

An entropic approach for calculating the Human Development Index (HDI) in rural communities: a case study in Ștefan Vodă, Republic of Moldova

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Abstract: The Human Development Index (HDI) is an essential tool for assessing socio-economic progress, but its traditional calculation methods, based on equal weights, can ignore significant variations between indicators. This study proposes an alternative method, using information entropy to objectively determine weights in the HDI calculation, with practical application in the Ștefan Vodă rayon, Republic of Moldova. The analysis focuses on one urban and 22 rural localities, highlighting regional disparities and the necessity for an even more nuanced approach. Data for HDI calculation were analyzed for five key dimensions: education, economy, infrastructure, health and demography. The calculation process followed three stages: normalization (P_{ij}), entropy calculation (E_j) and determination of weights (w_j). The entropy revealed the following objective weights: infrastructure (38.7%), economy (27.7%), health (11.6%), education (11.0%) and demography (11.0%). These differ significantly from the equal weights (20% each), underlining the predominant importance of infrastructure and economy in the context of rural development. The comparison between the initial HDI and the corrected HDI shows significant variations: Purcari (+10.87%, due to strong economic and infrastructure performance); underestimated localities – Alava (-25.13%) and Ștefănești (-20.67%), where the initial HDI overestimated the development due to the uniform weighting; and the case of Ștefan Vodă city, where the corrected HDI (0.747) is slightly lower than the initial one (0.756), reflecting a more realistic assessment when priorities are objectively weighted. The application of entropy highlighted two critical aspects: the high weight of the infrastructure indicator (38.7%), which highlights the critical investment deficit in rural areas, and the significant weight of the economic indicator (27.7%), which reflects pronounced inequalities between localities and requires targeted interventions. The results are aligned with similar studies from Eastern and South-Eastern Europe, where entropy was used to correct composite indices in regional development contexts. The study demonstrates that the entropy approach provides a more accurate assessment of the HDI in rural areas, identifying critical dimensions that require interventions.

1. Introduction

Human development is a fundamental pillar of societal progress, going beyond traditional approaches that are limited to economic indicators. The concept, theoretically initiated by Mahbub ul Haq and later developed by Amartya Sen, focuses on creating an environment in which people can fully realize their potential, enjoying a long and healthy life, with access to knowledge and a decent living standard (Haq, 1995; Sen, 1999). Although it has been subject to criticism and adaptations in recent decades, the Human Development Index (HDI) has remained an essential tool for holistic measurement of

progress, providing a broader perspective on human well-being and the real freedoms enjoyed by individuals (Hickel, 2020). Thus, the trend is moving towards overcoming measurements based exclusively on Gross Domestic Product (GDP), favoring the use of well-being indices that include health and education. Torre (2023) emphasizes that, in the context of growing territorial disparities, the HDI and its adjusted variants are necessary tools to adequately consider the demographic and social characteristics of the local population.

In the European context, many regions face significant vulnerabilities, manifested by sharp socio-economic disparities, high migration rates and unequal access to essential services. These challenges become particularly relevant in the case of Eastern European countries, where economic and political transitions have created deep gaps. In the same context, the Southern Region of the Republic of Moldova is characterized by multiple challenges, such as poverty, accelerated population migration and limited access to basic infrastructure and quality public services (Law of R.M. no. 315/2022; UNDP Moldova, 2023; World Bank, 2022). A rigorous and continuous assessment of human development at the local level is therefore crucial for understanding the dynamics of these phenomena and to develop effective public policies that respond to the specific needs of communities (Ataman, 2022).

Besides the need to quantify progress, an essential element in addressing these challenges is strengthening community's resilience. This resilience involves the capacity of communities to adapt to change, absorb economic or social shocks and innovate, while maintaining social cohesion (Berkes et al., 2013). Approaches that target both human development and resilience align with the principles of sustainable development, a framework that integrates social, economic and environmental dimensions.

Thus, detailed research focused on local needs becomes an essential prerequisite for ensuring equitable and sustainable long-term progress. In this context, this study addresses an essential methodological and empirical gap: the traditional HDI approach, which relies on equal weights (20% for each component), fails to accurately reflect intrinsic disparities and the unequal structure of development at the local level, particularly in vulnerable regions such as rural areas in the Republic of Moldova. This limitation renders assessments less relevant for targeted public policy formulation. The primary objective of this research is, therefore, to propose and apply an alternative methodology based on information entropy to objectively weigh the HDI components at the locality level within the Ștefan Vodă rayon. Specifically, authors aim to:

- 1) determine the objective weights of the HDI components (economy, infrastructure, education, health, and demography) based on their variability;
- 2) assess the variations in the corrected HDI compared to the initial one, identifying underestimated or overestimated localities;
- 3) provide a robust analytical basis for differentiated interventions, supporting the efficient allocation of resources in line with the communities' priority needs. Through this, the study contributes to develop a more accurate and regionally relevant HDI assessment framework at the subnational scale.

