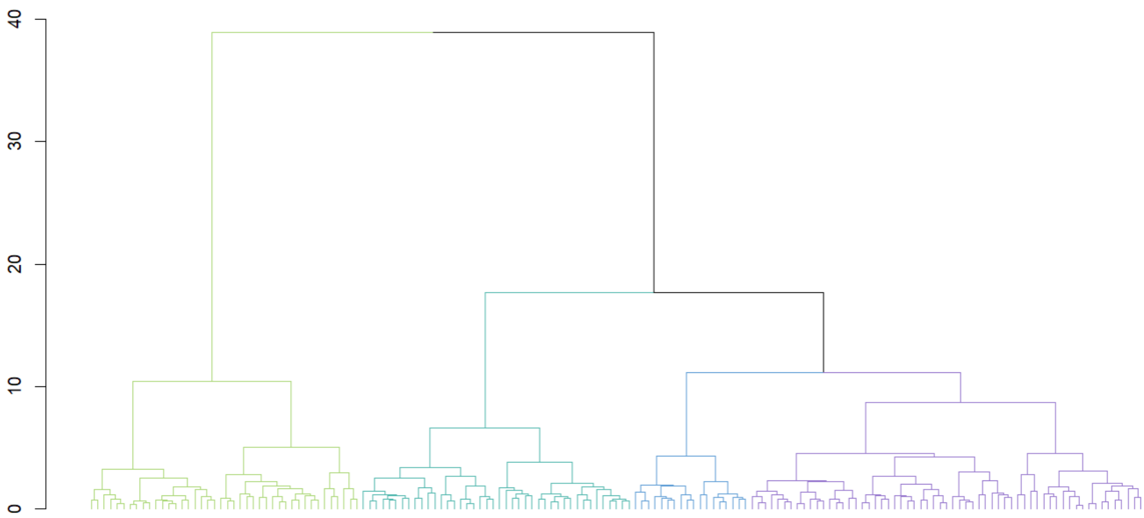

Fig. 7. Dendrogram plot

As illustrated in Figure 7, the hierarchical clustering results obtained from the dataset of 163 countries are presented using a dendrogram, which provides a clear visualization of the hierarchical relationships among the observations. The dendrogram illustrates the similarity levels between countries and shows the stages at which individual observations and clusters are merged throughout the clustering process. Its branching structure provides a detailed representation of the distances between observations and the hierarchical formation of clusters. Based on the selected cut-off level, the dataset is divided into four distinct clusters. Countries grouped within the same cluster exhibit similar Positive Peace profiles, whereas those belonging to different clusters display noticeable differences across the evaluation criteria. Overall, the dendrogram provides an intuitive visual representation of the clustering structure and the degree of separation among the identified clusters.

The dendrogram presented in Figure 7 illustrates the sequence of cluster merging and the distance levels between observations. In particular, the noticeable jumps observed at higher levels of linkage indicate the presence of a well-defined cluster structure within the dataset. When the dendrogram is cut at an approximate distance level of 10 units, the observations are grouped into four distinct clusters. The selection of the four-cluster solution is based on a joint evaluation of the visual separation observed in the dendrogram and the results of cluster validity indices. This solution is considered appropriate as it both preserves inter-cluster separation and provides a more detailed representation of structural differences within the dataset. Accordingly, all interpretations in this study are based on the four-cluster structure. The two-dimensional distribution of the clusters obtained through the hierarchical clustering algorithm is presented in Figure 8.

