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A NUTS 3 LEVEL SOCIO-ECONOMIC ANALYSIS USING MULTIVARIATE METHODS

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Abstract

This study applies factor analysis and cluster analysis to explore county-level differences, with emphasis on economic performance, employment, industrial activity, demographic trends, education, and tourism potential. The focus is on the Romanian NUTS-3 regions (named 'counties'). The results highlight Cluj and Sibiu as the most advanced counties in economic terms, while Harghita and Covasna rank among the less developed regions. The cluster analysis groups the counties into five distinct categories, with Harghita, Covasna, and Mureș classified as "moderately progressing" areas. Based on these insights, the study outlines recommendations to promote economic diversification, enhance the quality of education, develop tourism infrastructure, and strengthen regional connectivity – key measures that could reduce territorial disparities and support a more balanced spatial development in Romania.

Keywords: Multivariable Analysis, Regional Economy, Spatial planning, Territorial Inequalities
JEL Classification: R11; R50; C82

1. Introduction

In this paper a NUTS-3 level analysis using multivariate statistical methods is conducted with a spotlight on the Romanian counties. The general aim of the research presented here is to lay the foundation for various secondary research methods, thereby gaining deeper insights into the country's territorial structure and development dynamics, contributing to the development of more effective and targeted regional development policies and their implementation.

The special focus of our further research is the detailed analysis of the NUTS 2 level Central Romania Development Region (CRDR) in the context of regional development opportunities. For this purpose, it is also essential to conduct a comprehensive economic and social examination of the counties at NUTS 3 statistical level, surveying the territorial and developmental differences among them, taking into account the issues of prosperity and well-being. It is important to note that the economic performance of Mureș, Harghita, and Covasna counties - as the part of their NUTS 2 level region - is lower compared to the other counties of the CRDR. In our long-term research we intend to thoroughly examine this economic and social differentiation and seek opportunities and development directions that can reduce territorial disparities, thereby contributing to the long-term competitiveness growth of these counties.

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However, in this study, as the first step of our research plans in the long run, we conduct a multivariate secondary research analysis focusing on NUTS 3-level counties in Romania, with a particular emphasis on uncovering the relationships between regional development and economic performance. Utilizing various multivariate statistical methods and data sources, we endeavour to

provide a comprehensive overview of the developmental dynamics of different counties by comparing these data sets. Based on the results obtained, we plan to conduct further, more detailed research, contributing to a deeper understanding of territorial disparities and development opportunities.

2. Literature review

Regional disparities represent a key priority both in Romania, within the European Union, and globally, considering the importance of establishing economic and social balance to achieve paramount welfare objectives. The debate on the changing regional disparities and the process of spatial convergence within regional sciences has always oscillated between two extremes. The first theory aligns with the neoclassical paradigm, which posits that the free movement of market forces ensures the equalization of spatial disparities, facilitated by mobile labor and capital (Richardson, 1973), or the trade of goods (Ohlin, 1933). According to this view, economic processes generally exhibit a tendency towards reducing spatial disparities. In contrast, the approach of regional polarization fundamentally builds upon Myrdal's concept of circular cumulative causation (Myrdal, 1957), arguing that the tendency of spatial inequalities is increasing due to feedback and self-reinforcing processes. The essence of this perspective lies in the notion that inequalities in individual regions either contract or expand, and these changes stimulate each other within the processes. This viewpoint underscores the mechanisms and processes that reinforce and sustain inequalities within the socio-economic system's inherent logic, providing valuable insights for long-term regional development strategies.

Regional science is an interdisciplinary field comprised of the synthesis of various disciplines, including geography, sociology, economics, spatial planning, and more. Together, these disciplines aim to elucidate the regularities and mechanisms governing spatial processes (Enyedi, 2007; Vaz, 2020). Furthermore, regional science encompasses the integration of methods and theories derived from the examination of diverse social processes. These methods and theories are designed to address and ameliorate regional or territorial disparities (Nemes Nagy, 2009), while also acknowledging the role of hierarchical structures in shaping territorial development and innovation dynamics (Tartaruga et al., 2024). This interdisciplinary approach allows for a comprehensive understanding of the complex dynamics shaping regional development and highlights the importance of interdisciplinary collaboration in tackling regional challenges. By examining these factors, researchers can identify solutions to mitigate territorial inequalities, which remain a pressing issue for both national and regional policymakers. In this context, the importance of research and development (R&D) in fostering regional economic growth is particularly relevant. According to Goschin (2014a), R&D is

a crucial driver of regional development, offering empirical evidence of its significant impact on economic growth.

It is important to emphasize that regional disparities have their roots in historical determinants both globally and locally (Dogan, 2004; Szirmai et al., 2016). These disparities are shaped by various factors, including shifts in political ideologies, the impacts of industrial revolutions (Lőrinc and Káposzta, 2023; Bhandari, 2023), uneven distribution of endogenous resources, as well as the diversity of exploitation opportunities and geographical locations (Horváth, 2015). Moreover, disruptive innovations have also played a role in shaping spatial inequalities, as their uneven emergence and diffusion contribute to regional economic divergence (Kemeny et al., 2025). These dynamic and complex factors continue to shape regional development and dictate the roles of different alliances and unions in reducing territorial inequalities. As Ileanu et al. (2009) argue, intellectual capital plays a central role in the persistence of regional disparities, with human and structural capital being key contributors to the economic and social outcomes within a given region. The availability and quality of intellectual capital can either mitigate or exacerbate the development gaps between regions. In this sense, addressing the factors that influence intellectual capital becomes critical for reducing regional inequalities. Additionally, as noted by Constantin et al. (2019), the provision of services of general interest is integral to achieving territorial cohesion within the European Union. In their study on the accessibility of internet services in the North-East Region of Romania, they highlight how the accessibility and quality of such services influence regional disparities, especially in rural and intermediate areas. These services not only enhance the quality of life but also contribute to regional economic development by improving access to information, education, and economic opportunities. Ensuring equitable access to essential services is vital in fostering balanced regional growth. However, as Mogila et al. (2022) point out, despite efforts like the Cohesion Policy, structural differences between regional economies persist, hindering the narrowing of development gaps in the long run.

Regional development initiatives encompass multifaceted strategic endeavors geared towards ameliorating the economic, social, and environmental landscapes of distinct geographical areas, concurrently mitigating territorial disparities (Bachtler et al., 2019). These actions typically manifest as programs orchestrated by governmental bodies, international institutions, or regional entities, with the overarching aim of fostering economic expansion, bolstering infrastructural frameworks, enriching educational and vocational avenues, fostering employment opportunities, and tackling societal and environmental dilemmas prevalent within regional contexts (Horváth, 2006; Kouskoura et al., 2024). Moreover, they aspire to cultivate conditions conducive to sustainable progression across all regions, whilst ensuring equitable access to opportunities for th populace (Benedek, 2014; Ticona

Machaca et al., 2025). Rural development plays a crucial role in reducing regional disparities, particularly in areas with a high proportion of rural population. Rural regions, which often cover a significant portion of a country's territory, face challenges such as reliance on subsistence agriculture, low-income levels, and limited access to essential services. These issues contribute to widening rural-urban disparities and have led to increased migration from rural areas to urban centers. As Dachin (2008) highlights, a sustainable, multifunctional rural development strategy is essential to address these imbalances. Such a strategy aims not only to reduce regional inequalities but also to tackle labor force deficits and improve the overall well-being of rural populations. Additionally, as Laidin and Berriet-Solliec (2023) note, rural development strategies have evolved within different policy paradigms, from agricultural modernization to broader territorial development approaches that emphasize economic and social cohesion.

The territorial delimitation of Romania and the establishment of its development regions occurred prior to its accession to the European Union, aiming to forecast and coordinate regional development efforts, thereby ensuring necessary integration and harmony among different areas. The final establishment of Romania's county system took place within the framework of the 1968 Romanian administrative reform, enacted by Law No. 2 of 1968, which determined the organization of territorial administration in the Socialist Republic of Romania. Through this law, the administrative units existing until then, namely the provinces, were transformed into 39 counties (LEGEA no. 2, 17 February 1968). Later, further changes were made based on Decree No. 15 of 1984, aiming to improve territorial administration. According to this decree, Ialomița and Ilfov counties were divided, and four new counties were established (Decret no. 15, 23 January 1981). Ultimately, Law No. 50 of 1997 amended the previous administrative law, creating the independent Ilfov County as a separate administrative unit (LEGEA no. 50, 9 April 1997). As a result of this final modification, the current county system was formed, consisting of 41 counties and the capital county of Bucharest. The 42 counties of Romania are grouped into eight development regions, which collectively correspond to the European Union's regional development policy and the NUTS (Nomenclature of Territorial Units for Statistics) classification system for regions. According to this system, Romania comprises 4 macro-regions at NUTS 1 level, 8 development regions at NUTS 2 level, and 42 counties at NUTS 3 level (Figure 1), which are suitable for precise economic and social analyses, thereby contributing to the formulation of regional policies (Eurostat, 2022).

Based on the preliminary literature review of the territorial disparities in regional level in Romania, the following findings have emerged: researchers have employed a wide range of research methods (e.g., comparative analyses, cluster analysis and discriminant analysis, multinomial logistic regression model, principal component analysis, core-periphery analysis, etc.) which have facilitated

a detailed and comprehensive understanding of regional disparities (Brisc and Bodocan, 2025; Dornean and Oanea, 2015; Lazar and Litan, 2022; Nagy, 2015; Popescu et al., 2022; Reveiu and Constantin, 2023; Rotaru et al., 2023; Sandu, 2022).

