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CLUSTER ANALYSIS AS A TOOL FOR STUDYING THE SOCIO-ECONOMIC DIVERSITY OF AFRICAN COUNTRIES

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Purpose: This paper examines the socio-economic diversity of African countries in light of the continent's rising importance in the global economy. The aim is to identify clusters of countries with similar development characteristics, providing insights into Africa's internal heterogeneity.
Design/methodology/approach: The research applies agglomerative hierarchical cluster analysis to a dataset of African countries, covering selected economic and social indicators such as GDP per capita, education, urbanization, infant mortality, gender inequality, corruption perception, and economic freedom. The analysis was conducted using the R statistical program, which provided the tools for building and interpreting clusters. The methodological approach allows for the identification of groups of countries sharing common socio-economic profiles, highlighting patterns and contrasts within the region.
Findings: The study identified distinct clusters of African countries, each reflecting different levels of socio-economic development and diversification. The results demonstrate significant internal diversity, revealing groups of countries with relatively advanced development indicators as well as those facing persistent socio-economic challenges. These findings confirm that Africa cannot be treated as a homogeneous entity but rather as a continent with complex and varied development trajectories.
Research limitations/implications: The research is constrained by the availability and comparability of statistical data across African countries.
Practical implications: The classification of African countries has practical value for policymakers, investors, and development institutions. The results can support the design of more tailored strategies, the allocation of resources, and investment planning aligned with the specific needs of different groups of countries.
Social implications: A better understanding of socio-economic diversity in Africa can help address inequalities, improve policy design, and promote inclusive and sustainable development. The findings may also inform initiatives aimed at improving living standards and social cohesion.
Originality/value: The paper provides a novel and systematic application of cluster analysis to socio-economic data on African countries. It contributes to the literature by offering an evidence-based classification of the region, adding value to researchers, practitioners, and policymakers concerned with economic development and regional studies.
Keywords: socio-economic development, Africa, cluster analysis, economic diversification.

1. Introduction

Africa, despite being perceived for many years mainly in terms of socio-economic problems, has been, since the beginning of the 21st century, increasingly recognized as an area with significant development potential. Dynamic economic growth in some countries, the abundance of natural resources, increasing regional integration and growing importance in international markets are attracting the attention of investors, international organizations and academia. However, the continent is characterized by significant internal diversity – there are economies with relatively high level of development and stable institutions, yet some countries are struggling with serious structural barriers and limited access to infrastructure.

The main objective of the study was to identify the structure of socio-economic differentiation among African countries by isolating groups of countries with similar development profiles. The analysis was based on a set of indicators covering both economic and social aspects, including the level of economic development, access to education, health status of the population, urbanization, gender equality and quality of institutions, among others. Agglomerative cluster analysis was used to identify individual groups, thus capturing similarities and differences between countries. Calculations and visualizations were performed in R using dedicated functions and statistical packages.

The results of the analysis carried out provide an in-depth knowledge of the internal development structure of African countries, and the resulting breakdown can serve as a starting point for further, more focused research.

2. The concept and measurement of socio-economic development

The concept of "socio-economic development" only began to be used more widely in the economic literature in the post-war period (Łopatka et al., 2024). Churski (2008, p. 19) defines socio-economic development as a process of sustained and targeted change involving both the social and economic sectors. It is a broad concept, which, according to Dach's (2011, p. 6) approach, is a combination of economic growth, economic development and social development, and takes into account paramount transformations in social relations and in the institutions that shape the functioning of the economy and society. In turn, Kupiec (1993) describes socio-economic development as a process of quantitative and qualitative changes of a positive nature, involving the improvement of existing and the creation of new phenomena in the area of economic, social and cultural activities. Measures of development should encompass not only the value of goods and services produced, but also the quality of life of citizens, including access to education, health care, equal opportunities, the level of infrastructure,

and the quality of public institutions (Stiglitz et al., 2019). Measuring socio-economic development solely on the basis of GDP fails to account for many key aspects such as inequalities, unmeasurable institutional factors or differences in quality of life. As a result, development is a multidimensional concept that requires broader measures (United Nations Secretary-General, 2023). Recognizing the numerous limitations of measures based solely on the material realm of the economy, efforts were undertaken to develop tools that also take into account the qualitative aspects of well-being. Despite the increasing number and complexity of proposed indicators, there is still no universally accepted, uniform method for constructing them (Kubiczek, 2014).