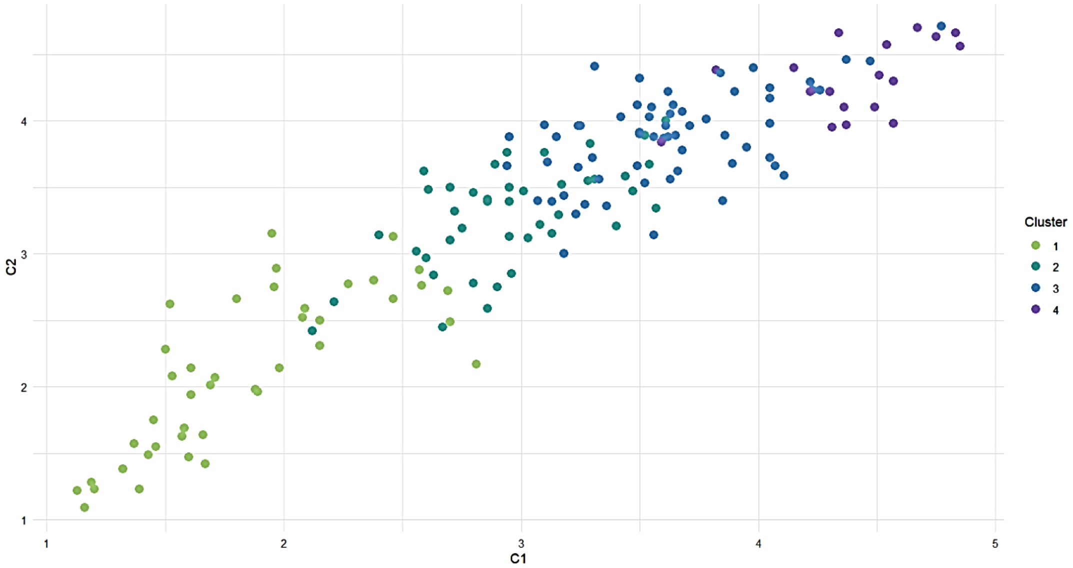

Fig. 8. Two-Dimensional Cluster Distribution Based on Hierarchical Clustering Analysis

The two-dimensional distribution plot presented in Figure 8 clearly illustrates the structural differentiation among the clusters obtained through hierarchical clustering analysis. The close positioning of countries within the same cluster indicates that they share similar characteristics in terms of positive peace components, whereas the greater distances between clusters reflect meaningful differences in institutional structure, social cohesion, and sustainable peace capacity across countries. The findings reveal that countries do not exhibit a homogeneous structure in terms of positive peace performance; rather, they are distinctly differentiated based on their underlying characteristics. This highlights the importance of considering country-specific priorities and structural needs in the development of policies aimed at strengthening positive peace. The tree diagram (dendrogram) obtained from the hierarchical clustering algorithm is presented in Figure 9.

The tree diagram presented in Figure 9 visually represents the four-cluster structure obtained from the hierarchical clustering analysis. Countries grouped within the same color and branching structure are considered to share similar characteristics in terms of positive peace indicators. The figure also shows that clusters differ in both size and branching density, indicating the presence of a non-homogeneous cluster structure within the dataset. In this phylogenetic layout, however, the key aspect is not the exact spatial positioning of countries on the plane, but rather how they are grouped under common branches and at which levels the clusters diverge. The countries included in the four clusters identified by the algorithm are presented in Table 8.

Table 8 presents the clustering results, showing that the countries are grouped according to similarities in their Positive Peace characteristics. The Positive Peace framework defines eight mutually reinforcing pillars: well-functioning government, low levels of corruption, a sound business environment, equitable distribution of resources, acceptance of the rights of others, free flow of information, high levels of human capital, and good relations with neighboring countries. Within this framework, the presence of countries such as Finland, Denmark, Norway, Sweden, Switzerland, New Zealand, the Netherlands, Germany, Canada, and Japan in Cluster 1 suggests that this cluster represents the strongest Positive Peace profile. These countries generally demonstrate high levels of institutional effectiveness, transparency, control of corruption, access to information, human capital development, and social cohesion. Accordingly, Cluster 1 can be interpreted as comprising countries with relatively strong institutional and social capacities that perform consistently well across most of the eight Positive Peace pillars. The Positive Peace framework similarly emphasizes that these pillars operate as an interconnected system, where stronger performance contributes to greater societal resilience and more favorable social and economic outcomes.

