Regional Resilience through a Multidimensional Lens: Exploring Romanian Counties

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ABSTRACT *This paper introduces an adaptable framework to facilitate comprehensive multidimensional analyses to assess regional resilience. The application of this framework is used for a case study in conceiving and synthesizing a suite of indicators tailored for Romanian counties' resilience assessment. These indicators are categorized into four distinct dimensions: "Socio-Economic Dynamics", "Urban Infrastructure and Green Areas", "Governance and Industry", and "Material and Energy Flows". Employing Principal Component Analysis (PCA), this study strategically condenses the dataset, emphasizes inter-variable relationships, and extracts valuable insights, thereby enabling an unbiased assignment of weights. The classification leverages discriminant variables to forge composite indicators for each dimension, creating an overall score and comparative counties' rankings. Additionally, combining PCA with k-means clustering simplifies data interpretation through categorical grouping. The analysis results are enriched using an interactive geographic information system (GIS) representation, vividly portraying regional disparities and commonalities across Romanian counties.*

Keywords: regional resilience, composite indicator, Principal Component Analysis, cluster analysis

1. INTRODUCTION

In today's complex societal landscape, the concept of resilient regions has become increasingly important for sustainable development and for enhancing adaptability to a range of economic, social, technological, geopolitical, and environmental uncertainties. Developing resilience is crucial for regions to respond effectively to these multifaceted pressures and maintain stability and growth. Consequently, there is a clear need for innovative and comprehensive strategies that can assess and improve regions' resilience. This approach must systematically address the intricate interactions among various resilience dimensions to ensure that regions can adapt and prosper in an ever-changing global environment. Resilient regions can maintain their functionality despite adverse situations [1], being able to adapt through plans and strategies to face new realities [2].

The motivation behind this study was to develop a framework to facilitate the creation of a composite indicator suite to provide a comprehensive overview of Romania's counties. This initiative demonstrates the practical application of the adaptable framework and facilitates detailed multidimensional analyses of regional resilience. By using these indicators, this study aims to enhance the understanding of regional dynamics and challenges. This approach can offer policymakers a practical, interactive tool that showcases the effectiveness of indicators in real-life contexts and provides valuable insights for better-informed decision-making. In this paper, the assessment of regional resilience is based on data collected over a recent period, reflecting their availability. Regional resilience is viewed as the capacity of regions to maintain essential functions and adapt effectively in the face of various uncertainties and challenges, encompassing socio-economic factors, urban infrastructure, green areas, governance, industry, and material and energy flows. It is crucial to emphasize that, although the data are aggregated to provide a comprehensive overview of regional capacities and vulnerabilities, they do not form a time series that allows for long-term trend analysis or the dynamics of adaptation and recovery. Therefore, the results should be interpreted as representations of regional conditions at specific time points. This provides valuable insights into the current state and identifies critical areas that require attention; however,

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it does not depict the detailed temporal evolution. The integrated data are at the NUTS-3 level and cover 41 counties and the Municipality of Bucharest. Official and credible data sources that openly expose relevant statistics were addressed: the National Institute of Statistics–Tempo Statistics (TEMPO), agricultural census (AGRIC), transport statistics (TRANSP), and the most complete published population and dwelling census (CENSUS), Romanian Association of Banks (BANK), Ministry of Regional Development and Public Administration—Revenue and Expenditure of Territorial Administrative Units (RETAU), Ministry of Environment (ENV), Romanian National Police (POL), and Legislative Portal (LEG). The proposed indicators were designed to help in resilience assessment at the county level and to group regions according to where they are situated by considering four dimensions. In building the indicator system, the complex interdependencies that compose the regions of Romania, as well as the risks to which the communities are exposed, were considered. The indicators can become a valuable resource allowing measurement of performance between different counties and offering a standardized comparison between these.
Moreover, in the case of disruptive events occurrence, the indicators may be relevant for evaluating counties following the application of countermeasures for return to a desirable state.
The paper is organized into six sections: the second section presents a review of the relevant literature; the third section approaches the method of principal component analysis from a theoretical point of view; the fourth section deals with the development of the methodological framework and presents the data and variables; the fifth section presents the analysis applied to the data and the empirical results obtained; and the final section concludes with a discussion of the findings and future research directions.

2. LITERATURE REVIEW

A comprehensive literature review reveals several approaches to regional resilience assessment and understanding. This work continues the study undertaken in the previous paper [3], which conducted a detailed exploratory analysis highlighting multiple systems of indicators and metrics applied by regions and cities in several countries. This represents the foundation for the design of the new indicators system to meet the specific needs of Romanian regions and to consider the available data at the county territorial administrative units' level.
According to [4], regional resilience is examined through the adaptive capacity of a system to maintain its functions or adapt in response to challenges. This concept encompasses the system's resilience against immediate shocks and its ability to recover and dynamically adapt to new environmental conditions. Another study [5] expands on this resilience concept by linking it to long-term regional development and adaptation, emphasizing the critical role of historical context, networks, and institutional dimensions in enhancing a region's resilience. These elements significantly contribute to a region's ability to develop new economic pathways and respond to external pressures. Given the multifaceted nature of resilience, comprehensive measures that capture its various dimensions are needed. For this purpose, indicators can serve as objective sources that guide stakeholders, including governments, local communities, NGOs, and the private sector, by identifying the strengths and weaknesses of regions. This guidance enables better-informed decisions and strategic planning. These tools are pivotal for quantifying how regions manage challenges and plan for future disruptions. Indicator systems, in the context of resilient regions, are defined and used to assess, monitor, and aid the development of effective public policies aimed at improving adaptation capacity, disaster management, and strategic planning [6]. As a resilience assessment tool, indicators help identify vulnerabilities and risks; as an informational tool, they assist in designing early warning systems and intervention plans for emergency situations. Additionally, as a monitoring tool, indicators determine how well a region is prepared to respond to and recover from disasters and shocks [7]. These comprehensive roles underscore the importance of indicators in fostering regional resilience and ensuring sustainable development.

The creation of a system of indicators is often approached in scientific research to manage problems in different fields, including studies on territorial analysis topics at various aggregation levels. Several studies have focused on the construction of indicator systems to measure territorial-level progress [8, 9, 10] and to facilitate detailed comparisons and assessments across regions. Each of these studies has applied a methodology that involves various methods of analysing indicators, whether we are talking about systems analysis, factorial analysis, or principal component analysis. The obtained results create an image of the specific needs for improvement and intervention at the political or authority level, becoming assessment methods at a specific level—of island areas [8], European healthcare systems [9], and climate change at the country level [10]. The studies also vary from the perspective of the number of indicators included in the analysis; in the case of an undersized sample, a multivariate analysis method is excluded [8]. Generally, studies employ a more limited scope, focusing on isolated facets, while a holistic approach encompassing multiple dimensions could provide a more faithful and useful overview for policy formulation.

Indicators allow the measurement and evaluation of complex phenomena or the performance of some systems. Several indicators can be aggregated and synthesized by creating composite indicators. This is essential for obtaining rankings when the initial indicators have different measurement units, and an arbitrary weighting method does not imply objectivity. Weight allocation methods can be represented by statistical models and techniques, the adoption of weight allocation techniques through focus groups and participatory methods, or the attribution of equal weights to all indicators [8]. The review of the existing literature on regional resilience highlights the prevalent use of diverse indicators and underscores the fragmentation in how these indicators are integrated and applied across regions. This study addresses this issue by developing a system of indicators that is specifically adapted to the Romanian context with the aim of providing a clearer and more consistent framework for regional resilience assessment.

3. THE METHOD OF PRINCIPAL COMPONENTS

The multivariate Principal Component Analysis (PCA) technique was applied to form the new indicator system. This scaling procedure is used to transform a large dataset into one with fewer variables, where the resulting variables explain the maximum variance in the dataset [11].

This method is indicated in the formation of indicators, as they suffer from multicollinearity and simultaneity. The benefit of using this method lies in maximizing the variance and minimizing the least squares distance [12]. This method reduces dimensionality and allows the summarization of the information set to a manageable form without suffering great informational losses while maintaining the original data content.

Unlike other ranking and indexing methods that offer arbitrariness and the allocation of equal weights in the construction of composite indicators, PCA is an accessible procedure that allows data to automatically determine optimal weights that capture the maximum variation [13].

The steps followed for the PCA analysis are presented below:

1. *Indicator selection, data collection, preparation, and initial evaluation*;
2. *Construction of the initial matrix* of data in the form of a $i \ x \ j$ matrix (X), having the form presented in Equation 1. This will be used for the principal components computation and data dimension reduction.

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1j} \\ x_{21} & x_{22} & \cdots & x_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} \end{pmatrix} \quad (1)$$

Where: i = number of indicators; j = number of counties;
x_{ij} = a value from i variable from j observation.

3. *Determining the original variables correlation* — shows the independencies between the initial variables and the collinearity detection [14]. The intervals for classifying the types of correlation are presented in Table 1.

