

Brussels, Bremen). Cluster 3 ("Tourism and service regions", 23 regions) - the highest tourism index (+1.28) and educational employment component (+1.10), typical of coastal, island, and alpine territories (Illes Balears, Canarias, Tirol, Kriti, Jadranska Hrvatska). Cluster 4 ("Catch-up regions", 38 regions) - the lowest innovation scores (-1.51) and employment PC1 (-1.10), predominantly CEE regions (Małopolskie, Közép-Dunántúl, Nord-Vest, Latvija). Cluster 5 ("Developed diversified regions", 76 regions) - the largest cluster, combining a suburbanised spatial structure (Urban PC2 = +0.90) with a well-developed post-industrial base (Stuttgart, Oberbayern, Lombardia, Noord-Brabant).

Analysis of cluster structure dynamics over 2013-2023 reveals considerable stability: most regions retained their cluster membership throughout the study period. Cluster 5 gradually increased in size, indicating an expansion of the diversified-region group. The highest GRP growth rates are recorded in Cluster 4 (above 10% in peak years), confirming the presence of β -convergence among the catch-up regions of CEE. The deepest contraction in 2020 is observed in the tourism-and-service cluster (approximately -7%), reflecting the extreme sensitivity of these regions to pandemic-related restrictions.

The proposed methodological chain "PCA $\rightarrow$ CLR $\rightarrow$ SOM $\rightarrow$ k-means" combines the advantages of linear dimensionality reduction, geometrically correct analysis of compositional data, and non-linear neural-network topological mapping. Unlike standard k-means, the SOM preserves the topological structure of the multidimensional regional space, providing more stable clustering under conditions of high data dispersion. The use of a global map trained on the full panel dataset enables analysis of inter-cluster regional mobility in the time dimension, which is a key advantage for assessing structural transformations under external shocks.

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Savina S. S.,
PhD in Economics, Associate Professor,
Kyiv National Economic University named after Vadym Hetman

CLUSTER ANALYSIS OF THE COUNTRIES OF THE WORLD BY HUMAN DEVELOPMENT INDICATORS

Assessing the quality of life of the population is an important area of modern socio-economic research, as it makes it possible to analyze the effectiveness of state social policy, the level of access to education, healthcare, and other components of public welfare. The use of modern information technologies and digital data processing methods creates opportunities for identifying current social problems and developing effective strategies for societal development. One of the key indicators for assessing quality of life is the level of human development, which characterizes the overall socio-economic progress of a country.

For international comparisons, the most widely used integral indicator is the Human Development Index (HDI), which takes into account life expectancy, the level of education, and population income. However, analyzing only the final HDI value does not always allow for a comprehensive assessment of the specific features of individual countries' development, since countries with similar index values may differ significantly in the structure of human development factors.

In this regard, the application of multivariate statistical methods, in particular cluster analysis, becomes especially important. The use of clustering methods makes it possible to group countries according to the similarity of their socio-economic characteristics, identify hidden patterns, and investigate structural differences among countries. The main objective of this study is to conduct a clustering analysis of the countries of the world based on key human development indicators and to compare the obtained results with the values of the Human Development Index.

The informational basis of the study consisted of statistical data for 74 countries of the world for 2023 [1]. The following indicators were used in the analysis: life expectancy at birth, expected years of schooling, mean years of schooling, and the value of the Human Development Index. Data processing and calculations were performed using the Statistica software package.

At the initial stage of the research, hierarchical agglomerative clustering procedures were applied in order to justify the choice of the optimal number of clusters. For agglomerative methods, the selection of a distance measure between objects and clusters is important, since not all combinations provide a clear identification of clusters in dendrograms. In the study, several dendrogram variants were analyzed using the most common distance metrics [2]. Based on the analysis of the constructed dendrograms, the most stable clustering solution was identified for all possible combinations of distance measures, consisting of five clusters, which served as the basis for the further application of the k-means method.

The results of the clustering analysis indicate its sufficiently high quality and adequacy. The graph of means demonstrated significant differences between the clusters in terms of the main human development indicators. According to the results of the analysis of variance, all variables were found to be statistically significant. This confirms that the formed clusters adequately reflect the structural characteristics of countries' development and provide a well-grounded classification of the studied sample [3].

As a result of the cluster analysis, five clusters of countries were identified, differing in the level and structure of human development. The main characteristics of the clusters are presented in Table 1.

Table 1

Main Characteristics of the Clusters

Cluster	Number of Countries	Level of Human Development	Main Characteristics
Cluster 2	11	Highest	The highest indicators of life expectancy and education, a high level of social protection and economic development
Cluster 3	20	High	High level of education and life expectancy, structural heterogeneity of development models
Cluster 5	12	Medium and above average	Relatively high social indicators, noticeable differentiation in economic development
Cluster 1	11	Moderate and heterogeneous	Average level of education and life expectancy, presence of structural imbalances
Cluster 4	20	Moderately lower	Lower values of certain education and income indicators, heterogeneity of socio-economic development

Source: calculated by the author based on [1].

The first two clusters combine countries with the highest indicators of life expectancy, education, and the Human Development Index. These clusters mainly include economically developed countries

of Europe, North America, and Asia. The third cluster includes countries with medium and above-average levels of human development, characterized by relatively high social indicators and a certain heterogeneity of economic development. The fourth and fifth clusters comprise countries with moderate or lower levels of human development. They are characterized by lower values of education and life expectancy indicators, as well as greater structural heterogeneity.

The obtained results show that countries with similar HDI values may belong to different clusters due to differences in the structure of human development factors. Out of 11 cases of identical HDI rankings, only 3 pairs of countries were assigned to the same cluster, while in most cases they were classified into different but developmentally close groups. This indicates differences in the structure of human development factors even with similar values of the integral indicator. For example, Germany and Sweden have the same HDI ranking but belong to different clusters due to differences in education and life expectancy indicators. A similar situation is observed for Czech Republic and Italy, as well as Argentina and Hungary. The obtained results confirm that the HDI does not always fully reflect the structural characteristics of countries' development, whereas cluster analysis makes it possible to identify hidden differences and increase the informativeness of human development assessment.

The results confirm that cluster analysis is an effective tool for studying human development, as it enables the identification of structural differences between countries that are not always reflected by the Human Development Index. It has been established that countries with similar HDI values may differ significantly in their component indicators. Therefore, the combination of the ranking approach and clustering expands the possibilities for comparative analysis, increases the informativeness of human development assessment, and creates a basis for more substantiated managerial decisions in the field of socio-economic policy.

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Skorobogatova N. Ye.,
PhD in Economics, associate professor,
National technical university of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute"

CORRELATION ANALYSIS OF THE DEVELOPMENT OF THE AGRICULTURAL SECTOR OF UKRAINE IN THE CONDITIONS OF DIGITAL TRANSFORMATION

Global digital transformation is fundamentally reshaping the principles of agricultural systems: from traditional farming to AI-based yield forecasting and digital governance platforms in the agro-industrial complex. However, the pace and depth of these changes vary considerably depending on the level of institutional development, investment climate, and overall digital maturity of the economy [1, 2]. For Ukraine – one of the world's leading agricultural producers and exporters – technological modernisation of the agro-industrial complex is of strategic importance, particularly in the context of post-war recovery and European integration. A comparative study of structural correlations in the