Figure 1. The spatial distribution of the 42 NUTS level 3 regions (counties) in Romania

Source: www.mapsofindia.com, 2023

Literature findings indicate that the Bucharest-Ilfov Region has undergone continuous economic development over the past 15–20 years, significantly outpacing other development regions. In terms of RDI expenditures, previous research highlights Cluj County as the leading spender in the North-West Region, Brașov County in the Center Region, and Iași County in the North-East Region. In the South-East, South Muntenia, and South-West Oltenia Regions, the highest expenditures were recorded in Galați, Argeș, and Dolj counties, respectively, while Timiș County led in the West Region, and Bucharest in the Bucharest-Ilfov Region (Nicolov, 2012). While these data provide a useful reference point for understanding regional disparities, more recent research is needed to capture the latest developments. According to Ogrean and Herciu (2022), Romania remains among the weakest performers in the EU in terms of innovation, ranking last in the European Innovation

Scoreboard (2021). The most significant shortcomings are observed in finance and support, intellectual assets, and firm investments. Although the Bucharest-Ilfov Region continues to show the highest innovation performance, it still lags behind leading European innovation hubs. These disparities highlight the persistent regional divide in innovation potential and underscore the need for targeted smart specialization strategies to strengthen regional innovation ecosystems.

Furthermore, through the analysis of literature data, it can be demonstrated that following the examination of regional socio-economic disparities in Romania, significant differences persist. Mitrică et al. (2022) highlighted that Romania remains one of the largest labor-exporting countries in the EU, with migration patterns showing regional characteristics: while less developed counties in Southern Romania experience outmigration of low-skilled workers, more developed areas such as Bucharest and Central-West Romania see the emigration of highly skilled professionals. Iordan et al. (2021) demonstrated that the GDP of the Bucharest-Ilfov region reaches 160% of the EU average, while the North-East region lags behind at only 44%, with the COVID-19 pandemic further deepening economic inequalities between regions. Mitrică et al. (2021) found that while competitiveness and cohesion indicators remained stable, less developed regions failed to catch up. Pop and Stamos (2024) emphasized that the North-West region continues to struggle with significant socio-economic disadvantages, such as high levels of material and social deprivation, low R&D investments, and poverty risks. Olar and Jitea (2021) examined the effectiveness of the LEADER program in rural development, concluding that its success is largely influenced by proximity to developed urban centers and the resources available to Local Action Groups (LAGs). Collectively, these findings support the conclusion that Romania's territorial inequalities are structural in nature, necessitating targeted regional policies to foster convergence.

Within the framework of this study, we present an in-depth multivariate analysis based on current and up-to-date data sources. Our objective is to delve deeply into the analysis of the Romanian counties, employing sophisticated methodologies that allow for a comprehensive exploration of the intricate interplay between territorial attributes and developmental metrics. Furthermore, our aim extends to gaining a nuanced understanding of the dynamics and disparities observed among regions, thereby contributing to a more comprehensive comprehension of regional disparities and development patterns.

3. Method

As part of our long-term research, here we conducted factor analysis and cluster analysis for the 41 NUTS level 3 counties in Romania, excluding the capital county due to its distorting effect. The database necessary for the analysis was compiled from the latest statistical data for the years 2021

and 2022 obtained from the Romanian National Institute of Statistics. We prepared the data for analysis by first organizing them using the Excel spreadsheet software, and then standardizing them. Subsequently, based on the literature and research experience we devised indicators that were relevant to the objectives of our research and aligned with our analytical framework. To conduct the analyses, we utilized the Statistical Package for Social Sciences (SPSS), a software widely recognized and utilized by the scientific community. The results obtained provide deeper insights into the territorial differences and developmental dynamics among the counties, contributing to the more effective planning and implementation of regional development policies.

To mitigate territorial disparities and regional differences, the first essential step is to conduct a comprehensive economic and social assessment, which can be accomplished through multivariate statistical methods (Cismas, Para and Tălmaciu, 2020; Goschin, 2014b; Lengyel, 2012). Among these methods are factor analysis and cluster analysis, which allow for a detailed and comprehensive examination of territorial characteristics and potential groupings. This systematic approach enables researchers and policymakers to design regional development policies based on reliable, data-driven information, thus contributing to the reduction of both economic and social disparities.

Factor analysis is a predominantly used statistical analysis method in regional and territorial studies, employed to uncover patterns and relationships among variables. The method was developed by Karl Pearson (1901) (cited in Cohen, 1988), and it began to be regularly utilized by researchers from the 1960s to 1970s, primarily for economic and social studies, as well as geographical research. Factor analysis is a statistical procedure that transforms a set of variables into a smaller number of variables with higher explanatory power through linear transformation. This allows for simpler handling of the original data and the extraction of fundamental patterns, aiding in better understanding of the given situation and the exploration of relationships (Szelényi, 2004). As a result of the transformation, the newly created variables, i.e., the factors, are uncorrelated with each other and efficiently represent the information contained in the original variables, explaining a significant portion of the variance of the observed variables (Loehlin, 2003). After conducting the analysis, we can determine the extent to which each factor influences the values of the observed variables (Tinsley and Tinsley, 1987). The factors identified through factor analysis can be widely used in further multivariate analyses, enabling the application of various multivariate statistical methods, such as cluster analysis, discriminant analysis, or multidimensional scaling techniques.

Cluster analysis, unlike factor analysis, focuses on grouping the observed units under study, aiming to identify relatively homogeneous groups based on the underlying variables (Ketchen and Shook, 1996). Cluster analysis serves to condense the data and reduce the number of variables while categorizing units into groups that are similar to each other but distinct from other groups (Székelyi

and Barna, 2002). During the analyses, it is advisable to try different clustering methods and compare the results to make the most appropriate decision. The concept of distance is crucial in clustering, which can be determined based on Euclidean or other association measures. The two main types of analytical clustering procedures include hierarchical methods, which encompass agglomerative and divisive approaches, and non-hierarchical clustering, where the most popular is the K-means method, based on the MacQueen algorithm. The results obtained from the analysis are often ambiguous, so it is worth trying multiple clustering methods and comparing them, taking into account the method, the desired number of clusters, the mode of distance measurement, and the refinement of the variable system, as the acceptability of cluster analysis is subjective and largely based on the researcher's expertise (Sajtos and Mitev, 2007).

The quality and reliability of the underlying data are critically important for the evaluability and dependability of the applied models, and they determine the credibility and interpretability of the research findings. In this context, we consider it essential to accurately interpret the basic indicators to ensure that the research results are relevant and reliable, thereby facilitating scientific progress. The basic indicators necessary for the research were provided by the National Institute of Statistics of Romania for the most recent years available (2021, 2022), including demographic, economic, infrastructural, agricultural, and tourism characteristics for 41 counties, excluding the capital county. The exclusion of capital cities from regional analyses is not only a widely accepted practice at the local level but also internationally recognized. Capital cities, as economic and political centers, often have a significant distorting effect on the economic and social indicators of individual regions or counties. The main reason for this is that capitals typically have superior economic and infrastructural development and exert significant influence over economic processes as the national decision-making hubs. Therefore, excluding capital cities helps to provide a more accurate and realistic picture of regional differences, avoiding the overpowering impact of capitals on the analyses. According to internationally accepted practices, excluding capital cities allows for economic and social indicators of individual regions to reflect local development characteristics and challenges, without being artificially distorted by the dominant role of the capitals. This approach contributes to a fairer comparison between regions and enables the more accurate identification of actual territorial disparities, which are necessary for the development of more effective regional development policies. The variables used for factor analysis and the derived indicators were defined based on recommendations from relevant literature in the field and our previous research knowledge. In selecting the variables, we paid special attention to comprehensively assessing the economic and social characteristics of the regions. Throughout this process, we consciously managed the limitations

of available data sources and aimed to exploit those opportunities that could provide the most reliable and representative results for the research.

4. Results and discussion

In the following sections, we will examine the economic and social conditions of Romanian NUTS 3-level counties using factor analysis and cluster analysis statistical methods. This will provide a comprehensive picture of regional development and identify the main factors contributing to differences, which can collectively aid in the formulation and implementation of regional development policies.

4.1. The results of the factor analysis

The primary aim of the current factor analysis for the NUTS 3 level counties of Romania is to identify underlying latent factors and achieve dimensionality reduction. The essence of factor analysis is to transform a large volume of data into a more concentrated set of indicators, which facilitates the identification of latent structures underlying territorial disparities. This procedure seeks to uncover the main factors that consolidate numerous variables into a more cohesive and interpretable framework, thereby simplifying data management and highlighting fundamental patterns. The information obtained in this way can later be used for clustering, allowing us to create groups focusing on regional disparities, each of which can be characterized separately. A secondary objective is to gain a detailed understanding of how the region under investigation for our long-term research, namely the three counties: Mures, Harghita, and Covasna, are positioned within these groups. By employing factor analysis methodology, our aim is to thoroughly explore the relationships and patterns among the aforementioned data, thereby contributing to the understanding and support of regional development.