Table 1. Classification of linear correlation degree according the Pearson correlation coefficient

Correlation coefficient range	Correlation classification
0.9 - 1.0	very strong correlation
0.9 - 0.7	strong correlation
0.5 - 0.7	moderate / average correlation
0.3 - 0.5	weak correlation
0.0 - 0.3	very weak / no correlation

4. *Variables rescaling* — the min-max normalization linear scaling function can be used. The dataset is scaled in the [0,1] interval. To consider the indicators' influence from the contribution point of view, Equation 2 is used for the positive contribution, respectively Equation 3 is used for the negative contribution.

$$x^{+} = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (2)$$

$$x^{-} = \frac{x_{max} - x}{x_{max} - x_{min}} \qquad (3)$$

Where: x^{+}, x^{-} = the normalized value for the positive, respectively negative indicators contribution; x = original value of indicators; x_{max}, x_{min} = the maximum, respectively minimum value that an indicator from the original dataset has.

Another method for data centring is standardization. This technique transforms the data so that the average is 0 and the standard deviation is 1, making the data comparable and easier to interpret. The calculation method is presented in Equation 4:

$$x_{standardized} = \frac{x - \mu_x}{\sigma_x} \qquad (4)$$

Where: x = original value of indicators; μ_x= average; σ_x= standard deviation.

5. *Covariance matrix computation* — based on the normalized data, the covariance matrix is generated, using Equation 5. This represents the covariance between each pair of features in the original dataset. Based on the covariance matrix decomposition, the principal components are determined by calculating the eigenvalues and eigenvectors.

$$Cov(x_i, x_j) = \frac{1}{N}\sum_{i,j=1}^{N}(x_i - \overline{x_i})(x_j - \overline{x_j}) \qquad (5)$$

Where: N=number of observation; $\overline{x_i}$,$\overline{x_j}$ = the average of the i/ j variable; x_i, x_j = the original variable i/ j.

6. *Eigenvectors and eigenvalues calculation from the covariance matrix* — each eigenvector has a corresponding eigenvalue. The eigenvector associated with the highest eigenvalue indicates the direction in which the data exhibit the largest variance. Therefore, eigenvalues can be used to identify which eigenvectors capture the greatest variability in the data. This eigenvector represents the first component. By the same logic, the eigenvector with the second largest eigenvalue is called the second principal component, and so on; in the eigenvectors computation, is used in Equation 6, and for the eigenvalues is used in Equation 7.

$$A \cdot v = \lambda \cdot v \qquad (6)$$

$$det(A - \lambda \cdot I) = 0 \qquad (7)$$

Where: A = the matrix for which the eigenvectors are calculated;
v = eigenvector of A; λ = eigenvalue corresponding to v; det = matrix determinant;
I = identity matrix, which is the same size as the A matrix.

7. *Eigenvalues descending order sorting* — to determine which eigenvector is most relevant in the dataset, the eigenvalues are sorted, showing the amount of information extracted by each principal component. The ratio is the percentage of variance explained for each major component of the dataset and is calculated using Equation 8.

$$Weight\ PCi = \left|\frac{\lambda_i}{\sum_{j=1}^{p} \lambda_j}\right| \qquad (8)$$

Where: $Weight\ PCi$ = contribution of the principal component;
λ_i = eigenvalue corresponding to the principal component;
$\sum_{j=1}^{p} \lambda_j$ = sum of all eigenvalues of the covariance matrix for all principal components.

8. *Selection of the optimal principal components number* — to ensure objectivity in the selection of the optimal number of principal components, multiple criteria can be used: the supra-unit value criterion (Kaiser), the slope criterion (Evrard), and the coverage percentage criterion (Benzécri). Kaiser's criterion consists of selecting the number of components for which the eigenvalues correspond to a value greater than one [15]. Evrard's criterion consists of using a graphic representation of the eigenvalues and tracking the sudden drops of inertia explained by them. Benzécri's criterion consists of choosing the number of components that explain more than 70%-80% of the total variation [16].

9. Constructing the new reduced matrix with the selected k vectors, using Equation 9.

$$X_{reduced} = X_{rescaled} \cdot v \qquad (9)$$

Where*: $X_{reduced}$ = resulted matrix; $X_{rescaled}$ = rescaled (centred) data matrix;*
v = the matrix formed by the covariance matrix eigenvectors.

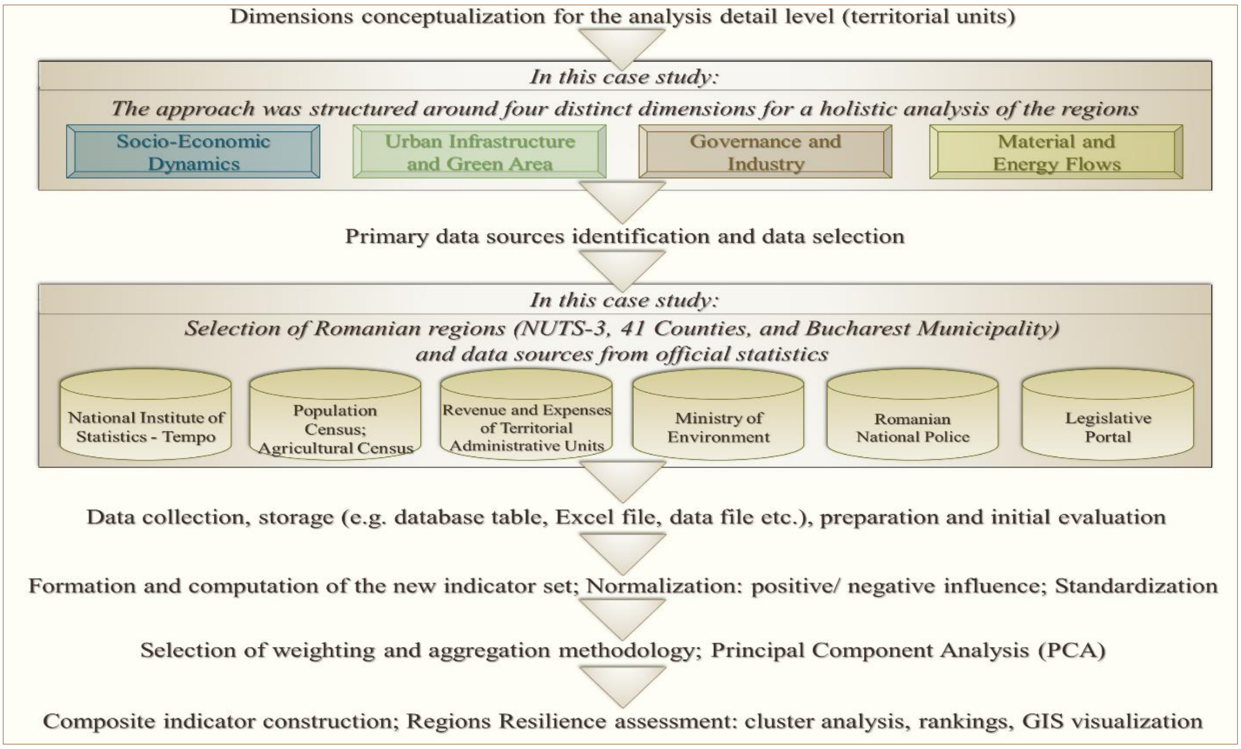
In various programing languages, there are implementations of the multivariate PCA technique. For this study, the R language was selected because it contains numerous packages and functions that facilitate analysis, thereby allowing flexible outputs for results interpretation and integration with Power BI for complex graphical diagrams and GIS representations.

4. METHODOLOGICAL APPROACH

Research framework

This paper proposes the development of an adaptable framework for analysing and assessing regional resilience from a multidimensional perspective. The proposed framework can be easily replicated across different geographic contexts. Using standardized analysis techniques that are well documented and widely accepted in the research field, the framework simplifies complex data to highlight and assess key factors contributing to regional resilience. The flexibility in selecting and adjusting indicators specific to each dimension allows the framework to be applied to various countries, regions, or cities, thus reflecting local particularities. Furthermore, data normalization and standardization procedures ensure results comparability, while the use of accessible software

packages, such as those available in the R language, facilitates the implementation and adaptation of the methodology in different contexts.
To validate the relevance of the developed framework, a case study was conducted. This involves conceptualizing four dimensions and defining indicators applicable at the territorial unit level, followed by the creation of composite scores to rank the analysed regions. Various open data sources at the county level in Romania were queried. The stages involved in the methodological approach are depicted in Figure 1.



(Source: author's own representation)

Figure 1. Steps involved in the methodological approach

First, the availability, relevance, and spatial coverage of data at the level of the 41 counties and the Municipality of Bucharest were considered. Each dimension was designed to capture multiple sub-dimensions, which are briefly described in the Exploratory Data Section. Thus, 69 representative indicators of the four dimensions were outlined:

1. Socio-Economic Dynamics (SE);
2. Urban Infrastructure and Green Area (UG);
3. Governance and Industry (GI);
4. Material and Energy Flows (ME).