The most commonly used measure is gross domestic product (GDP) per capita, particularly in terms of purchasing power parity (PPP), which allows for the comparison of living standards between countries by eliminating the effect of price differences (Todaro, Smith, 2020). Although GDP is a simple and widely available indicator, its limitation is that it does not take into account quality of life, social inequalities or access to public goods (Stiglitz et al., 2019). In addition to GDP, there are other quantitative indicators of economic development, such as GDP per capita, GNP (Gross National Product), GNP per capita, NNP (Net National Product or national income) and NNP per capita. To obtain a more comprehensive picture, synthetic indicators are used, such as the Human Development Index (HDI), which combines information on income, education, and health (United Nations Development Program, 2023), or the Gender Inequality Index (GII), which assesses gender disparities in health, education, and the labour market (Sen, 1999). In development analyses, health indicators are gaining increasing importance, including infant mortality, which serves as a sensitive measure of the quality of medical care, living conditions, and the overall level of social development (Todaro, Smith, 2020). Another important aspect is the degree of urbanization, which reflects access to technical infrastructure, public services and modern technology (World Bank, 2023). Institutional indicators, on the other hand, such as the Corruption Perceptions Index (CPI) or the Index of Economic Freedom, provide information on the quality of governance, transparency of institutions and the freedom of business activity, which are key to sustainable growth and development (Stiglitz et al., 2019). However, the literature emphasizes that the above can also be complemented by poverty indicators such as the Poverty Headcount Ratio or the Multidimensional Poverty Index (MPI), which capture deprivation along multiple dimensions – from income and education to housing (Alkire, Santos, 2010, p. 38). Measures of income inequality are also an important component, e.g. the Gini coefficient to assess how evenly the benefits of development are distributed (De Maio, 2007). There is also an emphasis on the need to complement traditional indicators with measures of economic well-being that take into account environmental aspects and sustainability, such as DEN/MEW (Net Economic Welfare/ Measure of Economic Welfare), ISEW (Index of Sustainable Economic Welfare) or EAW (Index of the Economic Aspects Welfare). The inclusion of these indicators in the analyses allows for a more comprehensive understanding of development differentiation, particularly in

the context of developing countries. A comprehensive view of development therefore requires the use of a set of indicators describing its various dimensions.

3. Empirical classification of African countries using agglomerative cluster analysis

To conduct an analysis of the socio-economic disparities among African countries, a multidimensional approach was employed, encompassing seven carefully selected indicators. These variables represent different, complementary dimensions of development. The variables chosen for the cluster analysis are indicators measuring the fundamental dimensions of development. The components of complex indices were broken down into their individual elements to avoid redundancy and enhance the interpretative transparency of the results. The aim of this chapter is to empirically identify the internal socio-economic differentiation of African countries on the basis of selected development indicators. For this purpose, agglomerative cluster analysis was used, a method that falls into the category of hierarchical techniques allowing objects to be grouped in such a manner that within one cluster there are objects with the greatest possible similarity and between clusters there are the greatest possible differences (Walesiak, Gatnar, 2009).

The concept of cluster analysis was coined by R.C. Tryon in 1939 in his work of the same title (Tyron, 1939). Cluster analysis refers to various techniques and numerical methods that are part of statistical classification methods, enabling the identification and evaluation of groups (clusters), the creation of classifications, and data mining.

This study uses Ward's (1963) agglomerative method together with the squared Euclidean distance as a measure of similarity. This method minimizes the sum of squared deviations of points from the cluster center, thereby producing groups that are as homogeneous as possible. The process involves dividing a set of S observations into classes (groups, clusters). However, the number of classes is not predetermined – it is determined by analysis of the dendrogram and agglomerative steps. Objects that express similarity (i.e. are close to each other in variable space) are assigned to the same class, while objects that differ are assigned to different classes (Migdał-Najman, Najman, 2005).

The study used data for 2023 covering 42 African countries. The analysis was carried out in R. Empirical data were obtained from the following websites: World Bank Group, The Heritage Foundation, Transparency International. The indicators used in the study reflect key areas of development and include:

- economy – GDP per capita (PPP),
- education – average years of adult schooling,
- infrastructure and society – urbanization index,

- health – infant mortality rate,
- social inequality – gender inequality indicator,
- institutional transparency – corruption perceptions index,
- economic environment – index of economic freedom.