During the analysis, the first step involved considering all normalized indicators, followed by narrowing down the variables to enhance the explanatory power of the model. Specifically, we filtered out low-weighted and highly correlated variables, as well as indicators with less significant factor loadings from the analysis. Additionally, we excluded standardized input variables with low explanatory power from the examination. The methodology aimed to maximize the explanatory power of the models and select the most relevant variables, taking into account the results of correlation and factor analyses. From the initial 61 variables, we identified 36 standardized input variables after the reduction process, which were suitable for the comparative analysis of the counties. The range of indicators created in this way effectively reflected the diversity among the counties and allowed for a comprehensive examination of the differences. The highlighted 36 indicators, divided into 5 groups, are presented below:

Demography:

- Natural increase rate (‰) per 1000 inhabitants – 2022
- Population density (inhabitants/km²) – 2022
- Students enrolled in pre-university education (per 1000 inhabitants) – 2022
- Population with primary education (per 1000 inhabitants) – 2021
- Graduates of secondary school with a high school diploma (per 1000 inhabitants) – 2021

Economy:

- GDP - Gross Domestic Product (RON per capita) – 2021
- Employment rate (%) – 2022
- Unemployment rate (%) – 2022
- Active enterprises (per 1000 inhabitants) – 2022
- Private entrepreneurs (per 1000 inhabitants) – 2022
- Recipients of social assistance (cases per 1000 inhabitants) – 2022
- Recipients of childcare allowance and monthly incentive benefits (cases per 1000 inhabitants) – 2022
- Family support allowances (cases per 1000 inhabitants) – 2022
- Average number of employees (per 1000 inhabitants) – 2022
- Average number of employees in industry (per 1000 inhabitants) – 2022
- Average monthly pension (RON) – 2022
- Pensioners (number per 1000 inhabitants) – 2022
- Average gross nominal monthly salary (RON) – 2022
- R&D employees (number per 1000 inhabitants) – 2022
- Total R&D expenditure (RON per 1000 inhabitants) – 2022
- Construction permits issued for buildings (number per 100 inhabitants) – 2022

Infrastructure:

- Number of healthcare units (per 1000 inhabitants) – 2022
- Number of hospitals (per 1000 inhabitants) – 2022
- Length of sewage network (km per 1000 inhabitants) – 2022
- Length of gas distribution network (km per 1000 inhabitants) – 2022
- Share of population connected to sewage and wastewater treatment systems (%) – 2022
- Natural gas consumption (m³ per 1000 inhabitants) – 2022
- Educational institutions (number per 1000 inhabitants) – 2022

Agriculture:

- Average number of employed persons in agriculture (per 1000 inhabitants) – 2022
- Value of crop production (RON per 1000 inhabitants) – 2022
- Value of animal husbandry (RON per 1000 inhabitants) – 2022
- Area of main crop cultivation (ha per 1000 inhabitants) – 2022

Tourism:

- Tourist accommodations (number) per 1000 inhabitants – 2022
- Number of tourists per 1000 inhabitants – 2022
- Number of guest nights per 1000 inhabitants – 2022

– Index of net occupancy rate of operating tourist accommodation capacity (%) – 2022

Based on the standardized input variables presented above, a factor analysis was conducted resulting in the optimal creation of 6 factors, which explain 79,073% of the total information content of the dataset (Table 1). This value can be considered adequate, considering that according to Székelyi and Barna (2002), the explanatory power of factors exceeding 33% is acceptable.

Table 1. The information content of the factors obtained during the analysis

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings*		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1.	13,974	37,768	37,768	13,974	37,768	37,768	6,429	17,376	17,376
2.	6,035	16,312	54,080	6,035	16,312	54,080	6,331	17,111	34,487
3.	3,187	8,612	62,692	3,187	8,612	62,692	4,528	12,238	46,725
4.	2,348	6,345	69,037	2,348	6,345	69,037	4,069	10,998	57,723
5.	2,083	5,629	74,666	2,083	5,629	74,666	3,982	10,762	68,484
6.	1,631	4,407	79,073	1,631	4,407	79,073	3,918	10,589	79,073

Source: Own research and representation.
Note (*): with Varimax rotation.

The suitability of the initially obtained data for factor analysis was determined using the Kaiser-Meyer-Olkin (KMO) measure and the Bartlett's test (Table 2). Regarding the value of the KMO measure, it is important that the partial correlations remain within an acceptable range, which should be at least 0.5 for the strongest suitability, while the maximum suitability is achieved with a value of 1 (Dodge, 2008).

Table 2. The results of the analysis' KMO measure and Bartlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0,700
Bartlett's Test of Sphericity	Chi-Square	1839,511
	df	666
	Sig.	,000

Source: Own research and representation.

The Bartlett's test examines whether the correlations between the variables are significant, as pairs of variables with no correlation cannot form a latent structure. This test is essentially a chi-square test that compares the correlation matrix of the measured variables with an identity matrix representing the independence of variables in pairs. The suitability is indicated by the significance level of the test, which is generally less than 0,05 (Székelyi and Barna, 2002). Based on Sajtos and Mitev (2007), the following conclusions can be drawn from the obtained measurement data: the value of the Kaiser-Meyer-Olkin (KMO) measure is 0,700, indicating that the degree of partial correlations is considered particularly low, and the input variables are suitable for performing factor analysis.

Additionally, the significance level of the Bartlett's test shows that the input variables are not independent in pairs, making them appropriate for running the analysis. Therefore, it can be stated overall that the basic indicators are adequate, and the 6 factors sufficiently encompass the space defined by the variables. The retention of the information content of the factors obtained during the analysis, meaning the percentage of the variance in the variables represented by each factor, can be determined from the communalities (hj^2) values (Table 3). Any variable with a communality of 0,25 or higher can be considered acceptably representative (Székelyi and Barna, 2002). Based on these interpretations, we are convinced that our results are acceptable and reliable.

Table 3. The communalities of the input variables

No.	Variable name	hj^2	No.	Variable name	hj^2
1.	Natural increase rate (‰) per 1000 inhabitants	0,889	19.	R&D employees (number per 1000 inhabitants)	0,870
2.	Population density (inhabitants/km²)	0,881	20.	Total R&D expenditure (RON per 1000 inhabitants)	0,798
3.	Students enrolled in pre-university education (per 1000 inhabitants)	0,852	21.	Construction permits issued for buildings (number per 100 inhabitants)	0,802
4.	Population with primary education (per 1000 inhabitants)	0,731	22.	Number of healthcare units (per 1000 inhabitants)	0,676
5.	Graduates of secondary school with a high school diploma (per 1000 inhabitants)	0,806	23.	Number of hospitals (per 1000 inhabitants)	0,704
6.	GDP - Gross Domestic Product (RON per capita)	0,886	24.	Length of sewage network (km per 1000 inhabitants)	0,716
7.	Employment rate (%)	0,944	25.	Length of gas distribution network (km per 1000 inhabitants)	0,606
8.	Unemployment rate (%)	0,755	26.	Share of population connected to sewage and wastewater treatment systems (%)	0,727
9.	Active enterprises (per 1000 inhabitants)	0,881	27.	Natural gas consumption (m³ per 1000 inhabitants)	0,631
10.	Private entrepreneurs (per 1000 inhabitants)	0,670	28.	Educational institutions (number per 1000 inhabitants)	0,631
11.	Recipients of social assistance (cases per 1000 inhabitants)	0,756	29.	Average number of employed persons in agriculture (per 1000 inhabitants)	0,816
12.	Recipients of childcare allowance and monthly incentive benefits (cases per 1000 inhabitants)	0,875	30.	Value of crop production (RON per 1000 inhabitants)	0,765
13.	Family support allowances (cases per 1000 inhabitants)	0,837	31.	Value of animal husbandry (RON per 1000 inhabitants)	0,760
14.	Average number of employees (per 1000 inhabitants)	0,960	32.	Area of main crop cultivation (ha per 1000 inhabitants)	0,866
15.	Average number of employees in industry (per 1000 inhabitants)	0,818	33.	Tourist accommodations (number) per 1000 inhabitants	0,714
16.	Average monthly pension (RON)	0,812	34.	Number of tourists per 1000 inhabitants	0,864
17.	Pensioners (number per 1000 inhabitants)	0,906	35.	Number of guest nights per 1000 inhabitants	0,888
18.	Average gross nominal monthly salary (RON)	0,842	36.	Index of net occupancy rate of operating tourist accommodation capacity (%)	0,589

Source: Own research and representation.

In order to properly interpret the factors, we deemed it necessary to perform rotation, specifically the rotation of the factors. The resulting rotated factor matrix was suitable for explaining the economic and social differences between the counties using the structured factors (Table 4). The rotation process did not alter the model fit, meaning that the final communalities and the information content of each variable, represented by the retained factors, remained unchanged.

Table 4. The rotated factor matrix and the content of the factors

Variable name	Factors					
	1.	2.	3.	4.	5.	6.
Average gross nominal monthly salary (RON)	0,800	0,153	0,232	0,294	-0,196	
R&D employees (number per 1000 inhabitants)	0,794	0,173	0,153	0,404	-0,139	
Number of healthcare units (per 1000 inhabitants)	0,716	0,184			0,248	0,243
GDP - Gross Domestic Product (RON per capita)	0,704	0,434	0,228		-0,247	0,292
Number of hospitals (per 1000 inhabitants)	0,697	0,158	0,158	-0,307	0,185	0,201
Total R&D expenditure (RON per 1000 inhabitants)	0,656	0,260		0,459	-0,275	
Average number of employees (per 1000 inhabitants)	0,649	0,608	0,192		-0,219	0,288
Active enterprises (per 1000 inhabitants)	0,610	0,361	0,322	0,334	-0,352	0,197
Share of population connected to sewage and wastewater treatment systems (%)	0,570	0,422	0,143	-0,249		0,370
Natural gas consumption (m^3 per 1000 inhabitants)	0,503	0,168	0,479		-0,279	0,206
Average number of employees in industry (per 1000 inhabitants)	0,358	0,781	0,229		-0,129	
Length of sewage network (km per 1000 inhabitants)		0,780				0,319
Employment rate (%)	0,484	0,761	0,106	-0,198		0,273
Private entrepreneurs (per 1000 inhabitants)	0,175	0,754	0,144		0,199	0,100
Recipients of childcare allowance and monthly incentive benefits (cases per 1000 inhabitants)	0,444	0,621	0,324	0,388		0,191
Educational institutions (number per 1000 inhabitants)		0,544	-0,384	-0,250	0,340	
Unemployment rate (%)	-0,140	-0,443	-0,421	-0,335	0,354	-0,352
Average number of employed persons in agriculture (per 1000 inhabitants)	-0,243		-0,820		-0,271	
Area of main crop cultivation (ha per 1000 inhabitants)		-0,375	-0,801		-0,230	-0,130
Value of crop production (RON per 1000 inhabitants)	-0,121	-0,302	-0,755	-0,102	-0,255	-0,116
Value of animal husbandry (RON per 1000 inhabitants)	-0,418	0,379	-0,551	-0,205	0,297	
Population density (inhabitants/km^2)	0,289	-0,272	0,515	0,515	-0,435	
Average monthly pension (RON)	0,436	0,111	0,490	-0,470	-0,130	0,364
Length of gas distribution network (km per 1000 inhabitants)	0,276	0,452	0,488	0,125	-0,267	
Pensioners (number per 1000 inhabitants)	0,134	0,276		-0,879		0,167
Construction permits issued for buildings (number per 100 inhabitants) – 2022	0,155		0,321	0,752	-0,320	
Natural increase rate (‰) per 1000 inhabitants	0,215	0,293	0,348	0,713	0,301	0,192
Index of net occupancy rate of operating tourist accommodation capacity (%)	0,303			0,506	-0,153	0,459
Students enrolled in pre-university education (per 1000 inhabitants)	0,128	0,326			0,793	0,295
Graduates of secondary school with a high school diploma (per 1000 inhabitants)		0,100	0,284	-0,329	0,773	0,101
Population with primary education (per 1000 inhabitants)	-0,354		0,137		0,760	