The primary data sources were collected after identification according to availability, framed into one of the four dimensions, and verified to guarantee that there were no abnormal or missing values that would affect the analysis. This procedure was performed by applying descriptive statistics and automated options available at the level of R programing language packages. After transformation and computation, the primary dataset became the new indicator set. The data normalization process considers the positive or negative contributions of the indicators to the construction of composite scores.
The technique for reducing the dimensionality of indicators within each of the four dimensions was implemented using the multivariate statistical method of Principal Component Analysis (PCA). This approach reduces the number of variables, enabling a comparative visualization of the Romanian counties in based on their positions within the proposed dimensions during the

reference year. PCA can be applied from the data type perspective, as there are only quantitative variables and a significant number of variables and individuals. Based on the analysis results, composite scores at each dimension level, and an overall score were constructed. Combining PCA with cluster analysis enabled data grouping for easier understanding and interpretation. The counties' assessment included rankings creation and spatial representation using a GIS tool. Even if the analysis is conducted at Romania's level, the framework can be easily replicated in other regions and contexts, providing relevant and comparable results.

Exploratory data

The selection of variables to assess regional resilience is inspired by the need for a holistic approach that integrates multiple dimensions of society. The paper [1], particularly emphasizes the importance of approaching urban and regional resilience through the prism of multiple dimensions—social, economic, infrastructural, and environmental. This suggests that a full understanding of resilience cannot be achieved without considering the complexity and interconnectedness of these factors.

In the analysis of regional resilience for Romanian counties, the proposed study offers a complex framework, structured on four main dimensions, each with a series of carefully selected variables (indicators) to evaluate different aspects of regional development and stability. This framework identifies not only the vulnerabilities of each county, but also the potential paths toward sustainable and adaptive development. The detailed description of each dimension and related indicators provides a clear picture of the regions' resilience capacity, thus clarifying directions for intervening to increase resilience and ensure long-term sustainable development. The choice of indicators was based on theoretical and empirical principles that suggest that an optimal mix of economic resources, sustainable infrastructure, and effective environmental policies can significantly contribute to the resilience of a region. An important factor in selecting indicators was the availability of consistent data from recent periods for all studied counties, thus ensuring a uniform comparative basis for regional resilience analysis. The selected indicators are aligned with the specific challenges of each region and directly reflect critical resilience aspects.

The "*Socio-Economic Dynamics*" dimension covers a wide range of aspects that ensure the stability and development of a region, such as public health, economy, finance, education, and culture, as well as social aspects. Each indicator was selected for its ability to reflect the status and progress in these areas and have a direct impact on how a community can respond to crises and develop sustainably. The 29 indicators offer a detailed assessment of economic health, investments in health and education, support for vulnerable population, as well as the promotion of community cohesion. These indicators are evaluated for their positive or negative influence on the aggregate index, allowing an analysis of the region's strengths and weaknesses.

The expense-related data from the counties' budgets, which are used to determine the composition of indicators, were obtained from the RETAU data source. Total expenses allocated at county level are represented by SE5 indicator. All expenses are weighted to each county's population at the 2020 reference year level. Social Insurance Expenses (SE1) refer to assistance provided to: older citizens; those with illnesses and disabilities; families and children; and other social assistance expenses [17]. Public Education Expenses (SE3) includes: primary school, school, special education, and other specific expenses. Public Health Expenses (SE4) refer to medical services offered in health facilities with beds, general hospitals; other health-related expenses. Public Culture Expenses (SE13) include cultural services provided by libraries, museums, performance, and concert institutions; traditions, arts, and crafts schools; centres for traditional culture promotion; monument restoration; recreational, sports, and religious services. County revenues (SE29) include taxes, fees, and other revenue from local budgets. All selected indicators of this dimension are presented in Table 2:

Table 2. Socio-Economic Dynamics Indicators

Acronym	Indicator	Measurement unit	Data source and Reference Year	Influence
SE1	Social Insurance Expenses	RON/ inhabitant	RETAU, 2020	▲
SE2	Family Medical Practices	%1,000 inhabitants	TEMPO SAN104A, 2019	▲
SE3	Public Education Expenses	RON/ inhabitant	RETAU, 2020	▲
SE4	Public Health Expenses	RON/ inhabitant	RETAU, 2020	▲
SE5	County Expenses	RON/ inhabitant	RETAU, 2020	▲
SE6	Doctors density	%1,000 inhabitants	TEMPO SAN104A, 2019	▲
SE7	Population density	inhabitant/ km^2	TEMPO POP105A, 2019	▼
SE8	Libraries	at 1,000 inhabitants	TEMPO ART101B, 2019	▲
SE9	Young NEETs[1] (aged 15-29)	%	CENSUS, 2011	▼
SE10	Museums	at 1,000 inhabitants	TEMPO ART104A, 2019	▲
SE11	Economically Active Population	%	CENSUS, 2011	▲
SE12	Illiterate population	%	CENSUS, 2011	▼
SE13	Public Culture Expenses	RON/ inhabitant	RETAU, 2020	▲
SE14	Teachers	for 30 students	TEMPO SCL103D/ SCL104A, 2019	▲
SE15	Young population (aged <=14)	%	TEMPO POP105A, 2019	▲
SE16	Older population (aged >=65)	%	TEMPO POP105A, 2019	▼
SE17	Medical staff	%1,000 inhabitants	TEMPO SAN104A, 2019	▲
SE18	Population with higher education (25-65 years)	%	TEMPO SCL109B/ POP105A, 2019	▲
SE19	Number of beds in health facilities	%1,000 inhabitants	TEMPO SAN102B, 2019	▲
SE20	Employed women rate	% of total employees	TEMPO FOM105F, 2019	▲
SE21	Unemployed women rate	%	TEMPO SOM103A, 2019	▼
SE22	Infant mortality rate	%1,000 inhabitants	TEMPO POP205B, 2019	▼
SE23	Mortality rate	%1,000 inhabitants	TEMPO POP207A, 2019	▼
SE24	Birth rate	%1,000 inhabitants	TEMPO POP202A, 2019	▲
SE25	Employee rate	% of total population	TEMPO FOM105A, 2019	▲
SE26	Natural growth rate	%1,000 inhabitants	TEMPO POP202A, 2019	▲
SE27	Unemployment rate	% of total population	TEMPO SOM103A, 2019	▼
SE28	School units	at 1,000 inhabitants	TEMPO SCL101C, 2019	▲
SE29	County revenues	RON/ inhabitant	RETAU, 2020	▲

[1]*NEET = Not in Education, Employment, or Training*

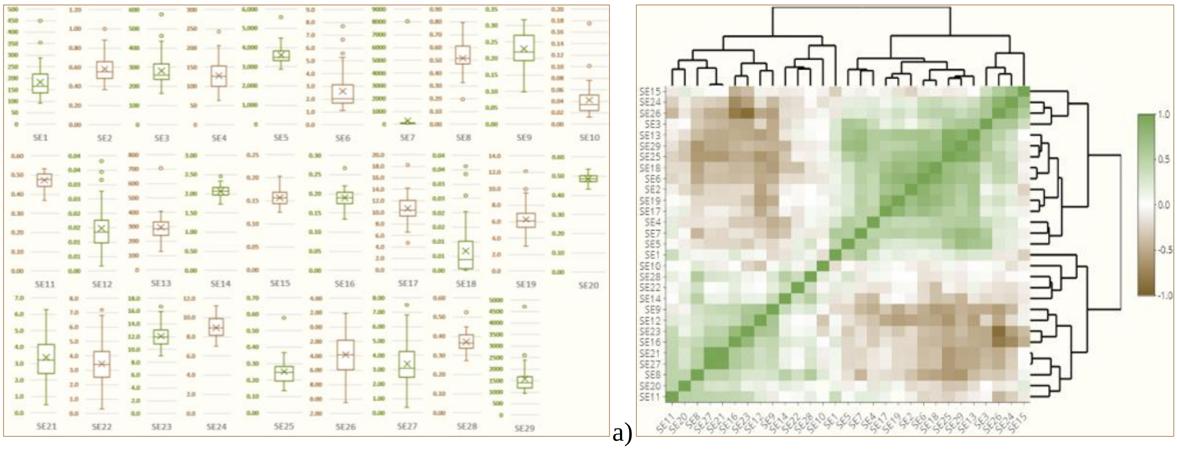
(Source: author's own representation)

To observe the central trends and shape of the data distribution, a boxplot representation was used, which graphically reflects the minimum, median, maximum value, quartiles 1 and 3, as well as the outliers depicted in Figure 2a. For the Boxplot diagram, the values were obtained before the normalization process.

At the level of all counties, one general practitioner is assigned to more than 1,000 people (SE2), with Bucharest being the only county that benefits of 1 doctor per thousand inhabitants. The number of medical staff (SE17) on average per county is higher (all categories of medical personnel are included), with the average value for medical personnel being approximately 10 per thousand inhabitants. The situation of teachers (SE14) at the county level is in average of more than 2 teaching staff for 30 students.