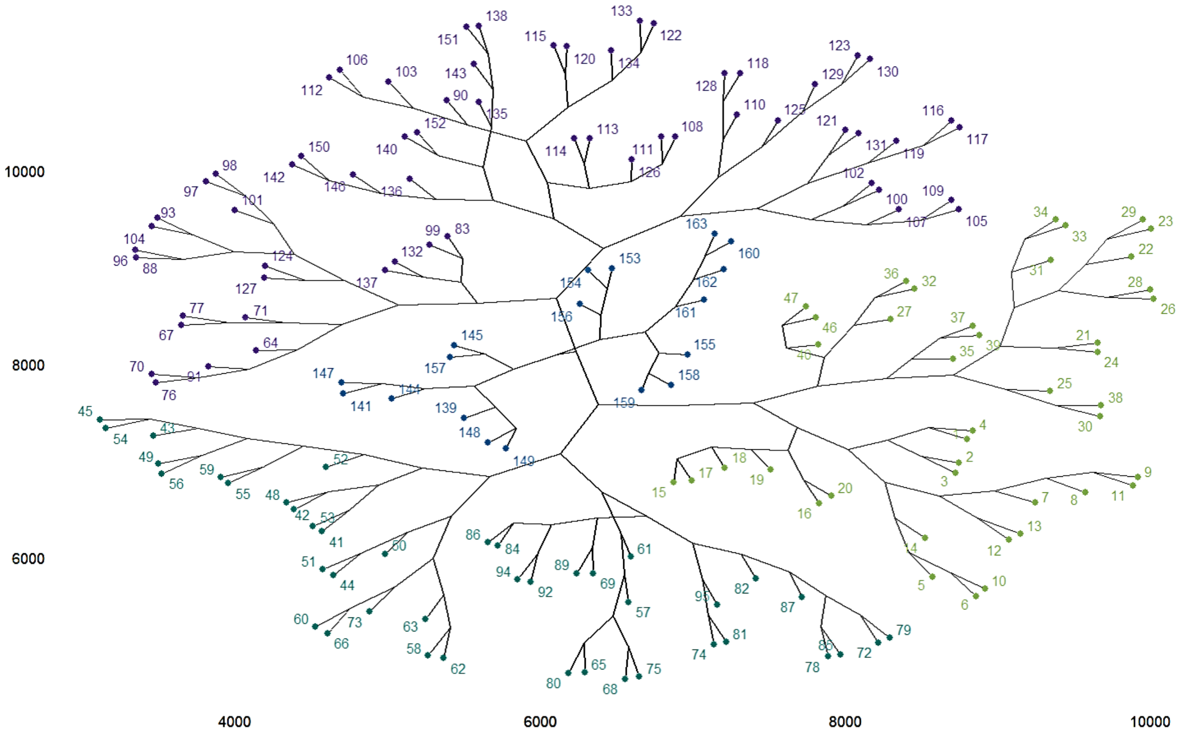

Fig. 9. Tree Diagram of the hierarchical clustering algorithm

It is noteworthy, however, that Cluster 1 is not composed exclusively of high-income countries from a single geographical region. The inclusion of countries such as Japan and New Zealand, despite their distinct geographical, cultural, and historical contexts, indicates that Positive Peace cannot be explained solely by economic prosperity. Rather, the results suggest that strong institutions, accountable governance, social trust, and inclusive public policies are capable of producing similar Positive Peace profiles regardless of geographical location. This finding highlights institutional quality and governance capacity, rather than economic wealth alone, as the primary factors underlying the clustering structure.

Clusters 2 and 3 exhibit a more transitional and heterogeneous structure. The inclusion of countries such as Mauritius, Romania, Bulgaria, Argentina, Botswana, Kuwait, Oman, and South Africa in Cluster 2 indicates that these countries possess strengths in certain Positive Peace pillars while displaying a more uneven overall performance across the eight dimensions. Although some countries in this cluster perform relatively well in areas such as the business environment, human capital, or specific institutional capacities, they continue to face limitations in governance quality, corruption control, equitable resource distribution, and social inclusion. A particularly interesting finding is that Gulf countries such as Kuwait and Oman are grouped together with several transition economies in Europe and upper-middle-income African countries. At first glance, these countries differ considerably in terms of economic structure and income levels. However, the Positive Peace framework emphasizes the balanced functioning of institutional systems rather than economic output alone.