Family support allowances (cases per 1000 inhabitants)	-0,329	-0,415	-0,223		0,561	-0,437
Number of guest nights per 1000 inhabitants	0,192				0,102	0,911
Number of tourists per 1000 inhabitants	0,299	0,211	0,159		0,120	0,831
Tourist accommodations (number) per 1000 inhabitants		0,328		-0,154	0,149	0,748
Recipients of social assistance (cases per 1000 inhabitants)	-0,127	-0,425	-0,310	-0,374	0,329	-0,463

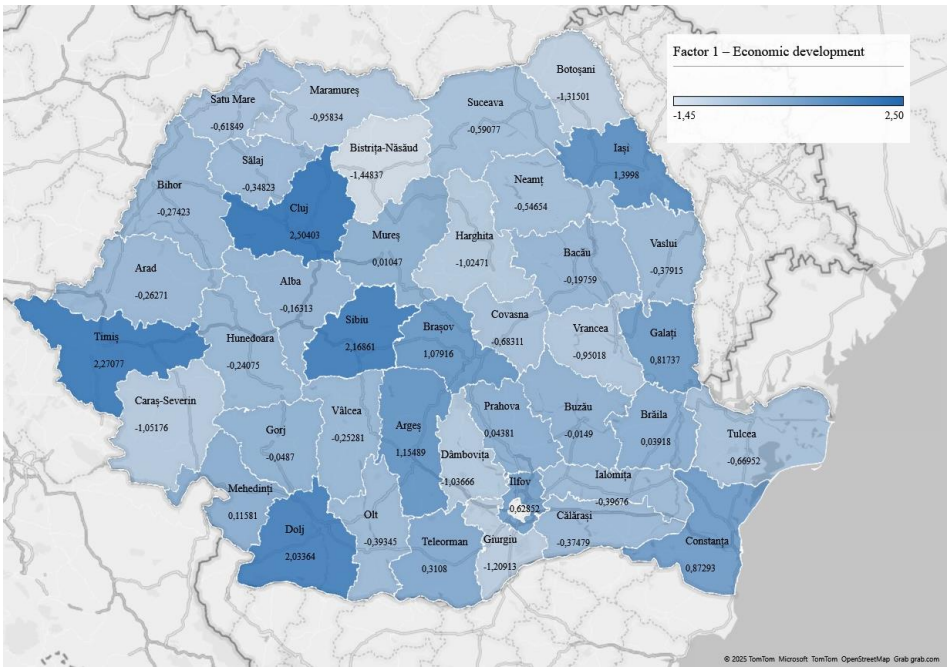
Note: with Varimax rotation.
Source: Own research and edition.

However, the distribution of the amount of information retention among the factors changed (Székelyi and Barna, 2002). The following detailed analysis of each factor helps to understand the indicators that shaped the observable phenomena and processes, as well as the names assigned to the factors, which were determined based on the factor loadings. The indicators included in the factors, along with the corresponding factor weights, help in the interpretation of the obtained factors, allowing for a more effective description and understanding of territorial processes and county-level differences.

Factor 1 – Economic development

The first factor (see Table 4), extracted through rotated factor analysis based on the set of investigated variables, is interpreted as representing economic development and has been designated accordingly. It possesses an eigenvalue of 6,429 and accounts for 17,376% of the total variance. Higher and positive factor scores are indicative of regions exhibiting superior economic performance, whereas lower or negative scores correspond to economically less developed areas. This factor aggregates variables that capture various dimensions of economic activity, including wage levels, research and development (R&D) intensity, the provision of healthcare services, gross domestic product (GDP), and the level of infrastructure development. The counties of Cluj (2,50403), Sibiu (2,16861), Timiș (2,27077), Dolj (2,03364), and Iași (1,3998) register high positive factor loadings (see Figure 2), suggesting that these territories exhibit outstanding levels of economic development, characterized by elevated wage levels, substantial R&D activity, and advanced healthcare infrastructure.

Figure 2. Values of Factor 1 in Romanian NUTS3 level Counties



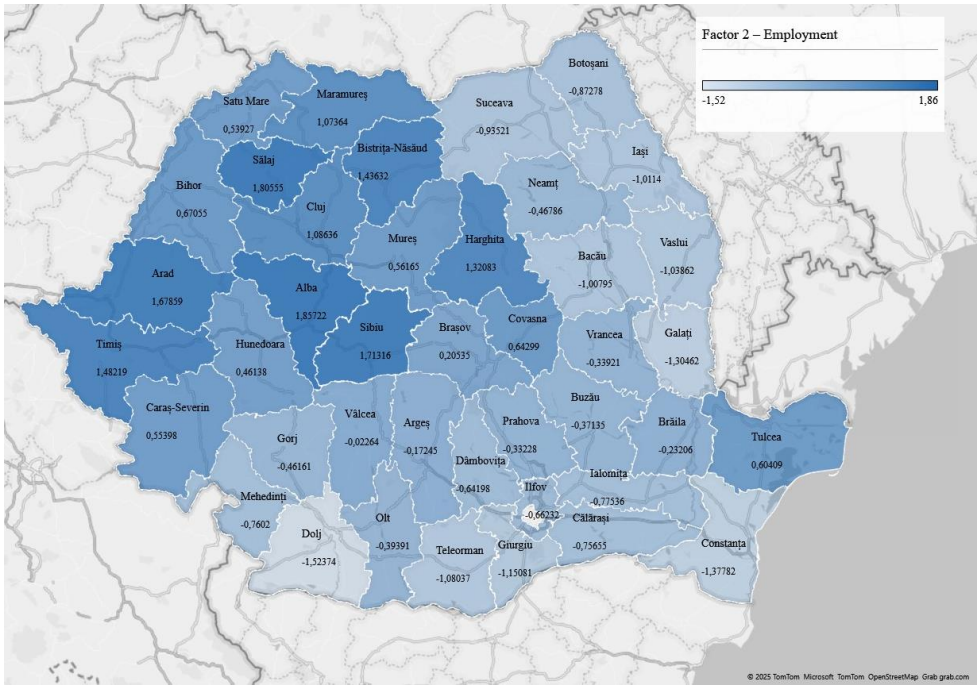
Source: Own research and representation.

Counties exhibiting negative factor loadings, such as Bistrița-Năsăud (-1,44837) and Giurgiu (-1,20913), are characterized by lower levels of economic development. Based on the first factor, the economic performance of Harghita and Covasna counties also remains below the average, as indicated by their negative factor scores (-1,02471 and -0,68311, respectively). These counties are associated with lower economic output, limited research and development activity, and less developed healthcare services. The factor score of Mureș County (0,01047) reflects an economic situation close to the average, with balanced indicators but without notable economic advancement.

Factor 2 – Employment

The second factor (see Table 4), identified based on the analyzed variables, is interpreted as representing the employment situation and has been designated accordingly. It has an eigenvalue of 6,331 and explains 17,111% of the total variance. This factor comprises variables that capture aspects related to employment levels, industrial activity, the presence of private enterprises, and educational institutions. Higher and positive factor scores are characteristic of regions with more favorable employment conditions and more dynamic industrial activity, while lower or negative scores indicate areas with lower levels of economic development and employment. The counties with high positive factor scores (see Figure 3) are Alba (1,85722), Sălaj (1,80555), Sibiu (1,71316), and Arad (1,67859).

Figure 3. Values of Factor 2 in Romanian NUTS3 level Counties



Source: Own research and representation.