The process of performing the cluster analysis in R consisted of the following steps:

- normalizing metric variables,
- calculating the distance matrix between countries using Euclidean distance,
- performing a hierarchical cluster analysis using Ward's method,
- creating a dendrogram that illustrates the process of grouping countries together,
- establishing a division into k classes and forming four groups of similar countries,
- interpreting the results.

Before calculating the distance matrix, the variables were standardized. This ensured that the variables expressed in different units were scaled to a comparable level. The entire data cleaning and standardization process was performed in R using the packages (Kabacoff, 2022):

- readxl – for importing data from Excel files,
- scale() – R's built-in function for standardizing variables.

The squared Euclidean distance, widely used in analyses of standardized data, was used to measure similarity between objects, which makes it possible to emphasize larger differences between objects more strongly and to obtain a clearer cluster division (Everitt et al., 2011). The following were used for the analysis (R Core Team, 2024):

- stats::dist() – calculation of the Euclidean distance matrix,
- stats::hclust() – performing hierarchical agglomerative cluster analysis using Ward's method,
- factoextra::fviz_dend() – dendrogram visualization with class labeling.

The results of the analysis are presented in Figure 1 in the form of a dendrogram – a hierarchical tree illustrating the process of grouping countries together. The dendrogram allows the graphical identification of the tree's "cut" point corresponding to a specific number of classes.

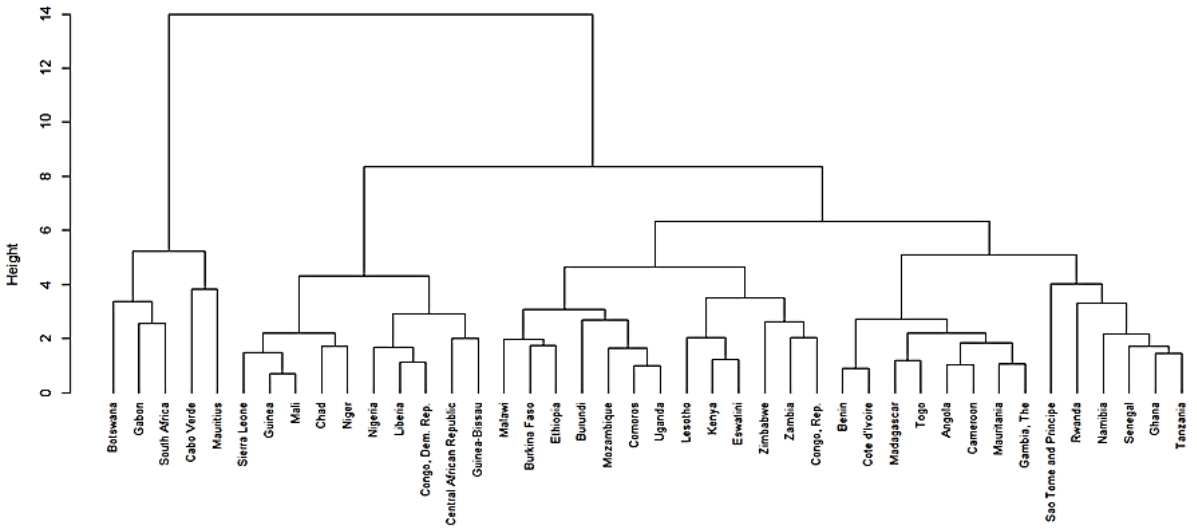

Figure 1. Dendrogram showing hierarchical cluster analysis of 42 African countries.
Source: own elaboration.

In hierarchical cluster analysis, the initial merging steps involve the most similar objects, resulting in a small increase in the distance measure. If the number of classes had been selected solely on the basis of the first large increase in this measure, a very large number of groups would have been obtained, so the first mergers were omitted and the analysis was carried out focusing on the later stages, where the increase in distance indicates the merging of more diverse groups (Everitt et al., 2011). In order to determine the optimal number of classes, an analysis was carried out using various methods to minimize the risk of arbitrary division (Thorndike, 1953).