Table 8. Cluster distribution based on hierarchical clustering analysis

Cluster 1	Cluster 2	Cluster 3	Cluster 4
Finland	Mauritius	Thailand	Ethiopia
Denmark	Romania	China	Myanmar
Norway	Bulgaria	Bahrain	Iraq
Sweden	Trinidad and Tobago	Kazakhstan	Libya
Switzerland	Kosovo	Saudi Arabia	Republic of the Congo
Ireland	Montenegro	Vietnam	Burundi
New Zealand	Georgia	Belarus	Cameroon
Iceland	Jamaica	Sri Lanka	Sudan
Netherlands	Argentina	Benin	Equatorial Guinea
Australia	Albania	Türkiye	Afghanistan
Germany	Panama	Russia	Eritrea
Canada	Armenia	Philippines	Syria
Japan	Macedonia	Palestine	Democratic Republic of the Congo
Singapore	Mongolia	Uzbekistan	Chad
Belgium	Botswana	Cuba	Central African Republic
France	Kuwait	Tanzania	Somalia
Austria	Serbia	Kyrgyz Republic	Yemen
Portugal	Moldova	Algeria	South Sudan
South Korea	Bhutan	Lesotho	
United Kingdom	Oman	Azerbaijan	
Slovenia	Tunisia	Malawi	
Estonia	Ghana	Zambia	
Czech Republic	Ukraine	Honduras	
Lithuania	South Africa	The Gambia	
Uruguay	Peru	Kenya	
Spain	Brazil	Rwanda	
United States	Bosnia and Herzegovina	Burkina Faso	
Italy	Dominican Republic	Sierra Leone	
Cyprus	Namibia	Nepal	
Chile	Colombia	Gabon	
Latvia	Jordan	Cote d'Ivoire	
Taiwan	Senegal	Madagascar	
Slovakia	Indonesia	Laos	
Croatia	Guyana	Togo	
Greece	Ecuador	Cambodia	
Israel	Mexico	Papua New Guinea	
Poland	Paraguay	Nicaragua	
Costa Rica	India	Mozambique	
Hungary	El Salvador	Egypt	
United Arab Emirates	Timor-Leste	Iran	
Malaysia	Bolivia	Bangladesh	
Qatar	Morocco	Swaziland	
		Lebanon	
		Pakistan	
		Guatemala	
		Uganda	
		Tajikistan	
		Turkmenistan	
		Liberia	
		Niger	
		Djibouti	
		Mali	
		North Korea	
		Angola	
		Zimbabwe	
		Mauritania	
		Guinea-Bissau	
		Nigeria	
		Guinea	
		Haiti	
		Venezuela	

Consequently, limitations related to governance, access to information, social inclusion, or the protection of rights in some high-income Gulf states, combined with institutional reforms and gradual improvements in certain transition economies, may have resulted in similar multidimensional Positive Peace profiles. This observation further demonstrates that economic prosperity by itself is not sufficient to achieve high levels of Positive Peace.

Cluster 3 includes countries such as Türkiye, China, Russia, the Philippines, Iran, Egypt, Bangladesh, Nigeria, Venezuela, and Pakistan, representing a moderate-to-low Positive Peace profile despite considerable differences in their geographical locations and structural characteristics. Although several of these countries possess substantial economic capacity, state capability, or infrastructure development, they continue to experience weaknesses in pillars such as acceptance of the rights of others, free flow of information, control of corruption, well-functioning government, and good relations with neighboring countries.

At first glance, the placement of Türkiye, China, and Russia within the same cluster may appear unexpected, given their substantial differences in economic size, political systems, and geopolitical influence. However, the clustering algorithm classifies countries based on the combined patterns observed across all eight Positive Peace pillars rather than on a single indicator. As a result, countries with markedly different economic and geopolitical characteristics can still be grouped together when they exhibit similar institutional profiles in areas such as governance quality, access to information, protection of rights, corruption control, and social inclusion. This finding reinforces the multidimensional nature of Positive Peace, demonstrating that institutional performance, rather than economic or geopolitical power alone, plays a decisive role in shaping national peace capacity. Moreover, Cluster 3 appears to represent countries undergoing institutional and developmental transitions. Although many of these countries have made significant progress in selected economic or governance-related areas, improvements have not occurred simultaneously across all Positive Peace pillars. Consequently, this cluster reflects countries where institutional transformation remains incomplete and where structural imbalances continue to constrain overall Positive Peace performance. Accordingly, Cluster 2 may be characterized as representing countries with moderate yet relatively balanced Positive Peace performance, whereas Cluster 3 reflects countries with moderate-to-low Positive Peace levels accompanied by more pronounced structural vulnerabilities. The Positive Peace Report similarly emphasizes that differences between countries largely arise from imbalances in institutions, societal attitudes, and structural conditions.