The most highlighted outlier values in the representation are given by the Municipality of Bucharest, which concentrates a large population reported to surface area, but also from the perspective of revenues and expenses. Other outliers: at the level of the Social Insurance Expenses (SE1) Mehedinti County registers a value of 354.29 RON/inhabitant, the median value for this indicator being 163.20 RON/inhabitant; at the level of Public Education Expenses (SE3) Ilfov County registers 463.58 RON/inhabitant, the median value being 258.28 RON/inhabitant; at the level of County Expenses (SE5) – Tulcea County registers 5589.70 RON/inhabitant, median value being 3491.66 RON/inhabitant; at the level of County revenues (SE29) Tulcea County registers 2662.97 RON/inhabitant, Ilfov County - 2594.54 RON/inhabitant, and Cluj County - 2388.98 RON/inhabitant, the median value being 1413.35 RON/inhabitant.

The correlation matrices of the indicators were determined to observe pairs of strongly correlated variables and the interdependencies between variables, providing a deeper understanding of the data structure. This analysis will help determine the number of required key components, which can also be viewed as a number of strongly correlated groups of variables. By analysing the correlogram depicted in Figure 2b, we can see that the procedure highlighted the correlation between the variables analysed. Thus, the variables that are strongly correlated are "County revenues" (SE29) with "Employee rate" (SE25) with 0.91, "Birth rate" (SE24) with "Public Education Expenses" (SE3) with 0.84–strong correlation, "Family medical practices" (SE2) with "Doctors density" (SE6) with 0.84–strong correlation. At the opposite pole, the most uncorrelated variables under analysis are "Older population >=65 years" (SE16) with "Natural growth rate" (SE26) with -0.82 (negative strong correlation), "Illiterate population" (SE12) with "Employee rate" (SE25) with -0.64 (negative moderate correlation), etc.



a) b)

(Source: author's own representation resulting from the analysis)

Figure 2. Socio-Economic Dynamics Dimension: a) Boxplot for each individual indicator, b) Correlation Matrix Heatmap

The "*Urban Infrastructure and Green Area*" dimension is essential for understanding how urban planning and access to natural resources influence quality of life and adaptability to climate change and ecological challenges. The 20 indicators in this dimension measure aspects such as urban planning and buildings, environment, climate and green spaces, technology and innovation, transport and infrastructure. Their classification according to positive or negative influence reflects the quality of essential infrastructure and the protection of natural areas.

"Public housing Expenses" (UG12) include water supply and hydro-technical facilities and other expenses in the fields of housing, services, and communal development. "Transport expenses" (UG13) refer to the amounts allocated to road transport - roads and bridges, air transport - civil aviation, as well as other expenses in this field. All selected indicators for this dimension are presented in Table 3:

Table 3. Urban Infrastructure and Green Area Indicators

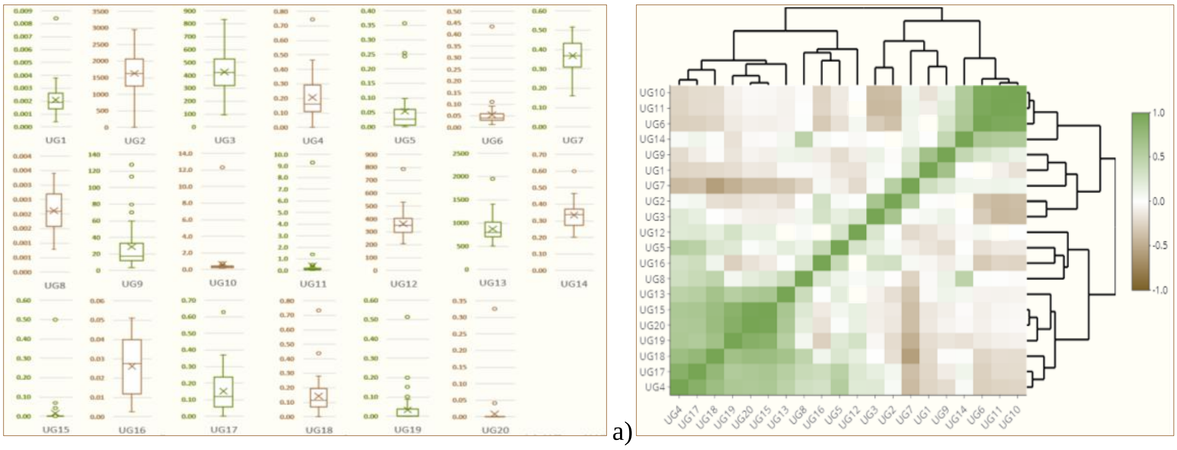
Acronym	Indicator	Measurement unit	Data source and Reference Year	Influence
UG1	Construction licenses for buildings	at 1,000 inhabitants	TEMPO LOC108B, 2020	▼
UG2	County/municipal roads accessibility	km/ km^2	TEMPO TRN139A, 2019	▲
UG3	National road accessibility	km/ km^2	TEMPO TRN139A, 2019	▲
UG4	Natural protected areas	% of total area	ENV, 2018	▲
UG5	RONPA[1] protected natural area	% of total area	ENV, 2018	▲
UG6	Rail density	km/ km^2	TEMPO TRN143A, 2019	▲
UG7	Road density	km/ km^2	TEMPO TRN139A, 2019	▲
UG8	Sewer pipe length	km/ km^2	TEMPO GOS110A, 2019	▲
UG9	Housing completed in reference year	per 10,000 inhabitants	TEMPO LOC104C, 2019	▲

UG10	Water network length	km/ km^2	TEMPO GOS106A, 2019	▲
UG11	Gas network length	km/ km^2	TEMPO GOS116A, 2019	▲
UG12	Public housing Expenses	RON/ inhabitant	RETAU, 2020	▲
UG13	Public transport Expenses	RON/ inhabitant	RETAU, 2020	▲
UG14	Proportion of the population using the Internet	%	CENSUS, 2011	▲
UG15	ROMAB[2] Biosphere Reservation	% of total area	ENV, 2018	▲
UG16	Forest area	% of total area	TEMPO AGR301A, 2019	▲
UG17	Natura 2000 ROSCI[3] site	% of total area	ENV, 2018	▲
UG18	Natura 2000 ROSPA[4] site	% of total area	ENV, 2018	▲
UG19	RAMSAR[5] site	% of total area	ENV, 2018	▲
UG20	UNESCO[6] heritage site	% of total area	ENV, 2018	▲

(Source: author's own representation)

[1]RONPA = Natural protected area of national interest – 13,961 km^2 ; [2]ROMAB = Biosphere Reservation - 5,393 km^2; [3]ROSCI = community importance site – 40,449 km^2 ; [4]ROSPA = avifaunistic special protection area – 37,261 km^2; [5]RAMSAR = wet area site – 9,731 km^2 ; [6]UNESCO = site belonging to the UNESCO World Heritage – 3,067 km^2

Analysing the Urban Infrastructure and Green Area correlogram, depicted in Fig.3b, we can see that the variables that are very strongly correlated variables are “Water network length” with “Gas network length” with 0.99, “Natural protected areas” with “Natura 2000 ROSCI site” with 0.88. At the opposite pole, the most uncorrelated variables under analysis are “Natura 2000 ROSPA” with “Road density” with -0.58 (negative moderate correlation) and “Gas network length” with “National road accessibility” with -0.42 (negative weak correlation).



a) b)

(Source: author's own representation resulting from the analysis)

Figure 3. Urban Infrastructure and Green Area Dimension: a) Boxplot for each individual indicator, b) Correlation Matrix Heatmap

The "*Governance and Industry*" dimension is fundamental to exploring how governance structures and industrial performance contribute to the economic and administrative development of regions. The 12 indicators in this dimension analyse aspects such as the allocation of financial resources, public safety and environmental protection, as well as the infrastructure capacity to support economic development. The indicators reflect how governance allocates expenditure for subsidies and external funds, invests in public defence and environmental protection, and supports the development of tourism and financial infrastructure. Categorizing indicators according to their positive or negative influence highlights concerns about security and administrative efficiency, providing an overview of how these elements contribute to regional stability and growth.