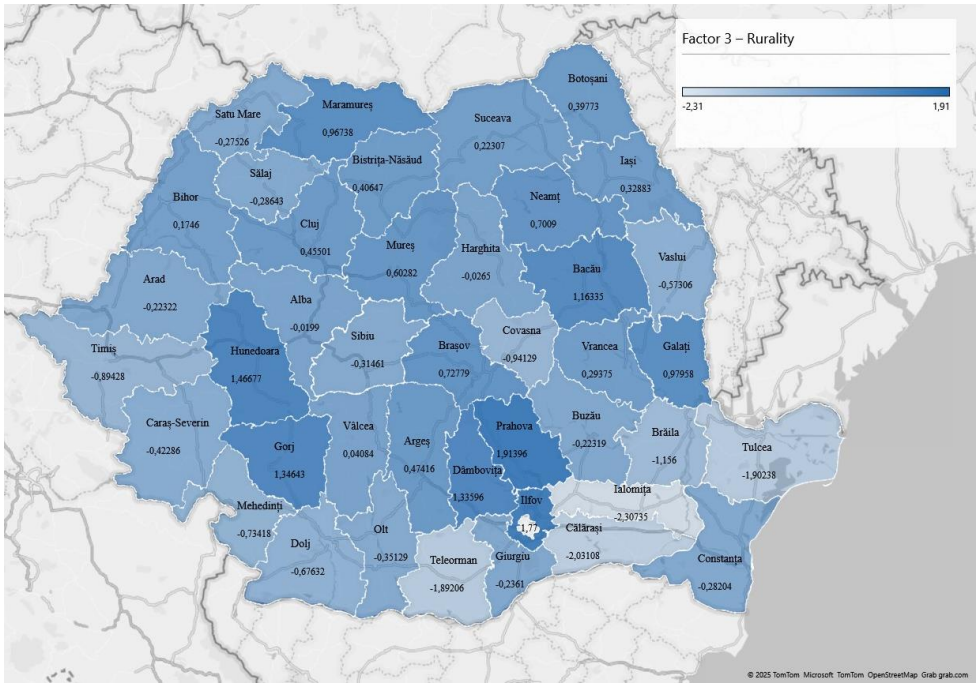
Counties displaying negative factor scores, such as Constanța (-1,37782) and Dolj (-1,52374), perform relatively poorly in economic terms. In addition to higher unemployment rates and weak economic dynamism, the low number of industrial workers and underdeveloped infrastructure may also contribute to their unfavorable indicators. Among the counties analyzed, the positive factor scores of Harghita (1,32083) and Covasna (0,64299) suggest relatively higher employment levels in these areas. The presence of the industrial sector is evident, while the relatively higher per capita number of educational institutions and childcare support schemes are associated with economic activity. Mureș County (0,56165), with its moderate positive factor score, reflects a generally favorable employment situation; however, further development of infrastructure and economic dynamism appears necessary.

Factor 3 – Rurality

The third factor (see Table 4) incorporates variables related to the role of the agricultural economy and, indirectly, indicators of the degree of urbanization; therefore, this factor has been designated as "Rurality". It has an eigenvalue of 4,528 and explains 12,238% of the total variance. Higher and positive factor scores are characteristic of more densely populated, better gas-supplied, and more urbanized areas, where higher pension levels and predominantly non-agricultural activities prevail.

In contrast, lower or negative scores indicate regions characterized by more intensive agricultural activities and a generally more rural profile (see Figure 4).

Figure 4. Values of Factor 3 in Romanian NUTS3 level Counties



Source: Own research and representation.

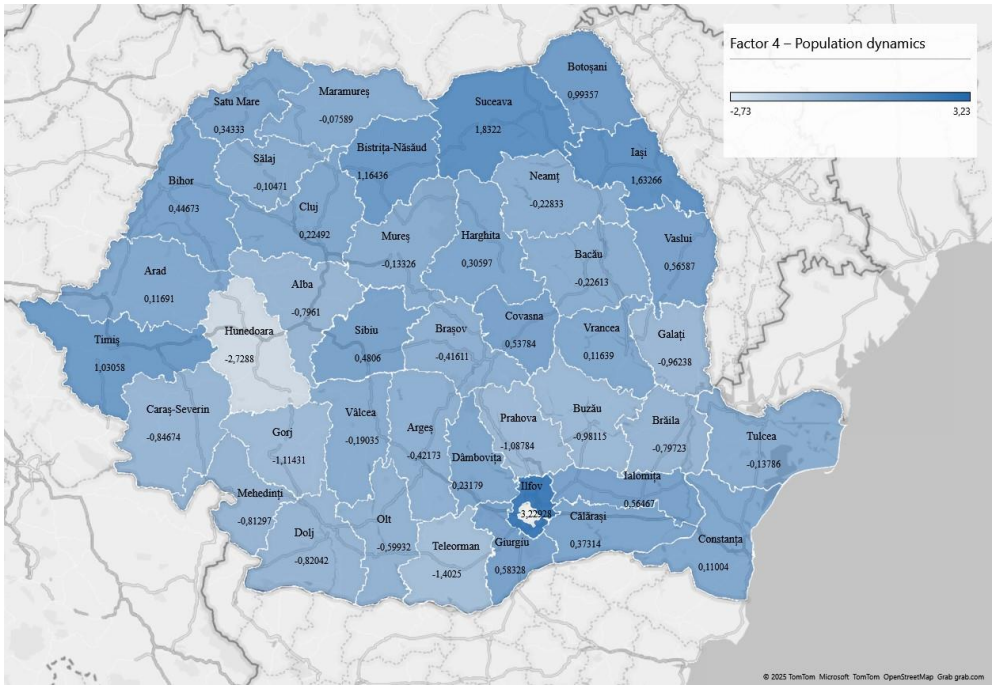
Hunedoara (1,46677), Gorj (1,34643), Dâmbovița (1,33596), Bacău (1,16335), and Galați (0,97958) counties, exhibiting high positive factor scores, indicate more urbanized regions with stronger activity in non-agricultural sectors. Based on the available data, it can be assumed that the higher pension levels in these counties are associated with stronger economic performance. Counties with negative factor scores, such as Ialomița (-2,30735) and Călărași (-2,03108), are characterized by rural areas with a predominance of agricultural activities. The situation of the counties under study, according to the third factor, can be summarized as follows: Mureș County (0,60282) displays a positive factor score, suggesting a more urbanized profile where, in addition to agricultural activities, other economic sectors also contribute significantly to regional development. Urban and rural features are both present, but urban characteristics are dominant. Harghita County (-0,0265) has a factor score close to the neutral value, indicating a predominantly rural character. In this county, agricultural and other economic activities are present at a moderate level, but the economy remains more heavily reliant on agriculture. Infrastructure and other economic factors show moderate development, providing a stable, though not outstanding, foundation for further economic growth. Covasna County (-0,94129), with a negative factor score, reflects a strongly rural character, where agriculture is the

dominant economic sector and the development levels of the industrial and service sectors are lower. The economy is highly dependent on agricultural production, and economic activity is primarily built around it.

Factor 4 – Population dynamics

The fourth factor (see Table 4), identified based on the analyzed variables, primarily reflects the demographic situation and has therefore been designated as "Population dynamics". It has an eigenvalue of 4,069 and explains 10,998% of the total variance. Higher and positive factor scores indicate dynamically developing regions characterized by a growing housing stock, high natural population growth, and active tourism, all contributing to shaping the economic structure. Conversely, lower or negative scores correspond to regions with opposite demographic trends. Counties with high positive factor scores, such as Ilfov (3,22928), Suceava (1,8322), Iași (1,63266), Bistrița-Năsăud (1,16436), and Timiș (1,03058), demonstrate strong population dynamics, whereas counties with negative scores, such as Hunedoara (-2,7288) and Teleorman (-1,4025), face significant demographic challenges and lower levels of tourism activity (see Figure 5). Based on the fourth factor, the demographic situation of Harghita, Covasna, and Mureș counties is as follows: Harghita County (0,30597) shows a slightly positive factor score, indicating a relatively youthful society and moderate natural population growth. Covasna County, with a higher factor score (0,53784), suggests more dynamic demographic growth, active construction activity, and a more vibrant tourism sector, all of which may contribute positively to economic development.

Figure 5. Values of Factor 4 in Romanian NUTS3 level Counties



Source: Own research and representation.

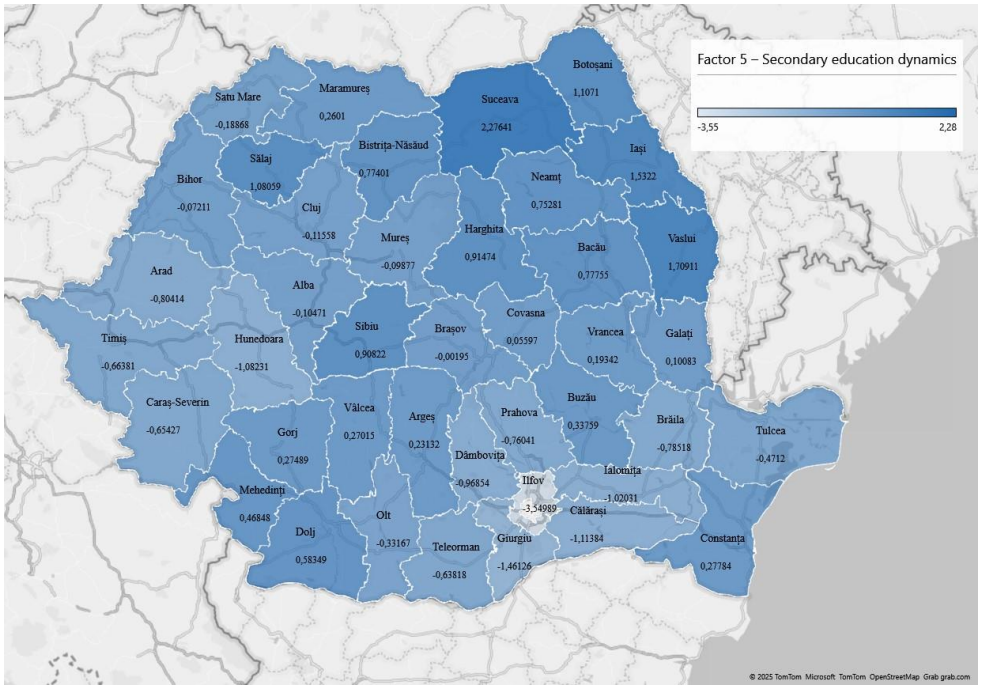
Mureș County (-0,13326) exhibits a negative factor score, suggesting a weaker demographic situation characterized by lower natural population growth and more restrained construction activity.