The average silhouette width for different class sizes was calculated using the function fviz_nbclust (method = "silhouette"). The highest value (0.45) was obtained for 2 classes, indicating the best separation of groups. The values for k = 3 and k = 4 were slightly lower (0.19 and 0.17, respectively) (Figure 2). The Gap Statistic method used the clusGap() function from the cluster package and the fviz_gap_stat() visualization from the factoextra package to compare clustering results with randomly generated data. The point of greatest difference between the actual and random data indicated 2-4 classes as the potentially optimal solution (Figure 3). In addition, an agglomeration schedule was analyzed, which shows the incremental value of the distance measure in subsequent stages of cluster merging. The graph of height increment differences indicated a clear local jump at the stage when the last 4 groups were combined into 3 classes. According to the recommendations of the method, the optimal cut of the dendrogram should take place before such a jump, which in this case corresponds to a division into 4 classes (Figure 4) (Yim, Ramdeen, 2015). In addition, the Elbow Method was used. The fviz_nbclust (method = "wss") function revealed clear "breakpoints" in the curve at two and four clusters, which confirmed the earlier observations. The Dindex (Difference Index) method is an approach used to determine the optimal number of classes, which analyses the rate at which the value of the within-group measure (or other fit index) decreases as the number of

classes increases. Figure 5 shows the Dindex values (left) and their second differences (right), which allows us to identify the "curve breakdown point" – the point at which further increases in the number of classes bring a slight improvement in clustering quality. The study shows a clear turning point around 4 classes which is the rationale for choosing this number of groups (Charrad et al., 2014).

Although many methods pointed to the optimality of 2-class division, this solution yielded very unequal group sizes – 5 countries in the first class and 40 in the second. This large disparity makes it difficult to interpret the results and does not allow subtle differences between countries to be discerned. All methods indicated the need to consider several options for the number of classes. After analyzing the graphs and indicator values, it was considered that the division into four classes best reflected the internal diversity of the countries reviewed. The division into 4 classes was found to be the most satisfactory, as it provided a more equal group size, allowed greater socio-economic variation between states to be captured, and was consistent with observations of dendrogram height increments (agglomeration review), which indicated an optimal cut with 4 groups.

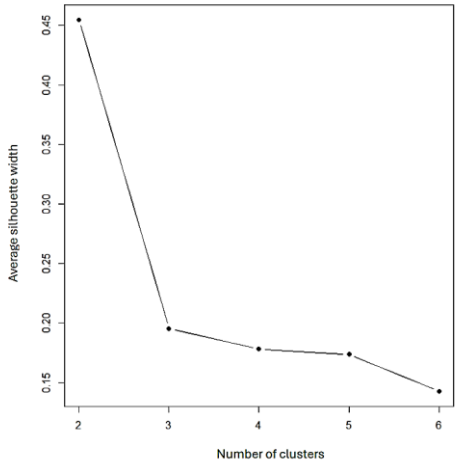

Figure 2. Results of the silhouette index-based criterion for selecting the optimal number of classes
Source: own elaboration.

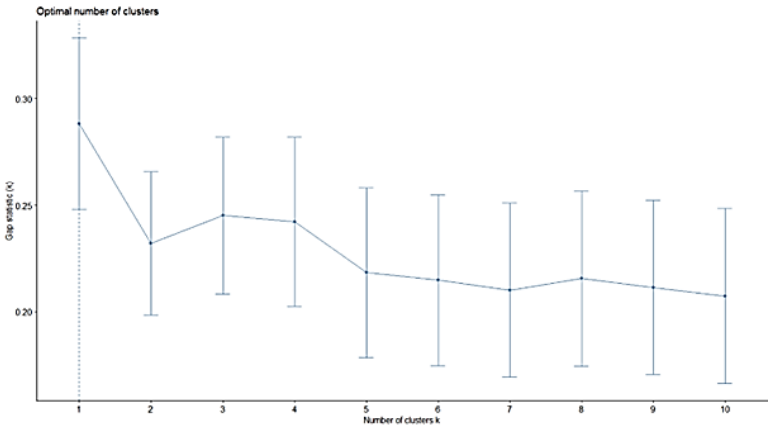

Figure 3. Results of the Gap Statistic method for selecting the optimal number of classes.
Source: own elaboration.