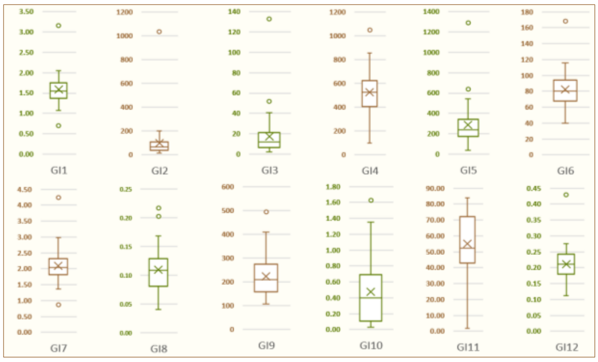
“Subsidy expenses” (GI4) include national defence, public order, community police, civil planning expenses, and fire protection expenses. “Public environmental protection expenses” (GI9) refer to the amounts spent on sanitation; waste management, collection, treatment, and destruction; sewerage and wastewater treatment. All selected indicators of this dimension are presented in Table 4:

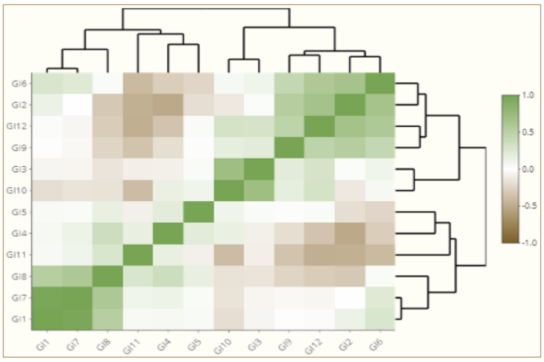
Table 4. Governance and Industry Indicators

Acronym	Indicator	Measurement unit	Data source and Reference Year	Influence
GI1	Number of road accidents	per 1,000 inhabitants	TRANSP, 2017	▼
GI2	Crime coefficient	index	POL, 2020	▼
GI3	Tourist capacity	per 1,000 inhabitants	TEMPO TUR102C, 2020	▲
GI4	Subsidy expenses	RON/ inhabitant	RETAU, 2020	▲
GI5	External funds expenses	RON/ inhabitant	RETAU, 2020	▲
GI6	Public Defence Expenses	RON/ inhabitant	RETAU, 2020	▲
GI7	Rate of seriously injured people in road accidents	per 1,000 inhabitants	TRANSP, 2017	▼
GI8	Rate of people died in road accidents	per 1,000 inhabitants	TRANSP, 2017	▼
GI9	Public environmental protection expenses	RON/ inhabitant	RETAU, 2020	▲
GI10	Tourist reception structures	per 1,000 inhabitants	TEMPO TUR101C, 2020	▲
GI11	Agricultural area	% of the total area	AGRIC, 2010	▲
GI12	Bank units	per 1,000 inhabitants	BANK, 2018	▲

(Source: author's own representation)

Analysing the Governance and Industry Indicators correlogram, depicted in Fig.4b, we can see, thus the very strongly correlated variables are "Number of road accidents" with "Rate of seriously injured people" with 0.97, "Crime coefficient" with "Public defence expenses" with 0.67 (moderate correlation). At the opposite pole, the most uncorrelated variables under analysis are "Agricultural area" with "Bank units" with -0.48 (negative weak correlation), "Agricultural area" with "Tourist reception structures" with -0.40 (negative weak correlation).


a)


b)

(Source: author's own representation resulting from the analysis)

Figure 4. Governance and Industry Dimension: a) Boxplot for each individual indicator, b) Correlation Matrix Heatmap

The "*Material and Energy Flows*" dimension focuses on the sustainability of natural resource management, using indicators that measure efficiency in the use of resources, waste management, and access to essential services such as water and energy. These indicators are crucial for assessing a region's ability to maintain a balance between resource consumption and ecological needs, a fundamental element in supporting sustainable development. The 8 selected indicators measure aspects such as access to water and energy and the ability to recycle waste. Their classification according to positive or negative influence highlights the basic infrastructure necessary for sustainable development and efficient resource management. The selected indicators of this dimension are presented in Table 5:

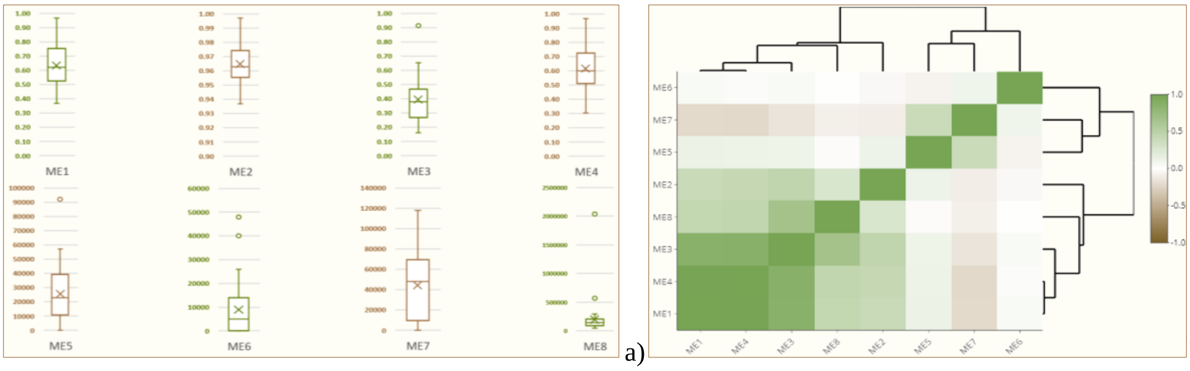
Table 5. Material and Energy Flows Indicators

Acronym	Indicator	Measurement unit	Data source and Reference Year	Influence
ME1	Access to running water	% of total houses	CENSUS, 2011	▲
ME2	Access to central heating	% of total houses	CENSUS, 2011	▲

ME3	Access to electricity	% of total houses	CENSUS, 2011	▲
ME4	Access to the sewage system	% of total houses	CENSUS, 2011	▲
ME5	The amount of solid waste	tonnes	TEMPO GOS111C, 2004	▼
ME6	Waste management capacity in transfer stations	tonnes/year	LEG, 2017	▲
ME7	Waste management capacity in composting stations	tonnes/year	LEG, 2017	▲
ME8	Capacity to manage recyclable waste in separate sorting and collection stations	tons/year	LEG, 2017	▲

(Source: author's own representation)

Analysing the Material and Energy Flows correlogram depicted in Fig.5b, we can see that the variables that are strongly correlated are “Access to running water” with “Access to the sewage system” with 0.99, “Access to central heating” with “Access to the sewage system” with 0.87 (strong correlation). At the opposite pole, the uncorrelated variables under analysis are “Access to the sewage system” with “Waste management capacity in transfer stations” with -0.23 (negative very weak correlation).



(Source: author's own representation resulting from the analysis)

Figure 5. Material and Energy Flows Dimension: a) Boxplot for each individual indicator, b) Correlation Matrix Heatmap

5. MAIN RESEARCH FINDINGS

Data analysis

Application of Principal Component Analysis. Following the methodological steps of PCA, specific packages from the R programing language were used to perform the analysis. First, the set of indicators was read from the data file using “library("readxl")”, following the normalization of these. It was decided to apply the analysis separately for each of the 4 dimensions. Before starting the analysis, it was considered that each indicator contained quantitative data.

In the first phase, indicators belonging to the "Socio-economic dynamics" dimension were loaded in R Studio. Were selected variables that had positive or negative contributions, scaled them accordingly, and reconstructed the matrix using the 29 centred variables. From the "FactoMineR" package, the "PCA" function is used, which implements the algorithms used to determine PCs. To interpret the PCA, more precisely to extract the eigenvalues and the proportion of variance retained by the PCs, the "get_eigenvalue" function from "factoextra" package is used. Through the descending order of these values, the component with the largest variation was observed in the dataset, as well as the subsequent ones. These steps were applied to each of the 4 dimensions of the presented indicators.

The selection of PCs was objectively realized by successively applying the criteria presented in the theoretical chapter of this study. Thus, by applying Kaiser's criterion, we can observe that 7 eigenvalues are greater than 1. According to Kaiser's criteria, we can say that we have 7 main components informationally synthesized all 29 original variables. Thus, through the first main component PC_1 (SE), the preservation of 36.76% of the total variance was preserved, and 83.36% of the 7 cumulated components were preserved, resulting in an information loss of 16.64%.

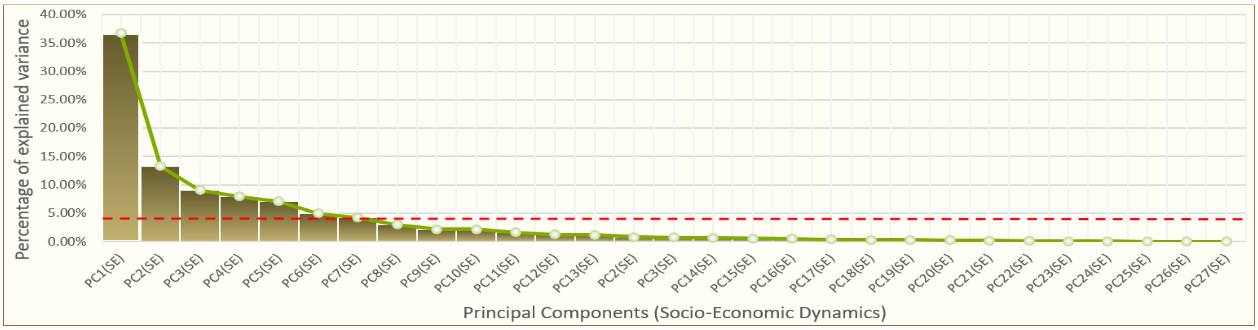
Table 6. Sorted eigenvectors and coverage percentage - Socio-Economic Dynamics.