2. Literature Review

The analysis of the concept of human development and the HDI has generated references and literature, which has evolved from theoretical underpinnings to nuanced critiques and proposals for adaptation. The conceptual framework, initially put forward by Nobel laureates Amartya Sen and Mahbub ul Haq, represented a paradigm shift, going beyond the simple measurement of economic progress (Anand et Sen, 2000). Furthermore, it has paved the way for a holistic approach of the well-being, which includes health and education. This perspective aligns with contemporary studies emphasizing the need to move beyond GDP, particularly in the context of growing territorial disparities. Torre (2025) specifically highlights the utility of the HDI in this regard, maintaining that it adequately incorporates characteristics such as life

expectancy and education, which are crucial for measuring true well-being and local population performance.

Despite the recognized value of the HDI in encompassing the multidimensionality of development, a fundamental criticism against composite indicators is that they often lack a clear rationale for the chosen weighting and aggregation techniques, compromising their overall comprehensiveness (Moreira & Crespo, 2017).

However, the HDI has been subject to significant methodological criticism (Klugman et al., 2011; Permanyer, 2013). These have mainly concerned the way in which the sub-indices are aggregated, the weight given to each component and possible limitations in reflecting internal inequalities. The challenge of accurately capturing distribution is further complicated when measuring inequality within the HDI framework. For instance, studies analyzing global human development inequality have found conflicting results, where some indices (Gini, Theil, Atkinson) suggest improvement, while others (Kolm Index) suggest a worsening distribution (Martínez, 2012). Thus, numerous proposals for revision have emerged, ranging from adjustments to the income component (Kula et al., 2025) to the integration of additional factors such as environmental sustainability (Hickel, 2020), or its use in specific contexts such as economic history (Amendola et al., 2023; Felice et al., 2015). Alternative uses have also been explored, such as analyzing the HDI as a media narrative in developed countries, raising questions about its relevance in the context of well-being and life quality (Morse, 2023). A comprehensive study even tracked HDI changes in Central and Eastern Europe over a century, from 1913 to 2010, showing the historical dynamics of human development in the region (Holubec et Tomka, 2023).

A significant part of research focuses on the application and relevance of the HDI in assessing disparities at the subnational level, a phenomenon particularly pronounced in Eastern Europe. Case studies from Poland, for example, demonstrate the persistence of development gaps between regions, despite overall progress at the national level (Kusideł, 2013; Pawlas, 2018). A similar approach has been applied in Ukraine, where a geospatial study of the HDI highlighted the uneven distribution of well-being (Kuzyshyn, 2014), and in Serbia, analyses have shown that depopulation, aging and urbanization have a different impact on regions, accelerating population decline in the Eastern and South-Eastern areas while large cities continue to grow (UNDP Serbia, 2022). Also, research applied to Romania has highlighted the existence of social and regional development gaps, underlining the applicability of the HDI in addressing territorial inequalities (Sandu, 2015). A broader perspective, at the European Union level, has led to the development of a Regional Human Development Index, adapted to measure progress in EU regions (Hardeman and Dijkstra, 2014; JRC, 2014), while other studies analyze the composition of the HDI in various European countries, highlighting the fact that a similar score can be the result of unequal performances in the components of health, education and income (Ciupac-Ulici, 2015).

These regional analyses highlight a crucial point: a detailed understanding of small-scale social and economic dynamics is essential to underpin informed policy decisions and to design local, relevant and applicable development strategies.

The need for a comprehensive assessment is critical, particularly since traditional models of local development, such as Territorial Innovation Models (TIMs), have been criticized for lacking from conceptual ambiguity due to an overly narrow focus on technologically driven innovation and a business culture instrumental to the capitalist market logic (Moulaert & Sekia, 2003).