Factor 5 – Secondary education dynamics

The fifth factor (see Table 4), based on the analyzed variables, is related to the levels of primary and secondary education in the counties, the presence of the corresponding age cohorts, and the level of family support benefits; therefore, it has been named "Secondary education dynamics". Its eigenvalue is 3,982, explaining 10,762% of the total variance. This factor includes variables that represent the proportion of students with primary and secondary education, as well as the number of family support benefits. Higher and positive factor scores are associated with regions where the proportion of the relevant age group is higher, educational participation is more significant, and the prospects for obtaining secondary education qualifications are relatively favorable. In addition, these counties typically show a substantial share of the population with lower educational attainment. Counties with such characteristics include Suceava (2,27641), Iași (1,5322), Vaslui (1,70911), Botoșani (1,1071), and Sălaj (1,08059) (see Figure 6). Conversely, lower factor scores point to regions where the proportion of individuals with primary and secondary education is smaller (presumably due to a higher share of tertiary education attainment) and where the demand for family support benefits is lower due to the reduced presence of the relevant age cohort. This situation is reflected in the data for

Ilfov (-3,54989) and Hunedoara (-1,08231) counties, where the demographic and social structure significantly differs from the previously mentioned counties.

Figure 6. Values of Factor 5 in Romanian NUTS3 level Counties



Source: Own research and representation.

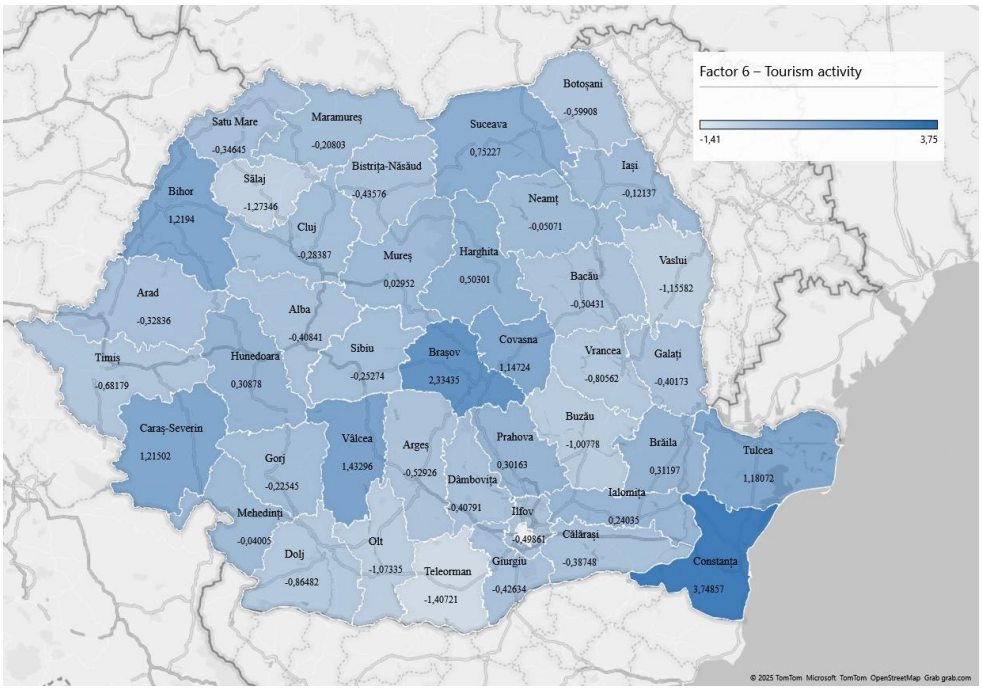
Based on the 5th factor, the situation of the counties under study is as follows: Harghita County (0,91474) shows a relatively high positive factor score, suggesting that the proportion of the younger age group is higher, educational participation is likely stronger, and the larger share of children leads to a higher uptake of family support benefits. Covasna County (0,05597), with a lower but still positive factor score, indicates that while the proportion of the younger age group remains relatively high and educational participation is positive, the uptake of family support benefits is somewhat lower, likely reflecting a slightly reduced share of the lower-educated population. Mureș County (-0,09877) has a negative factor score, suggesting lower educational and family support indicators. It can be assumed that the proportion of the young population is smaller here, which is linked to a decline in the number of children, secondary education graduates, and participants in pre-university education, thereby leading to a more moderate demand for family support benefits.

Factor 6 – Tourism activity

The sixth factor (see Table 4) primarily reflects the tourism processes and their intensity across counties; thus, it has been named “Tourism activity”. Its eigenvalue is 3,918, accounting for 10,589%

of the total variance. This factor includes variables representing different measures of tourism (such as the number of overnight stays, the number of tourists, and the availability of tourist accommodation), along with the proportion of individuals receiving social assistance. Higher (positive) factor scores characterize regions with higher tourist traffic and a higher relative number of accommodations. It is assumed that vibrant tourism correlates with stronger economic development, as indicated by the lower relative proportion of people reliant on social assistance. Thus, a well-functioning tourism sector likely provides a stable source of revenue for the local economy, contributing positively to the development and prosperity of the region. Counties with the highest positive factor scores include Constanța (3,74857), Brașov (2,33435), Bihor (1,2194), Tulcea (1,18072), and Covasna (1,14724) (see Figure 7).

Figure 7. Values of Factor 6 in Romanian NUTS3 level Counties



Source: Own research and representation.

Counties with the lowest negative factor scores, such as Teleorman (-1,40721) and Sălaj (-1,27346), exhibit less developed tourism sectors and a higher proportion of social assistance recipients. This suggests that in these counties, the lack of tourism is paralleled by a higher level of social need. The situation of Harghita, Covasna, and Mureș counties based on this factor is as follows: Harghita County (0,50301) has a positive factor score, indicating that the volume of tourism exceeds the average, and the proportion of social assistance recipients is relatively lower. It can be assumed that tourism activity contributes to improving the county's economic situation. Covasna County

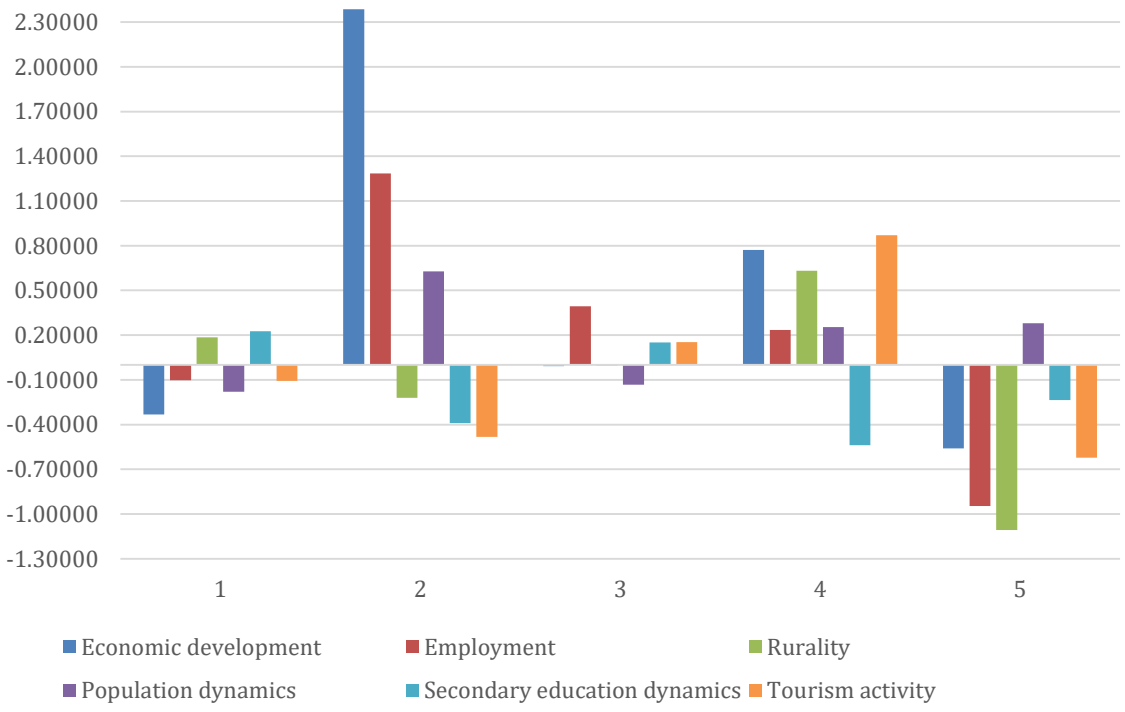
(1,14724) shows an even higher positive factor score, suggesting that tourism plays a particularly prominent role in the local economy. Alongside high figures for overnight stays and tourist numbers per capita, the low rate of social assistance recipients also reflects the economic development observed in the county. Mureș County (0,02952) has a factor score close to zero, indicating that both the level of tourism development and the rate of social assistance are near the national average. In this county, moderate tourism activity and a relatively low level of social assistance can be observed, implying that while the region is not outstanding in terms of tourism, its economic situation and social support structures are relatively stable.