Components	Sorted Eigenvalues	Difference	Proportion[1]	Cumulative[2]
		a) Socio-Economic Dynamics		
PC_1 (SE)	**10.6590**	6.8113	36.7551	*36.7551*
PC_2 (SE)	**3.8477**	1.2114	13.2678	*50.0229*
PC_3 (SE)	**2.6363**	0.3368	9.0906	*59.1135*
PC_4 (SE)	**2.2994**	0.2377	7.9291	*67.0426*
PC_5 (SE)	**2.0618**	0.6238	7.1095	*74.1521*
PC_6 (SE)	**1.4379**	0.2067	4.9583	*79.1104*
PC_7 (SE)	**1.2312**	0.3567	4.2454	83.3558
PC_8 (SE)	0.8744	0.2354	3.0152	86.3710
PC_9 (SE)	0.6390	0.0130	2.2036	88.5746
		(…)		
PC_{29} (SE)	0.0034	-	0.0117	100.0000

[1]*Proportion = share of each component in the total variance;*
[2]*Cumulative = share of all components up to that component in the total variance.*
(Values in bold are greater than 1, values in italics denote components that together explain 70-80% of the variance)

(Source: author's own representation resulting from the analysis)

According to the coverage percentage criterion (Benzécri criterion)—the total variance of the first 5 components exceeds the threshold value (> 70-80%), resulting in the retention of more than 5 components in the analyses. The slope criterion (Evrard criterion) represented with the Scree plot reconfirms the hypothesis of the 7 components selection. This representation was created based on "factoextra::fviz_eig" function and is shown in Figure 6.



(Source: author's own representation resulting from the analysis)

Figure 6. Socio-Economic Dynamics - slope criterion

Repeating the steps for the other dimensions, the PCA application yielded the eigenvalues presented in Table 7, distinct for each of the 3 dimensions.

Table 7. Sorted eigenvectors and coverage percentage - Urban Infrastructure and Green Area, Governance and Industry and Material and Energy Flows dimensions

Components	Sorted Eigenvalues	Difference	Proportion	Cumulative
		b) Urban Infrastructure and Green Area		
PC_1 (UG)	**6.0611**	2.1368	30.3054	*30.3054*
PC_2 (UG)	**3.9243**	1.5655	19.6213	*49.9268*
PC_3 (UG)	**2.3587**	0.4475	11.7937	*61.7205*
PC_4 (UG)	**1.9113**	0.5820	9.5564	*71.2769*
PC_5 (UG)	**1.3292**	0.2761	6.6461	*77.9230*
PC_6 (UG)	**1.0531**	0.0960	5.2655	83.1885
PC_7 (UG)	0.9571	0.4513	4.7855	87.9740
PC_8 (UG)	0.5058	0.0424	2.5289	90.5030
		(…)		
PC 20 (UG)	0.0020	-	0.0100	100.0000
		c) Governance and Industry		

PC_1 (GI)	**3.6188**	1.0262	30.1570	*30.1570*
PC_2 (GI)	**2.5926**	0.7671	21.6054	*51.7624*
PC_3 (GI)	**1.8255**	0.7713	15.2125	*66.9749*
PC_4 (GI)	**1.0542**	0.2479	8.7852	*75.7601*
PC_5 (GI)	0.8064	0.1478	6.7196	82.4797
PC_6 (GI)	0.6585	0.1511	5.4877	87.9674
(…)				
PC_{12} (GI)	0.0134	-	0.1120	100.0000
d) Material and Energy Flows				
PC_1 (ME)	**3.5272**	2.1253	44.0898	*44.0898*
PC_2 (ME)	**1.4019**	0.3534	17.5232	*61.6131*
PC_3 (ME)	**1.0485**	0.2894	13.1062	*74.7192*
PC_4 (ME)	0.7591	0.0445	9.4888	84.2080
PC_5 (ME)	0.7146	0.2702	8.9320	93.1400
(…)				
PC_8 (ME)	0.0042	-	0.0529	100.0000

(Values in bold are greater than 1, values in italics denote components that together explain 70-80% of the variance)

(Source: author's own representation resulting from the analysis)

The application of the objective selection criteria for the number of PCs is presented as follows:

- For Urban Infrastructure and Green Area Dimension—the first 6 main components explain 83.19% of the total variance of the 20 original variables, as depicted in Table 7b. The information loss was 16.81% according to the Kaiser criteria. According to the criterion of the coverage percentage (Benzécri criterion), the total variance of the first 5 components exceeds the threshold value (> 70-80%), but the slope criterion reconfirms the selection of 6 components;
- For Governance and Industry Dimension—the first 4 main components explain 75.76% of the total variance of the 12 original variables, with an information loss of 24.24%, as depicted in Table 7c. According to the coverage percentage criterion, the total variance of the first 4 components exceeds the threshold value (> 70-80%), reconfirmed with the slope criterion;
- For Material and Energy Flows Dimension—the first 3 main components explain 74.72% of the total variance of the 8 original variables. The information loss was 25.28%, as depicted in Table 7d. According to the coverage percentage criterion, the total variance of the first 3 components exceeds the threshold value (> 70-80%), reconfirmed with the slope criterion.

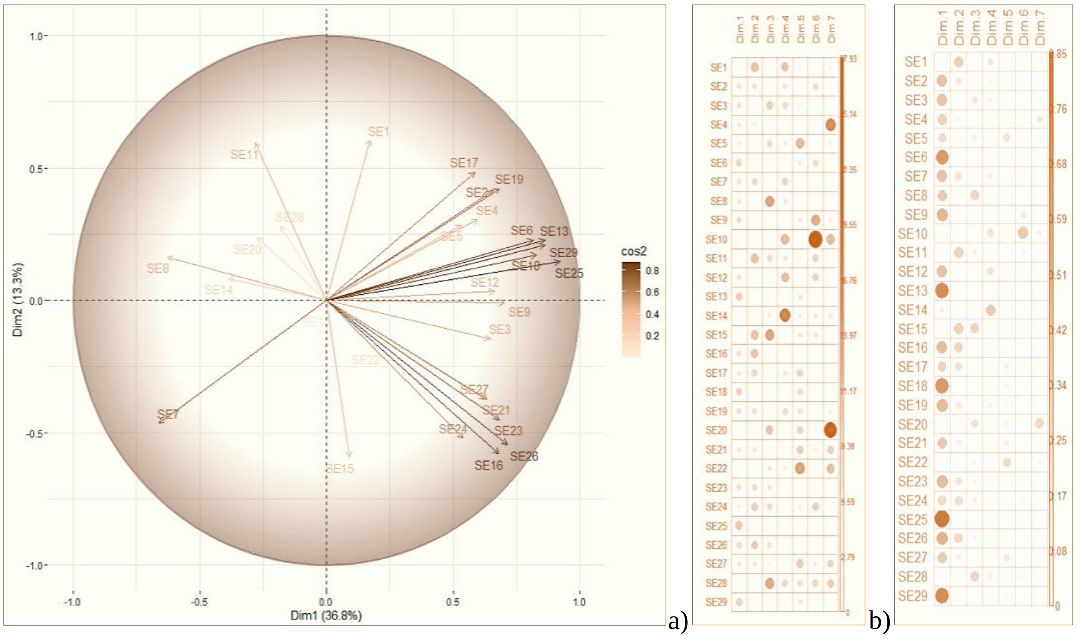
Creating new matrices: For the first dimension, the first 7 principal components are selected, resulting from the multiplication of the standardized data with the eigenvector components of the 7 selected principal components. From the new matrix, it follows that through the principal components, we can characterize the 42 counties through 7 variables for the "Socio-economic dynamics" category instead of the 29 initial variables, keeping 83.36% of the information contained in the initial data; analogously, for the other 3 categories. The calculation of the main components is performed as in Equations 9 and 10, and is analogous for the rest of the components in the first dimension and respectively for the other 3 dimensions and related components:

$$PC_1\,(SE) = 0{,}17 * SE1 + 0.66 * SE2 + 0.65 * SE3 + \dots - 0.18 * SE28 + 0.86 * SE29$$
$$PC_2\,(SE) = 0.60 * SE1 + 0.41 * SE2 - 0.15 * SE3 + \dots + 0.27 * SE28 + 0.21 * SE29 \quad (\dots) \quad (10)$$

The analysis led to the construction of some graphic representations to highlight the quality and contribution of the indicators to the new principal components, which are abstracted in the first phase from the point of view of the indicators they include. To simplify the visualization, a two-dimensional graph was selected that contained the two most representative principal components from the variability perspective, as depicted in Figure 7a. Continuing the representation to surprise the other components of "Socio-economic dynamics", Figure 7b and Figure 7c were created. The representations were constructed using the corrplot() function from library("corrplot"). The interpretation of the correlation diagram between indicators and the first two principal components for the Socio-Economic Dynamics dimension is as follows: the correlation circle diagram shows the relationships between the indicators; the positively correlated indicators are concentrated toward the centre, and the negatively correlated ones are positioned on opposite sides of the diagram origin; the distance between the variables and the origin measures the quality of the representation on the factor map, with indicators far from the origin being well represented.