By contrast, an integrated metric like the subnational HDI provides a more holistic basis for designing local strategies that explicitly account for social dimensions, alongside economic performance. This integrated approach is consistent with the theory of Territorial Capital, which defines it as a system of territorial assets of "economic, cultural, social and environmental components that ensures the development potential of places," recognizing the importance of interactions between different factors (Perucca, 2014). By measuring achievements across Health, Education, Economy, and Infrastructure, the

local HDI directly addresses these key assets and their multifaceted contribution to territorial development.

This detailed local assessment is performed against a backdrop of global challenges, where localities seek prosperity amid tumultuous shifts generated by globalization, financial instability, and climate change. Ultimately, the goal of research in this field is to identify frameworks and interventions that might constitute truly holistic, inclusive, progressive, and sustainable local and regional development (Pike et al, 2016).

This ultimate objective is supported by recent studies that advocate for an "ecosystem approach" to territorial sustainability assessment, arguing that the current global context requires a shift away from traditional economic growth policies towards the search for new sustainable models of internal territory development (Tolstyykh et al., 2020).

The Republic of Moldova is part of this general context, facing similar regional disparities, which requires a rigorous assessment of the situation at the local level to understand and combat territorial inequalities (Ataman, 2022).

3. Study Area

Ștefan Vodă rayon, located in the South-East of the Republic of Moldova, on the border with Ukraine, occupies an area of 998 km² (2.9% of the country's territory). It consists of 22 rural communes and a single urban center - the Ștefan Vodă city (Figure 1), which has 7.095 inhabitants and serves as the administrative residence (NBS, Population by age groups, 2023).

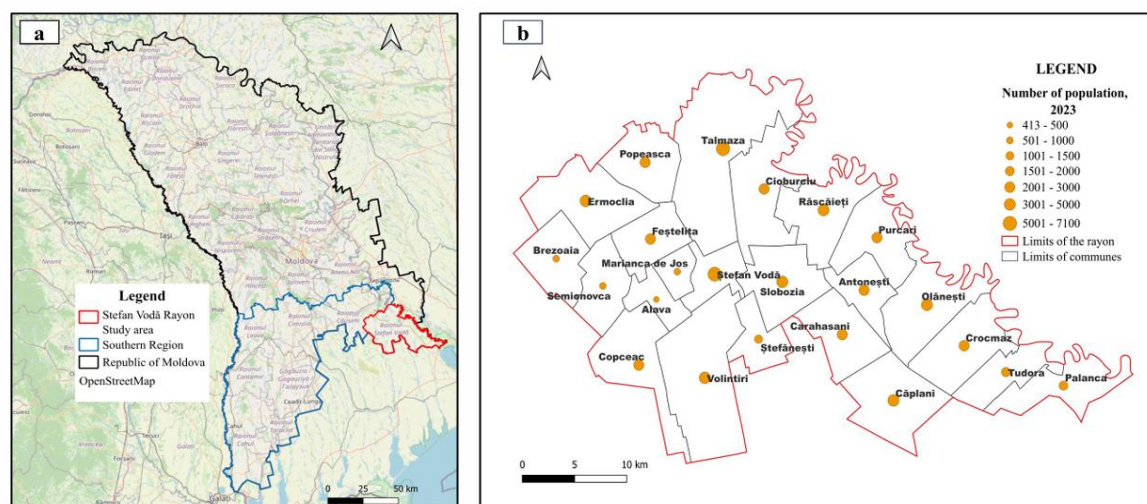


Figure 1. Geographical position (a) and localities network (b) of the Ștefan Vodă rayon, Republic of Moldova

From a demographic perspective, the rayon is facing a profound transformation process, marked among others by depopulation. The current population has decreased from 69.1 thousand inhabitants in 2014 to approximately 62.6 thousand in 2023, and the population density from 69.2 to 62.7 inhabitants/km². According to preliminary data from the 2024 Population and Housing Census, the rayon's population was 42.3 thousand inhabitants, a decrease of 27.3% compared to 2014 (NBS, 2025). This trend is especially evident in rural areas, where over 88.7% of the inhabitants live, with an uneven distribution: from larger communes such as Talmază and Olănești, with over 4.000 inhabitants, to small localities such as Marianca de Jos and Alava, with under 600 inhabitants. The district is facing a sharp demographic aging process. The average age increased from 37.3 years in 2014 to 41.4 years in 2023, being above the national average and in line with the trend of the Southern Region (41.3 years). At the same time, the Demographic Dependency Index rose from 41.9 to 55.7 in the same period, constantly exceeding the national average.