4.2. The results of the cluster analysis

Following the factor analysis performed for Romania's NUTS 3 level counties, we considered it necessary to carry out a complementary cluster analysis. The purpose of the cluster analysis was to create relatively homogeneous and coherent groups among the counties based on the factor-derived values, thereby reflecting both similarities and key disparities across the regions. This approach enables a deeper understanding of territorial structures and supports the formulation of differentiated development strategies. Another specific objective was to determine the relative position of Harghita, Covasna, and Mureș counties within the resulting clusters and to assess whether these counties belong to a similar development category, thus potentially enabling a unified regional policy framework. To ensure the reliability of the classification, we tested several hierarchical clustering methods – including single linkage, complete linkage, between-groups linkage, centroid, median, within-groups linkage, and Ward's method – alongside the non-hierarchical k-means clustering algorithm. The analysis was conducted using both standardized variables and factor scores. After a comparative assessment, Ward's method emerged as the most suitable for several reasons. First, this method minimizes within-cluster variance at each step of the clustering process, resulting in more compact and clearly distinguishable groups. Second, it proved to be more stable across multiple trials, consistently producing similar cluster structures regardless of whether standardized input variables or factor scores were used. Third, the dendrogram generated by Ward's method presented clear breakpoints, which allowed for a logical and interpretable selection of the number of clusters. In contrast, other methods such as single linkage and centroid clustering tended to produce chaining effects or unbalanced group sizes, which weakened internal consistency. When determining the optimal number of clusters, we tested multiple alternatives, but the five-cluster solution proved to be the most justified. This decision was supported by the structure of the dendrogram, which indicated a distinct breakpoint at five clusters – at a point where the differences between clusters remained meaningful, and internal homogeneity was preserved. Moreover, this model yielded a balanced

cluster distribution, avoiding the formation of excessively small or overly dominant groups. Each of the five clusters displayed clear socio-economic patterns, such as a separate grouping for the most developed counties (e.g., Cluj and Timiș), the moderately developing counties (e.g., Harghita and Covasna), and the lagging regions. These patterns accurately reflect Romania's territorial reality and thus enhance the interpretability of the results. Furthermore, the five-cluster structure facilitated meaningful comparisons between groups and enabled the presentation of distinct territorial profiles, thereby fulfilling the analytical objective of the cluster analysis: to provide a more detailed understanding of regional patterns and interactions. Both theoretical considerations and empirical results support the conclusion that Ward's method, in combination with a five-cluster solution, yields the most interpretable and stable grouping. The cluster structure, based on the six principal factors, is illustrated in Figure 8. Each cluster has well-defined characteristics, making the classification suitable for further analysis.

Figure 8. Characteristics of the established cluster structure along the average factor values



Source: Own research and representation.

Cluster 1 – Counties with average development needs

The first cluster includes the following counties: Bihor, Bistrița-Năsăud, Maramureș, Satu Mare, Covasna, Harghita, Bacău, Neamț, Suceava, Brăila, Buzău, Galați, Vrancea, Dâmbovița, Dolj, Mehedinți, Olt, and Hunedoara (for the spatial distribution of the clusters, see Figure 8). The

economic and social conditions of these counties are diverse but do not display extreme characteristics, a situation that can be accurately described based on various indicators (Table 5).

Table 5. The key factor values of the "Counties with average development needs" cluster

	Economic development	Employment	Rurality	Population dynamics	Secondary education dynamics	Tourism activity
Cluster average	-0,33178	-0,10184	0,18488	-0,18078	0,22594	-0,10577
Minimum	-1,44837	-1,52374	-1,15600	-2,72880	-1,08231	-1,07335
Maximum	2,03364	1,43632	1,46677	1,83220	2,27641	1,21940
Median	-0,47000	-0,35528	0,19883	-0,15101	0,22676	-0,27724
Standard deviation	0,77119	0,87323	0,77679	0,96220	0,76519	0,67154

Source: Own research and representation.

The situation of the counties belonging to the first cluster is characterized to some extent by a more urban profile alongside weaker economic development. The positive value of the rurality factor (0,18488) suggests that these counties tend to have a more urban character. The average of the economic development factor is negative (-0,33178), with a medium standard deviation (0,77119), indicating that, overall, the economic potential of this cluster requires improvement, although some counties, such as Dolj and Galați, are in a relatively more favorable economic position. Employment is similarly negative (-0,10184) and shows a high standard deviation (0,87323), pointing to considerable inter-county differences in labor market opportunities. A significant proportion of the counties within the cluster are affected by population aging and decline, as reflected by the negative cluster average of the population dynamics factor (-0,18078), which likely further complicates efforts to improve employment rates. The positive average value of the secondary education dynamics factor (0,22594) suggests a higher proportion of younger age groups within these counties, accompanied by higher educational participation and more frequent utilization of family support measures. Furthermore, when interpreting this factor within the cluster, the proportion of higher education graduates should also be considered for a more precise understanding. Economically stronger counties such as Bihor and Dolj exhibit higher levels of higher education attainment and more favorable educational indicators. The negative average of the tourism activity factor (-0,10577) combined with a moderate standard deviation (0,67154) implies that tourism plays a relatively limited role in the counties of this cluster, with lower levels of tourism development and a higher degree of social vulnerability. In summary, the counties belonging to the first cluster exhibit diverse economic and social conditions but generally require development interventions.

Cluster 2 – Economically strong counties

The second cluster consists of the counties of Cluj and Timiș (see Figure 8), which represent economically strong regions. However, they are less prominent in terms of secondary education attainment, tourism, and agricultural activities (Table 6).

Table 6. The key factor values of the "Economically strong counties" cluster

	Economic development	Employment	Rurality	Population dynamics	Secondary education dynamics	Tourism activity
Cluster average	2,38740	1,28427	-0,21963	0,62775	-0,38970	-0,48283
Minimum	2,27077	1,08636	-0,89428	0,22492	-0,66381	-0,68179
Maximum	2,50403	1,48219	0,45501	1,03058	-0,11558	-0,28387
Median	2,38740	1,28427	-0,21963	0,62775	-0,38970	-0,48283
Standard deviation	0,11663	0,19792	0,67464	0,40283	0,27411	0,19896

Source: Own research and representation.

The economic development indicator of this cluster shows a high cluster mean (2,38740) and a low standard deviation (0,11663), indicating that both Cluj and Timiș counties possess strong economic foundations. This economic performance is accompanied by a dynamic labor market, as reflected in the favorable employment factor (cluster mean of 1,28427) and low variability (standard deviation of 0,19792). The rurality indicator has a negative cluster mean (-0,21963), suggesting that the agricultural sector, on average, does not play a dominant role in the local economy (although agricultural activity varies between the two counties, as confirmed by the relatively high standard deviation of 0,67464). The positive mean value of the population dynamics factor (0,62775), coupled with a moderate standard deviation (0,40283), indicates a generally rejuvenating age structure in these counties, which likely contributes to their economic stability. Considering the secondary education dynamics factor and the proportion of higher education graduates, the human capital in these counties appears to be more favorable, while the reliance on family support measures is relatively moderate. The tourism activity indicator (cluster mean of -0,48283) suggests that tourism currently plays a marginal role; however, the development of tourism potential could offer significant opportunities for economic diversification within the cluster.

Cluster 3 – Counties with diversified development needs

The third cluster can best be described as consisting of counties with diversified development needs, including Sălaj, Mureș, Iași, Tulcea, Argeș, Gorj, Vâlcea, Arad, and Caraș-Severin (see Figure 8). This designation reflects the heterogeneous nature of the cluster (Table 7), where the diverse developmental patterns, strengths, and weaknesses of individual counties are particularly

pronounced. The economic development indicator of this cluster shows a mean value close to zero (-0,00762), suggesting that, on average, the economic performance of the counties is not outstanding, although significant territorial disparities are evident, as indicated by the high standard deviation (0,75305). The observed regional development differences within the cluster reflect varying economic endowments: for example, Argeș County benefits from significant industrial development and stable economic indicators, positively influencing the overall economic profile of the cluster, while Mureș County's economic indicators are closer to the average.

Table 7. The key factor values of the "Counties with diversified development needs" cluster

	Economic development	Employment	Rurality	Population dynamics	Secondary education dynamics	Tourism activity
Cluster average	-0,00762	0,39286	-0,00465	-0,13327	0,15120	0,15337
Minimum	-1,05176	-1,01140	-1,90238	-1,11431	-0,80414	-1,27346
Maximum	1,39980	1,80555	1,34643	1,63266	1,53220	1,43296
Median	-0,25281	0,55398	0,04084	-0,13786	0,23132	-0,12137
Standard deviation	0,75305	0,87826	0,84593	0,72571	0,73167	0,86847

Source: Own research and representation.

The employment indicator has a positive mean (0,39286) but also exhibits substantial variability (standard deviation of 0,87826), suggesting considerable differences within the cluster. For instance, in Arad County, the higher employment rate and a greater density of active enterprises improve the cluster's average employment indicator, while Gorj County, with lower employment rates due to the decline of the mining sector, drags the cluster average downward. The rurality factor mean (-0,00465) is close to neutral; however, the high standard deviation (0,84593) indicates that some counties are more urbanized while others retain a predominantly rural character. The population dynamics indicator displays a slightly negative mean value (-0,13327) and a moderate standard deviation (0,72571), suggesting minor intra-cluster differences, with an overall trend toward an aging population. The mean value for the secondary education dynamics factor is positive (0,15120), but again a relatively high standard deviation (0,73167) is observed. Nevertheless, the cluster counties generally exhibit a higher proportion of young people, active participation in education, and consequently, a higher rate of family support measures. Tourism activity also displays diverse results, with a positive mean value (0,15337) but a high standard deviation (0,86847), indicating differing tourism potentials among the counties. For example, Tulcea County boasts rich tourism resources, including historical and natural attractions, whereas Sălaj County has less developed tourism infrastructure. Overall, the development level of the counties in the third cluster is diversified, with

significant territorial disparities, although the factor values, apart from employment, are not particularly extreme.

Cluster 4 – Tourism-centered counties

The cluster comprising Alba, Brașov, Sibiu, Constanța, Prahova, and Ilfov counties (see Figure 8) can best be described as tourism-centered counties. This designation highlights the economic dynamism and touristic character of the cluster (Table 8), as well as the active role these counties play in regional development.

Table 8. The key factor values of the "Tourism-centered counties" cluster

	Economic development	Employment	Rurality	Population dynamics	Secondary education dynamics	Tourism activity
Cluster average	0,77165	0,23388	0,63253	0,25331	-0,53849	0,87080
Minimum	-0,16313	-1,37782	-0,31461	-1,08784	-3,54989	-0,49861
Maximum	2,16861	1,85722	1,91396	3,22928	0,90822	3,74857
Median	0,75073	-0,06347	0,35395	-0,15303	-0,05333	0,02444
Standard deviation	0,76162	1,19343	0,92233	1,43042	1,43487	1,60839

Source: Own research and representation.