According to Equation 10, but also to Fig. 7a, the indicators that participate in the formation of principal component 1 from the Socio-Economic dimension, having a significant contribution threshold value, are: SE25, SE13, SE29, SE18, SE6, SE9, SE19, SE23, SE16, SE12, SE7, SE2, SE3, and SE8. The total variance explained by this component is 36.8%. Continuing the analysis for the second component, it can be observed that the indicators that have a significant contribution are SE1, SE11, SE15, SE16, SE26, SE24, SE17, SE23, SE19, SE21, and SE27. The second component explains 13.3% of the total variation.

Both in the case of components 1 and 2, the specified values have a high value for $\cos^2$, which indicates a good representation of the variables, being positioned close to the circumference of the correlation circle, as depicted in Figure 7a. Indicators with low $\cos^2$ indicate that variables do not have a good representation and can be interpreted as part of other principal components. Figure 7c extends the representation to include also the rest of retained components from the Socio-Economic dimension and highlights the quality of representation represented by the colour and size of the circles.



a) b) c)

(Source: author's own representation resulting from the analysis)

Figure 7. a) Correlation diagram between indicators and two principal components - Socio-Economic Dynamics dimension b) Contribution of indicators to principal components c) Quality of representation diagram - Socio-Economic Dynamics dimension

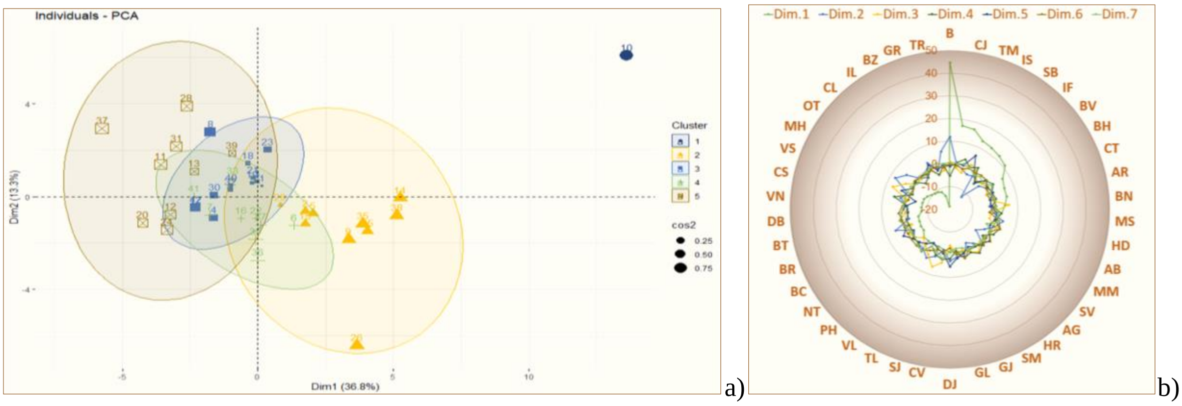
Romanian counties resilience empirical assessment

For the assessment of Romanian regions from the perspective of resilience, premises were set for the development of a standardized framework applicable for comparative analysis purposes, to cover different aspects of the 41 counties and Bucharest Municipality. In this context, the empirical results generated based on the obtained indicators can help to understand more thoroughly their complexity on multiple dimensions. One of the expected results of the analysis is to obtain a ranking of the counties, as well as create clusters, and generate representations using a GIS tool.

Moving the analysis from the variables area, represented by indicators, to the area of projection and representation in the plan of individuals, more precisely of the Romanian counties, the analysis of the contributions of the observations from the components PC_1(SE) and PC_2(SE) was performed. Various groupings are observed that indicate the similarity between the analysed counties, as well as the quality of the representation of individuals on the factor map - cos^2, as depicted in Figure 8a. Individual values were redistributed in a multidimensional space, individuals from the same category being grouped together, and those from different categories are represented far apart in the graph.

The same graphic representation was chosen to highlight the groupings resulting from the PCA analysis by combination with cluster analysis. One of the most popular clustering models [18] was chosen, more precisely, the K-Means algorithm. The optimal number of centroids was obtained by the Elbow method [19]; more precisely, the point at which the variation explained by the individual values stabilized was determined to be 5. This value was considered the optimal number of clusters. In R, was parameterized the "kmeans" model, resulting in the inclusion of each county in one of the 5 clusters, with members that have similar characteristics being grouped in a common cluster. Bucharest uniquely forms a cluster for the two most representative main components of the Socio-Economic dimension. The second cluster includes the following counties: Cluj, Timiș, Iași, Sibiu, Ilfov, Brașov, Bihor, Arad, Constanța, and Mureș. The third cluster includes the counties: Hunedoara, Alba, Argeș, Bacău, Brăila, Dâmbovița, Dolj, Galați, Gorj, Neamț, Prahova, Vâlcea, and Vrancea. The fourth includes the counties: Bistrița-Năsăud, Botoșani, Covasna, Hunedoara, Maramureș, Sălaj, Satu Mare, Suceava, and Vaslui. The fifth cluster consists of the following counties: Buzău, Călărași, Caraș-Severin, Giurgiu, Ialomița, Mehedinți, Olt, Teleorman, and Tulcea. Therefore, a greater explained variation suggests better-defined and more homogeneous clusters.

Extending the analysis also for the rest of the selected principal components of the first dimension, a radar representation was made to surprise in a comparative way the point at which the counties are located in the various sub-divisions of the Socio-Economic dimension obtained through the regrouping resulting from the PCA analysis. The schematization is presented in Figure 8b.



(Source: author's own representation resulting from the analysis)

Figure 8. a) The coordinates of the individual values for PC_1(SE) and PC_2(SE), the quality of representation (cos^2) and the groupings resulting from the cluster analysis b) Radar diagram including all 7 principal component selected for the SE dimension

Based on the individual values, it was decided to create an aggregate score, which allows the comparative analysis of the counties, obtaining a simplified and more informative representation from the data perspective. To obtain the aggregate value at the level of each dimension, Equation 11 was used:

$$Score_{Dimension} = \sum_{i=1}^{n}(PC_i loading \ * PC_i individual) \qquad (11)$$

Where: n = the number of principal components kept in the analysis;
$PC_i loading$ *= the loading coefficient for the i principal component;*
$PC_i individual$ *= the standardized value for the i county.*

By calculating the values at the level of all four dimensions, a ranking of the counties was achieved, which were sorted in ascending order according to the scores of each county. It can be seen that Bucharest occupies the first place in the SE and ME domains, having the largest allocations of the amounts spent on various domains, as well as of the revenues collected, Bucharest being the capital of Romania; Tulcea occupies the first place in the UG issue, presenting the most developed area of natural areas in the analysed country, with the most important natural land being the Danube Delta. Brasov occupies the first place in terms of GI issues, being a strong touristic area and a quiet county from the road traffic safety perspective. The scores obtained for all analysed counties are presented in Table 8:

Table 8. Ranking of Romanian counties based on PCA scores

Region	Socio-Economic Dynamics (SE) Rank	Urban Infrastructure and Green Area (UG) Rank	Governance and Industry (GI) Rank	Material and Energy Flows (ME) Rank	Rank based on Composite Score
Bucharest	1	2	3	1	1
Cluj	3	16	11	2	2
Brașov	9	14	1	9	3
Hunedoara	6	3	12	7	4
Tulcea	32	1	2	39	5
Sibiu	5	17	6	5	6
Bihor	10	10	8	10	7
Argeș	11	12	23	3	8
Constanța	23	8	9	6	9
Maramureș	19	11	7	12	10
Mureș	13	9	19	4	11
Harghita	17	15	17	8	12
Alba	7	7	15	20	13
Bistrița-Năsăud	8	18	4	21	14
Caraș-Severin	34	4	14	24	15
Arad	15	13	21	18	16
Iași	2	33	28	19	17
Timiș	4	19	32	16	18
Vâlcea	18	21	5	30	19
Gorj	12	6	16	33	20
Neamț	30	23	24	13	21
Covasna	14	29	13	25	22
Sălaj	16	24	10	28	23
Bacău	26	34	22	17	24
Vrancea	35	31	25	11	25
Prahova	29	22	29	15	26
Dolj	21	26	33	14	27
Suceava	25	20	20	23	28
Satu Mare	31	25	18	29	29
Galați	27	35	26	26	30
Mehedinți	28	5	38	34	31
Botoșani	20	28	27	36	32
Vaslui	24	32	40	32	33
Dâmbovița	33	38	30	35	34
Buzău	36	27	31	37	35
Olt	37	30	34	38	36
Ilfov	38	42	39	22	37
Călărași	40	41	35	31	38
Brăila	22	36	42	27	39