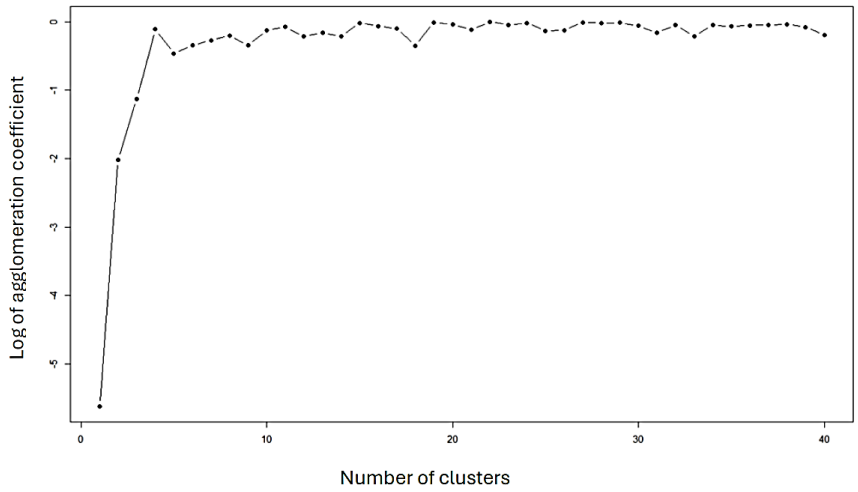

Figure 4. Graph of agglomeration increments (height differences) in hierarchical cluster analysis.

Source: own elaboration.

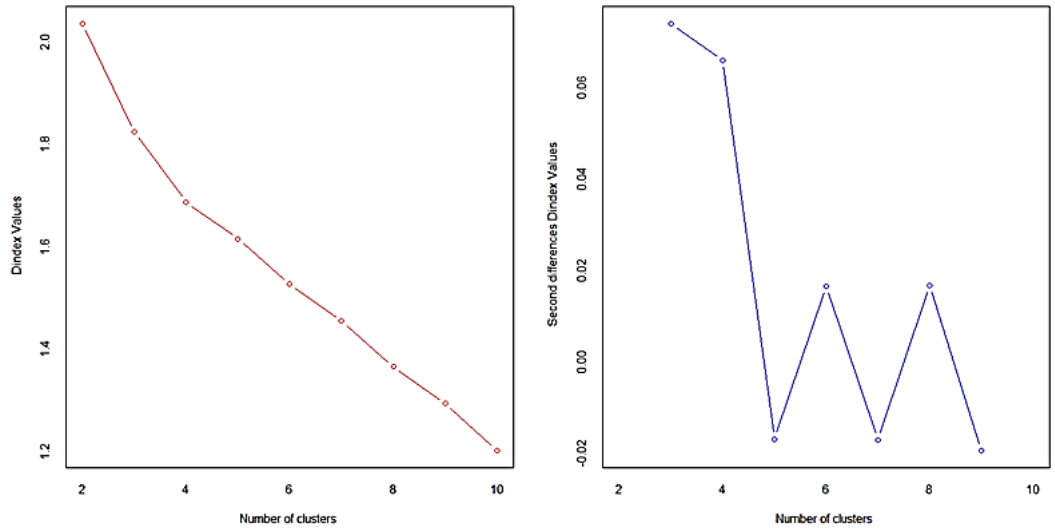

Figure 5. Results of the Dindex method for selecting the optimal number of classes (5a. Dindex values as a function of the number of clusters, 5b. Second differences of Dindex values depending on the number of clusters).

Source: own elaboration.

Figure 6 shows the result of the hierarchical analysis, in which the optimal cut of the dendrogram shows the division of the reviewed objects into four classes.