Cluster 4 includes countries such as Ethiopia, Myanmar, Iraq, Libya, Afghanistan, Eritrea, Syria, the Democratic Republic of the Congo, the Central African Republic, Somalia, Yemen, and South Sudan, suggesting that this cluster represents the weakest Positive Peace profile. These countries are generally characterized by severe deficiencies in well-functioning government, corruption control, business conditions, and human capital, together with persistent weaknesses in information flows, acceptance of rights, equitable resource distribution, and relations with neighboring states. Importantly, the countries grouped within Cluster 4 are not clustered simply because they have relatively low-income levels. Rather, they share common structural characteristics, including prolonged armed conflict, weak state capacity, institutional fragility, and persistent security challenges that simultaneously undermine multiple pillars of Positive Peace. This finding illustrates the mutually reinforcing nature of Positive Peace in the opposite direction, where institutional weaknesses generate cascading effects across governance, information systems, economic performance, social inclusion, and regional cooperation. Overall, the clustering structure reveals a gradual transition from countries with strong Positive Peace capacities to those experiencing profound institutional fragility.

The results further suggest that the observed differentiation among countries is not driven by a single dimension. Instead, governance quality, corruption control, access to information, human capital, and the protection of fundamental rights collectively emerge as the principal factors shaping the clustering structure. This finding provides additional empirical support for the multidimensional nature of Positive Peace and indicates that sustainable improvements require institutional reforms and social inclusion strategies alongside economic development policies. These findings imply that policies designed to strengthen Positive Peace should not follow a one-size-fits-all approach but should instead be tailored according to the specific weaknesses characterizing each cluster. In particular, improving institutional capacity, transparency, social inclusion, access to information, and human capital appears to be especially critical for countries belonging to the lower-performing clusters. Furthermore, countries located within the transitional clusters would likely benefit from differentiated policy strategies rather than uniform reform packages. While governance reforms may constitute the highest priority for some countries, others may achieve greater improvements through investments in education, human capital development, or expanding access to information. This underscores the importance of designing country-specific policy interventions that address the unique structural challenges associated with each Positive Peace profile, thereby supporting more sustainable and inclusive pathways toward peace.

5. Conclusion and Implications

This study combined the CILOS method with hierarchical cluster analysis to examine the similarities and differences among 163 countries included in the Positive Peace Report based on their Positive Peace characteristics. The research was conducted in two main stages. In the first stage, the objective weights of the eight core pillars of Positive Peace were determined using the CILOS method, one of the objective weighting techniques within the multi-criteria decision-making (MCDM) framework. The CILOS method was selected because it determines objective criterion weights by accounting for conflicts among criteria and the relative loss in other criteria that may arise from an improvement in a particular criterion. The analysis considered the following dimensions: well-functioning government, low levels of corruption, sound business environment, equitable distribution of resources, acceptance of the rights of others, free flow of information, high levels of human capital, and good relations with neighboring countries. By adopting this approach, the study established a data-driven weighting framework that minimizes subjective judgment in evaluating countries' Positive Peace performance.

In the second stage, hierarchical cluster analysis was employed to classify countries according to their similarities across these weighted criteria, resulting in the identification of distinct and meaningful country clusters. Furthermore, the Hopkins statistic, calculated as 0.9999424, confirmed a very strong clustering tendency within the dataset, indicating that the data structure was highly suitable for cluster analysis. The hierarchical clustering analysis revealed four distinct country clusters. Overall, countries in Cluster 1 exhibited the strongest Positive Peace profiles, demonstrating consistently high performance in dimensions such as well-functioning government, low corruption, a sound business environment, free flow of information, and high levels of human capital. Countries assigned to Clusters 2 and 3 showed progress across several Positive Peace dimensions but had not yet achieved balanced and consistently high performance across all indicators. In contrast, countries in Cluster 4 displayed greater structural vulnerabilities, particularly in governance quality, equitable distribution of resources, acceptance of the rights of others, relations with neighboring countries, and institutional stability.