The mean value of the economic development indicator is high (0,77165), indicating strong economic performance across the counties, although some variability is present, as suggested by the relatively high standard deviation (0,76162). Brașov County benefits from a robust industrial and service sector, positively influencing the cluster's economic average, while Ilfov County, due to its proximity to Bucharest, shows significant economic growth, hosting numerous multinational company headquarters, further strengthening the cluster's economic indicators. The employment indicator also shows a positive mean (0,23388); however, the higher standard deviation (1,19343) indicates considerable disparities in employment rates among the counties. Although the cluster's rurality index has a relatively high mean (0,63253), suggesting that the counties are more urbanized and less agricultural, the high standard deviation (0,92233) reflects substantial differences in the level of urbanization. For example, Sibiu County maintains a strong agricultural sector. The cluster's population dynamics indicator presents a positive mean (0,25331), but with an even higher standard deviation (1,43042), indicating significantly different demographic trends among the counties. Ilfov County, for instance, is characterized by a growing population and a high birth rate, positively influencing the cluster's demographic average, whereas in Alba County, demographic indicators are more varied, with migration and population aging negatively impacting the average. The negative mean value of the secondary education dynamics indicator (-0,53849) suggests that the share of the

younger age groups and their participation in education is relatively low across most counties, along with a more moderate uptake of family support benefits. The high standard deviation (1,43487) indicates substantial intra-cluster disparities in this regard as well. The tourism activity indicator has the highest average (0,87080) among the clusters but also shows a significant standard deviation (1,60839), suggesting that while the overall tourism potential is strong, there is a need for diversification and expansion of tourism services in certain areas. Brașov and Constanța counties stand out in terms of tourism, with the former contributing through winter sports and historical attractions, and the latter through its Black Sea coastline and summer tourism opportunities, thereby raising the cluster's tourism average.

Cluster 5 – Rural counties facing challenges

The fifth cluster includes the counties of Botoșani, Vaslui, Călărași, Giurgiu, Ialomița, and Teleorman (see Figure 8), which, due to their negative average indicator values (Table 9), are referred to as rural counties facing challenges.

Table 9. The key factor values of the "Rural counties facing challenges" cluster

	Economic development	Employment	Rurality	Population dynamics	Secondary education dynamics	Tourism activity
Cluster average	-0,56067	-0,94575	-1,10699	0,27967	-0,23623	-0,62260
Minimum	-1,31501	-1,15081	-2,30735	-1,40250	-1,46126	-1,40721
Maximum	0,31080	-0,75655	0,39773	0,99357	1,70911	0,24035
Median	-0,38796	-0,95570	-1,23256	0,56527	-0,82924	-0,51271
Standard deviation	0,55427	0,15217	1,01807	0,77496	1,19973	0,53835

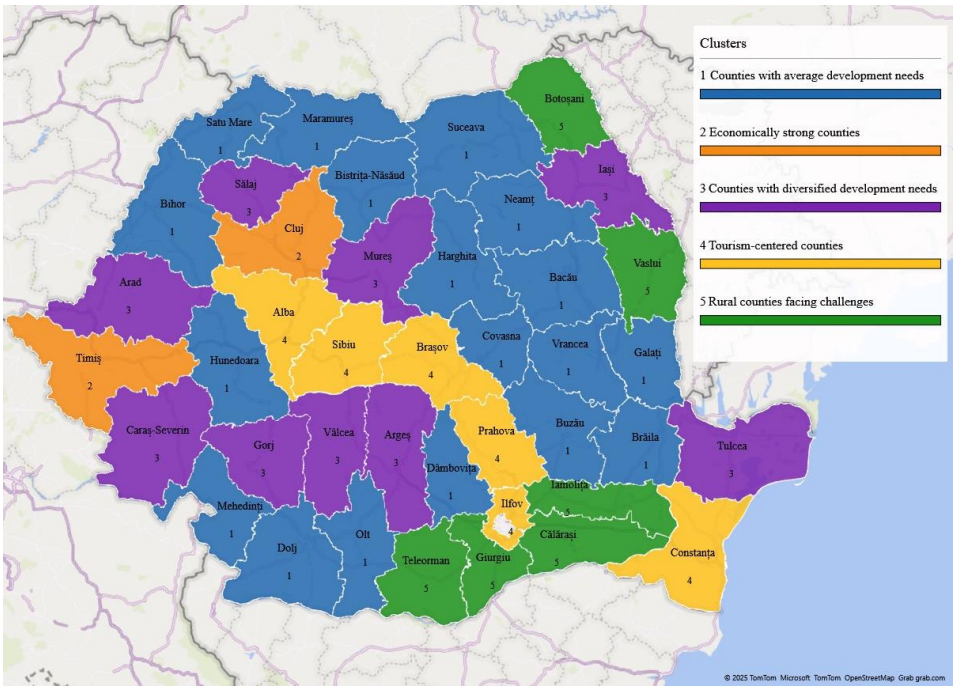
Source: Own research and representation.

The cluster average of the economic development indicator is the lowest here (-0,56067), indicating that the counties concerned face serious economic challenges. At the same time, a moderate standard deviation (0,55427) can be observed, suggesting relatively uniform economic performance across the counties. Regarding the employment indicator, the cluster average is negative and also the lowest (-0,94575) among the clusters, characterized by a similarly moderate standard deviation (0,15217). The region is marked by issues such as unemployment and low incomes, which correlate with the weak economic situation. The rurality indicator of the cluster is also the lowest (cluster average: -1,10699), suggesting that these are rural areas characterized by agricultural activities. Agricultural activities achieve varying degrees of success but are not strong enough to drive economic development. The positive average of the population dynamics indicator (0,27967) and the higher standard deviation (0,77496) reflect a non-uniform picture, but overall, they indicate correlations

between social issues and the weak economic situation. The average for secondary education dynamics is low (-0,23623), with a high standard deviation (1,19973), indicating significant differences among the counties. However, overall, low participation rates in education among the younger age group, low secondary education attainment, and a lack of higher education are characteristic, resulting in a general trend of undereducation. The average value of the tourism activity indicator is low (-0,62260), with a moderate standard deviation (0,53835), suggesting that the lack of tourism potential parallels the low economic performance.

Figure 8 provides a summarized overview of the classification and distribution of the counties across the country, allowing for a comprehensive understanding of the clusters and their territorial positioning within Romania.

Figure 8. Distribution of cluster groups and their constituent counties in Romania



Source: Own research and representation.

5. Conclusion

Territorial disparities at the NUTS3 level in Romania require multidimensional analysis, as these disparities can be attributed to significant economic, social, and infrastructural inequalities. In our research, we applied factor analysis and cluster analysis methods, which effectively revealed the main influencing factors and the differences at the county level.

The factor analysis highlighted the following key factors: economic development, labor market indicators, social factors, education, and tourism. Based on variables associated with the

economic development index, such as GDP, average wages, and research and development activity indicators, Cluj and Sibiu counties stand out, while Harghita and Covasna counties are economically less developed, significantly contributing to regional polarization. Harghita County shows favorable employment indicators, while Mureș County presents relatively favorable employment conditions; however, strengthening infrastructure and economic dynamism appears necessary. Meanwhile, Covasna County demonstrates positive but less remarkable results in this area. Agricultural dominance is particularly observed in Covasna and Harghita counties, where the economy is less diversified, placing them at a disadvantage regarding innovation and economic dynamism. Population indicators, such as natural increase and construction activity, serve as signals of the regions' demographic vitality. Harghita and Covasna counties display favorable demographic trends, in contrast with Mureș County, which struggles with demographic stagnation. In terms of secondary education dynamics, Harghita County's high positive factor value suggests a younger population, higher educational participation, and a greater demand for family support. Covasna County's lower but still positive factor value points to a relatively favorable situation, while Mureș County's negative factor value indicates lower educational and family support indicators, which may be associated with a declining number of young people and pre-university students. Covasna County's tourism performance is outstanding, offering a significant economic advantage to the region. Similarly, Harghita County also exhibits strong tourism activity, while Mureș County shows more moderate results in this sector.

Based on the cluster analysis, Romania's counties can be grouped into five main clusters, each characterized by different economic, social, and demographic features. Differences in development levels, industrial and agricultural structures, and educational and labor market dynamics contribute to these clusters reflecting distinct development paths and challenges. Harghita and Covasna counties are part of the cluster of counties requiring average development, while Mureș County belongs to the cluster of counties with diversified development. The counties in the average development cluster are economically and socially varied but generally require development. Although the rurality factor indicates a more urbanized character, the average values of economic development and employment are negative. Alongside population decline and aging, the proportion of younger age groups remains relatively high in the more developed counties, but tourism and social conditions continue to face challenges. The diversified development cluster includes counties that are economically diversified, possess balanced development, yet show substantial territorial disparities. Employment and industrial presence vary, and population dynamics are slightly negative, suggesting outmigration. Education and family support play an important role, particularly for younger generations. Tourism shows a

mixed picture, with some counties demonstrating outstanding potential while others remain underdeveloped in this area.

The results of the research indicate that reducing regional disparities cannot be achieved through uniform, general strategies, as the analyzed areas exhibit significant structural and functional differences. Accordingly, the effectiveness of interventions can only be enhanced if they are adapted to the specific characteristics of the respective area—whether county, region, or cluster. Although economic diversification, human resource development, tourism development, and infrastructural investments continue to play a key role in territorial development, the concrete content and implementation of these interventions require a regionally differentiated approach. The next phase of the research will therefore focus on the deeper exploration of place-specific development opportunities, with particular attention to the specific development trajectories of Harghita, Covasna, and Mureș counties and the intervention directions adapted to their characteristics.

The implementation of these diversified strategies may contribute to increasing regional competitiveness and reducing socio-economic inequalities, thus promoting Romania's more balanced development. However, the precise formulation of these strategies requires further and more location-specific research.

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