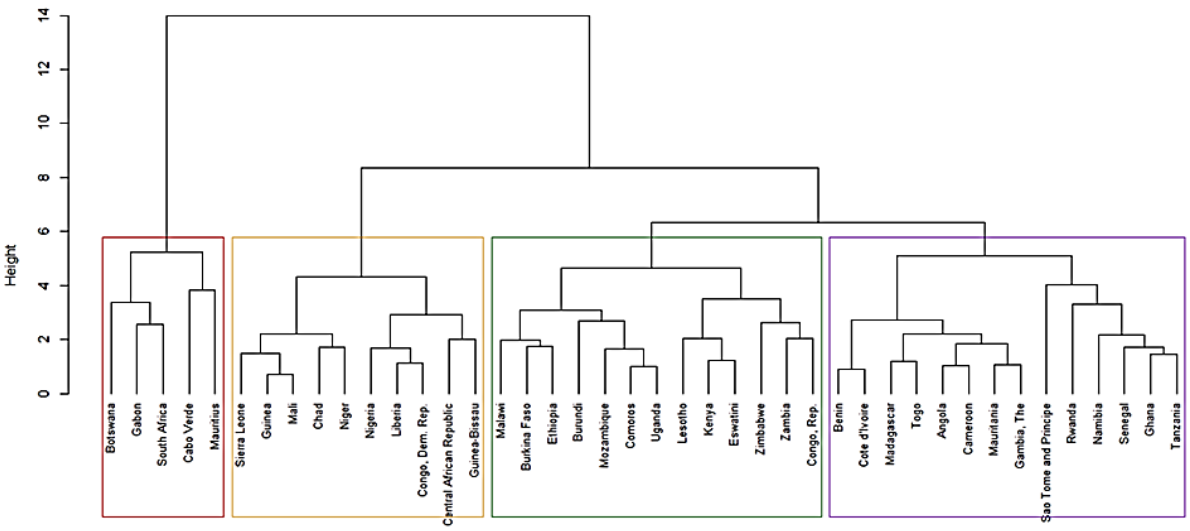

Figure 6. Dendrogram showing a hierarchical cluster analysis of 42 African countries divided into four classes.

Source: own elaboration.

Table 1 shows the division of African countries into four classes, distinguished on the basis of the socio-economic indicators analyzed.

Table 1.
Assignment of objects to clusters

Class	Country name
Class 1	Botswana, Gabon, South Africa, Cape Verde, Mauritius
Class 2	Sierra Leone, Guinea, Mali, Chad, Niger, Nigeria, Liberia, Democratic Republic of the Congo, Central African Republic, Guinea-Bissau
Class 3	Malawi, Burkina Faso, Ethiopia, Burundi, Mozambique, Comoros, Uganda, Lesotho, Kenya, Eswatini, Zimbabwe, Zambia, Republic of the Congo
Class 4	Benin, Côte d'Ivoire, Madagascar, Togo, Angola, Cameroon, Mauritania, Gambia, São Tomé and Príncipe, Rwanda, Namibia, Senegal, Ghana, Tanzania

Source: own elaboration.

Table 2 presents the basic descriptive statistics for the socio-economic indicators selected for the study by the four groups of African countries.

Table 2.
Basic statistical measures by class

Class	Risk	Mean	The median	Min.	Max.	The standard deviation	Coefficient of variation
1	Corruption Perceptions Index	48.60	51.00	28.00	64.00	14.43	29.70
1	Index of Economic Freedom	62.62	64.90	55.70	70.60	6.51	10.39
1	GDP per capita (PPP)	7592.75	7826.35	4861.29	11182.19	2402.82	31.65
1	Urbanization	68.31	68.82	40.87	91.03	17.96	26.29
1	Gender inequality index	0.41	0.39	0.30	0.51	0.09	21.91
1	Infant mortality rate	22.72	24.04	11.00	38.20	10.94	48.17

Cont. table 2.

1	Average years of schooling	9.59	10.10	6.09	11.61	2.09	21.74
2	Corruption Perceptions Index	25.07	25.00	20.00	35.00	4.88	18.98
2	Index of Economic Freedom	50.34	51.10	43.80	54.50	3.86	7.68
2	GDP per capita (PPP)	946.67	882.06	495.98	1596.64	373.71	39.48
2	Urbanization	41.44	44.88	17.05	54.28	12.01	28.97
2	Gender inequality index	0.61	0.61	0.51	0.68	0.05	8.04
2	Infant mortality rate	56.21	58.15	43.10	67.40	7.57	13.47
2	Average years of schooling	4.02	3.60	1.41	7.59	2.28	56.66
3	Corruption Perceptions Index	29.69	30.00	20.00	41.00	7.40	24.92
3	Index of Economic Freedom	50.04	51.60	39.00	56.20	4.98	9.95
3	GDP per capita (PPP)	1448.61	1272.36	192.07	3741.69	955.29	65.95
3	Urbanization	32.09	30.13	14.78	69.19	13.81	43.04
3	Gender inequality index	0.52	0.52	0.48	0.58	0.03	5.90
3	Infant mortality rate	37.14	35.70	27.06	55.40	8.34	22.47
3	Average years of schooling	6.15	6.32	2.27	8.93	2.39	38.87
4	Corruption Perceptions Index	38.50	40.00	25.00	53.00	8.34	21.65
4	Index of Economic Freedom	55.94	57.70	45.10	60.40	4.22	7.54
4	GDP per capita (PPP)	1854.33	1717.45	508.72	4187.61	980.73	52.89
4	Urbanization	52.42	54.02	17.89	76.40	14.54	27.74
4	Gender inequality index	0.53	0.54	0.39	0.60	0.06	11.39
4	Infant mortality rate	34.57	34.85	9.04	46.60	9.59	27.75
4	Average years of schooling	5.34	5.37	2.93	7.27	1.30	24.36

Source: own elaboration.