Ialomița	41	40	37	40	40
Teleorman	39	37	36	42	41
Giurgiu	42	39	41	41	42

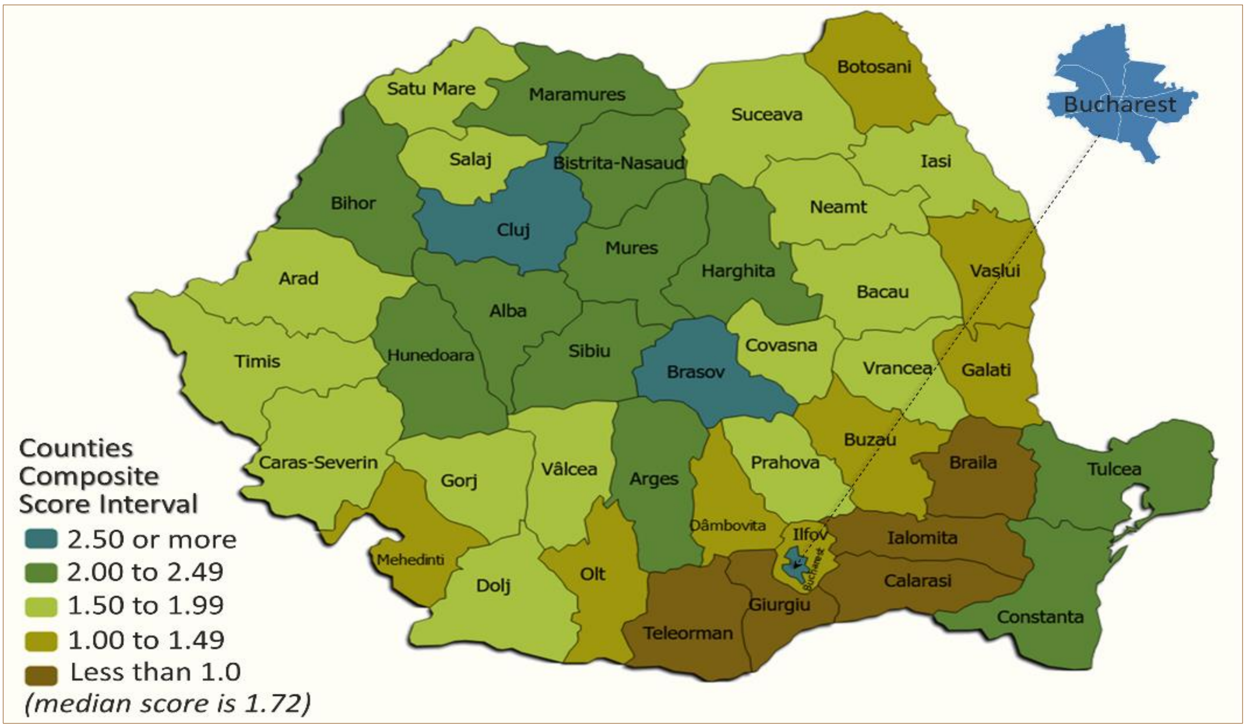
(Source: author's own representation resulting from the analysis)

All 41 counties and Bucharest Municipality received an overall composite score that captured all the analysed aspects. This was obtained by summing the normalized values using the min-max method of the 4 dimensions scores. The formula used to obtain the overall composite score is presented in Equation 12. Based on this, a hierarchy was created, as presented in the last column of Table 8.

$$Score_{Overall} = Score_{SE^+} + Score_{UG^+} + Score_{GI^+} + Score_{ME^+} \quad (12)$$

Where: $Score_{Dimension^+}$ = min-max normalized score for Socio-Economic / Urban Infrastructure / Governance and Industry / Material and Energy Flows dimension

The overall composite scores were also represented on a map that links the spatial data of the Romanian counties (polygon type) and associates them with the numerical values obtained from the analyses. An interactive thematic layer divided into 5 value ranges was created to summarize the analysis at the composite score level. Scores are in the range of 0-4. A score close to the maximum (4), such as that of the Municipality of Bucharest (3.6752), followed by Cluj (2.5783), suggests that on all 4 dimensions, all indicators were at a high level. At the opposite pole, the counties of Giurgiu (0.6878), Teleorman (0.7205), Ialomița (0.7880), Braila (0.9049), the values of the indicators indicate that, compared to the rest included in the analysis counties, they are deficient in all dimensions, which may indicate a low resilience potential in the face of adverse events.



(Source: author's own representation resulting from the analysis)

Figure 9. Spatial distribution of Overall Composite Score

The composite score is an analytical tool that aggregates multiple dimensions of regional performance into a single measure derived from a comprehensive set of indicators. It synthesizes complex information in a clear and easily interpretable form, making it easier to compare and

assess performance of regions. Calculated relatively between regions, the composite score provides a holistic picture of each region's strengths and weaknesses, facilitating the assessment of regional resilience.
The practical implications are significant: the composite score can serve as a basis for public policy formulation, allowing decision makers to identify priority areas and allocate resources efficiently. Regions with low scores can be targeted for specific development and investment programs, ensuring that resources are used where they are most needed. They can also support strategic planning and foster the development of targeted strategies to improve areas of deficiency. The composite score facilitates monitoring progress by tracking changes over time, assessing the impact of implemented policies, and adjusting strategies to ensure continuous improvement. It also contributes to increasing citizen awareness and involvement by providing a transparent and easy-to-understand measure of regional performance. This approach enables community involvement in local governance and development initiatives. In addition, companies and investors can use the composite score to make informed decisions, as regions with high scores are perceived as more stable and attractive for investment.
The multidimensional analysis of the Romanian regions reveals a complex panorama of the country, highlighting the existing discrepancies that reside in economic development, living standards and access to services, which make communities vulnerable. This analysis highlights the differences and sheds light on the needs of each county in ensuring equitable development. This analysis has limitations; there are multiple aspects that could be taken into account, and interested parties could expand this on the specific needs, by completing with relevant data; the created framework represents a foundation for more complex analyses.

6. CONCLUSIONS AND FURTHER RESEARCH

Data are valuable sources for understanding the evolution and development of a country's regions, offering objective and measurable information at various levels. Analysis and understanding are essential in the context of sustainable development and resilience improvement.
The development of a new set of indicators is driven by the evolving demands of regional analysis and the need for refined tools that can effectively capture the unique characteristics and dynamics of Romanian counties. A framework was developed using data from official statistics, which were grouped within the analysis into four dimensions: "Socio-Economic Dynamics", "Urban infrastructure and Green Area", "Governance and Industry", and "Material and Energy Flows". The data are available at the level of NUTS-3 regions (41 counties and the Bucharest Municipality). The original data were passed through intermediate stages of cleaning, evaluation, and calculations to establish the new set of indicators. The goal was to help evaluate the situation at the level of the reference year of the available statistics and obtain scores to rank the counties according to the four categories. The next step was the development of composite indicators at the level of dimensions, as well as an aggregate indicator that captures the four dimensions together.
The tools used were Principal Component Analysis (PCA) combined with Cluster Analysis, which enabled a deep understanding of the original data. The computerized implementation was implemented in R language, together with interactive representations generated using Power BI. The indicators resulting from the application of PCA include most of the variability of the initial dataset, selecting main components that exceed certain thresholds through checks for compliance with the Evrard, Kaiser, and Benzécri criteria. Thus, for the first dimension, SE, 7 main components were retained in the analysis, which cumulate 83.36% of the variance; for the UG dimension, 6 components were retained, which cumulate 83.19% of the variance; the GI dimension retains 4 components with 75.76%; and the ME dimension retains in the analysis 3 components that cumulate 74.72% of the variance. Following the analysis that determined each dimension composite score and then the overall composite indicators, it was observed that the counties of Giurgiu, Teleorman, Ialomița, Brăila, Călărași, Ilfov, Olt, Buzău, Dâmbovița, Vaslui, Botoșani,

Mehedinți, Galați, Satu Mare, Suceava, Dolj, Prahova, Vrancea, Bacău, Sălaj, Covasna are below the country median value (1.72). Scores aim to create an overall image of counties relative performance. The interactive visualization of the data was achieved through a GIS solution, at the level of which it is possible to interact with the indicators at the county level, but also by comparison on dimensions and composite indicators. The computerized framework was designed to be extended for further analysis with various complexity.
In further research, it is proposed to extend the study by developing a methodology that includes proxy indicators and the addition of nonconventional data sources (online real-time data, data extracted from social media etc.). Based on these, artificial intelligence algorithms will be applied to capture changes triggered by major events that can affect both the economic, social, technological, geopolitical, and environmental, either the counties, or even the entire country. It is desirable to develop the analysis to a more detailed level to cover the urban areas that are the largest population centres and poles of economic flows.

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