These findings reinforce the view that Positive Peace extends beyond the mere absence of violence or conflict and depends on the simultaneous functioning of multiple institutional and social dimensions. Differences between countries are not driven by a single indicator but emerge from the combined influence of governance quality, corruption control, access to information, human capital, equitable resource distribution, and the protection of fundamental rights. Positive Peace can therefore be understood as a multidimensional institutional ecosystem in which these pillars interact and reinforce one another, providing empirical support for the systemic perspective emphasized in the Positive Peace literature.

One of the most noteworthy findings is that the identified clusters cannot be explained solely by countries' income levels or geographical proximity. The placement of high-income Gulf countries such as Kuwait and Oman alongside several transition economies, as well as the grouping of Türkiye, China, and Russia despite their considerable economic and geopolitical differences, demonstrates that countries with different economic and political characteristics may nevertheless exhibit similar Positive Peace profiles. Conversely, countries with comparable income levels may display substantially different profiles because of variations in institutional quality. These patterns highlight the limitations of relying exclusively on conventional economic or geographical classifications when assessing Positive Peace and underscore the importance of institutional performance in explaining cross-country similarities and differences.

The results also indicate that countries with similar Positive Peace profiles may share certain historical, institutional, and socioeconomic characteristics. Accordingly, strategies aimed at strengthening Positive Peace should take into account the structural characteristics, developmental trajectories, and institutional vulnerabilities associated with different country groups. Nevertheless, the findings should primarily be interpreted as providing a comparative understanding of structural differences among countries rather than as a basis for universal policy prescriptions.

This study is subject to several limitations. First, the analysis relies on cross-sectional data from a single reporting period, making it impossible to capture temporal changes in Positive Peace performance or transitions between clusters over time. Second, because the analysis is based exclusively on the Positive Peace Report dataset, the findings remain constrained by the indicators and measurement framework adopted in that report. Third, clustering outcomes may vary depending on methodological choices, including the selected distance measure, hierarchical clustering procedure, and number of clusters retained. Consequently, the findings should be interpreted within the methodological framework adopted in this study. Finally, the analysis focused primarily on interpreting the resulting cluster structure rather than statistically identifying which Positive Peace pillars contributed most strongly to cluster separation.

From a policy perspective, the cluster structure provides a useful basis for identifying differentiated areas of intervention. Countries belonging to the lower-performing clusters may particularly benefit from simultaneous improvements in governance capacity, social inclusion, access to information, and human capital. For countries in the transitional clusters, strengthening governance capacity and pursuing institutional reforms may represent important priorities. In contrast, countries in the most fragile cluster may require more fundamental efforts aimed at rebuilding state capacity, enhancing social trust, improving access to information, and investing in human capital. For countries in the highest-performing cluster, maintaining institutional quality while strengthening resilience against emerging global risks may become the primary policy objective. These implications support the development of cluster-sensitive rather than uniform policy approaches. However, they should be regarded as a starting point for more detailed country- and region-specific investigations. Supporting cluster profiles with in-depth national analyses and additional contextual indicators would allow for more comprehensive and context-sensitive policy interpretations.

In conclusion, this study not only classifies 163 countries according to their Positive Peace profiles but also demonstrates that similarities and differences in Positive Peace emerge from the interaction of multiple institutional and social dimensions rather than from economic development alone. By integrating the CILOS objective weighting method with hierarchical cluster analysis, the study provides a systematic and data-driven framework for comparative country assessment and contributes empirical evidence to the growing literature on Positive Peace. The resulting four-cluster structure offers a differentiated perspective on countries' institutional strengths and vulnerabilities and illustrates the value of combining MCDM-based objective weighting with clustering techniques in cross-country Positive Peace research.

Future research could extend this framework by incorporating longitudinal data to examine changes in Positive Peace performance and transitions between clusters over time. Alternative objective weighting methods, such as MEREC, LOPCOW, and CRITIC, could be applied to assess the robustness of the CILOS-based results, while different clustering algorithms, including K-Means, Gaussian Mixture Models, and Spectral Clustering, could be compared with the hierarchical clustering solution. Future studies could also employ explainable artificial intelligence techniques to identify the variables that contribute most strongly to cluster formation, thereby addressing one of the methodological limitations of the present study. Finally, complementing quantitative clustering results with region- or country-specific case studies and additional contextual indicators could provide deeper insights into the institutional mechanisms underlying Positive Peace and enhance the practical relevance of the findings for policymakers.

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