Cluster analysis revealed four clearly distinguishable groups of African countries that differ in both their level of economic development and the structure of their social problems. These differences are evident in almost all the indicators reviewed.

Group 1 comprises countries with the highest level of socio-economic development. They are characterized by high GDP per capita, low gender inequality index, the highest level of the Corruption Perceptions Index, low infant mortality and the best educational performance. Their average GDP per capita (USD 7593) is more than four times that of Group 2 and more than five times that of Group 3. The average years of schooling (9.59) exceeds the other groups by at least three years, and the Corruption Perceptions Index (48.6) indicates a significantly better quality of institutions than in groups 2-4 (a difference of 16 points compared with the lowest score). The gender inequality index (0.407) is a third lower than in Group 2, and urbanization (68.3%) is the highest. This group includes five countries: Botswana, Gabon, South Africa, Cape Verde, Mauritius. The above group is composed of countries with stable economies, well-developed infrastructure and robust institutions.

Group 2 is the opposite of Group 1. It includes countries with the lowest average GDP per capita (USD 947) and the level of urbanization (42.7%) remains below the African average. The gender inequality index (0.611) is the highest of all groups – roughly 50% higher than in Group 1 – and infant mortality (58.6) is almost double that of Group 1. The CPI (32.0) and index of economic freedom (48.6) are moderate, but do not compensate for the poor social performance. This group comprises countries struggling with an array of economic and social problems, limited access to infrastructure, and difficult living conditions. Eleven countries were included, such as Sierra Leone, Guinea, Mali, Chad, Niger, Nigeria, Liberia, Democratic Republic of the Congo, Central African Republic and Guinea-Bissau.

Group 3 comprises countries with an average level of development and high average internal disparity (66%). They have low to moderate GDP per capita and education indicators. Social problems are evident in high GII values and infant mortality. Urbanization is relatively low. Compared to Group 2, it has a slightly lower Gender Inequality Index (0.566) and lower infant mortality (45.8), but lags significantly behind Group 1 on every development indicator. Urbanization (36.9%) is the lowest of all groups, highlighting the limited access to urban infrastructure. The group is composed of thirteen countries, including Malawi, Burkina Faso, Ethiopia, Burundi, Mozambique, Comoros, Uganda, Lesotho, Kenya, Eswatini, Zimbabwe, Zambia and Republic of the Congo. These are countries that are nearing continental averages in some areas, but lagging behind in others.

Group 4 is distinguished by a relatively high level of urbanization (53.7%), similar to Group 1, but in contrast is characterized by weak institutions (CPI = 32.6) and low economic freedom (51.5). GDP per capita (USD 1854) is higher than in Groups 2 and 3. The gender inequality index (0.550) is high and comparable to Group 3, indicating persistent social barriers. Fourteen countries were included in this group, such as Benin, Côte d'Ivoire, Madagascar, Togo, Angola, Cameroon, Mauritania, Gambia, São Tomé and Príncipe, Rwanda, Namibia, Senegal, Ghana and Tanzania. Although they have the potential for development it is hampered by corruption and governance issues.

4. Conclusion

The cluster analysis conducted identified four distinct groups of African countries, differing in terms of their level of socio-economic development and the structure of their key challenges. The results confirm that the continent is characterized by considerable socio-economic development disparities. The first group includes countries with relatively high levels of development, strong institutions and favorable social indicators, serving as a benchmark for all the others. At the opposite end is the second group, comprising countries with the lowest GDP per capita, the highest infant mortality, and significant gender inequalities, indicating

a concentration of development barriers. The third group represents a medium level of development, but is distinguished by a high degree of internal disparity, suggesting that the development strategy for these countries needs to take into account their specific circumstances. Group 4, on the other hand, is characterized by a relatively high level of urbanization but weak institutions and limited economic freedom, which constrain its growth potential. A comparison of the results shows that GDP alone is not a sufficient measure of development, and that taking into account social, demographic and institutional indicators allows a more complete understanding of the individual countries' situation.

For the lowest-performing countries, strengthening institutions, improving infrastructure, and reducing inequalities are crucial. The results of the analysis can provide a starting point for further comparative studies.

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