Although most localities have access to public water supply system, only 3 of them are also connected to the public sewage network, which indicates a major gap regarding development of sanitation infrastructure (NBS, Territorial Statistics, 2024). The demographic size and socio-economic situation of the localities directly influence their administrative capacity, so only 9 mayoralties in the rayon are considered to have adequate institutional capacity, defined by the share of administrative expenses below 50% of total own revenues, tax breakdowns and general transfers. Together, these challenges contribute to the widening of development gaps between rural and urban areas, creating difficulties in the efficient management of local development and in the provision of basic services, especially in small villages.

4. Materials and Method

4.1. Data sources and Study Variables

The HDI research methodology for the localities in the Ștefan Vodă rayon was based on the evaluation of statistical indicators structured on 15 subcomponents that make up 5 main components: economy (Ministry of Finance, Circular Budget, 2024-2026; M.F., Adjusted Information, 2024), infrastructure (NBS, Housing and Water Networks, 2016-2023), demography (NBS, Population by age groups, 2023), health (NBS; Morbidity from malignant tumors, 2014-2023) and education (NBS, Primary and Secondary Education, 2015/16-2023/24).

4.2. Validation of Indicator Robustness (Collinearity Testing)

Ensuring the quality and independence of indicators is a crucial step in the methodology of constructing any composite index, serving as a precondition for obtaining objective and reliable weights. In the case of the entropic approach used in this study, it is vital that each indicator provides a unique informational contribution, as the Information Entropy method assigns greater weights to indicators with higher variation (higher entropy). Redundant (highly correlated) indicators share the same information, reducing the unique variation perceived by the algorithm and thus distorting the weights.

Table 1. Robustness Validation of Multicollinearity for Indicators using the Variance Inflation Factor (VIF)

Dimension	Indicators	R ²	VIF	Robustness
Economy	Administrative Capacity (%)	0.4092	1.692	Maximum Robustness
	Own Revenues (%)	0.3482	1.534	Maximum Robustness
Infrastructure	Investments in Local Road Infrastructure (lei/km)	0.6066	2.542	High Robustness
	Access to the Own and Centralized Sewerage System (%)	0.742	3.876	Acceptable Robustness
Demography	Demographic Balance (%)	0.5699	2.325	High Robustness
	Demographic Dependency (%)	0.3916	1.644	Maximum Robustness
Health	Accessibility of Emergency Medical Services (EMS) (km)	0.5473	2.209	High Robustness
	Tumour Incidence Rate (per 10,000 population)	0.3536	1.547	Maximum Robustness
Education	Occupied Places in School Institutions	0.5499	2.222	High Robustness
	Generation Replacement Coefficient	0.4446	1.800	High Robustness

Note: Robustness thresholds are: Maximum Robustness (VIF ≤ 1.7), High Robustness (1.7 < VIF < 2.5), and Acceptable Robustness (VIF < 5.0).

Therefore, the study applied multicollinearity analysis to validate the final set of 10 key indicators (two per dimension, as used in the entropy calculation). Multicollinearity

manifests itself through strong correlations between indicators, indicating an informational redundancy which, if not addressed, would lead to an unjustified over-representation of a certain dimension in the final index.

To quantify the degree of collinearity and test the independence of the indicators, the Variance Inflation Factor (VIF) was used. This test measures how much the variance of an estimated coefficient is inflated due to its collinearity with the other indicators in the set. In statistical and econometric studies, a VIF value below 5.0 is generally considered an indicator of acceptable model robustness (Table 1). For a more nuanced analysis, we classified the results into three robustness levels: Maximum ($VIF \leq 1.7$), High ($1.7 < VIF < 2.5$), and Acceptable ($VIF < 5.0$).

Table 1 presents the results of the VIF test. All indicators show VIF values significantly below the critical threshold of 5.0, confirming the absence of severe multicollinearity. The indicator with the highest variance inflation is "Access to the Own and Centralized Sewerage System (%)" ($VIF = 3.876$), which remains within the acceptable robustness range. This statistical validation ensures that each variable in our final set contributes sufficiently distinct information, thereby fulfilling a fundamental precondition for the subsequent entropy-based weighting.

4.3. Data Normalization and HDI Calculation

Since the statistical indicators have different measurement units, it was necessary to standardize the values so as to reach a common denominator (Table 2). The formula applied to each data string (indicators) is:

$$IDU_j^i = a_j^i - a_j^{min} / a_j^{max} - a_j^{min} \quad (1)$$

where:

IDU_j^i – the value of human development index j in territorial unit i ;

a_j^i – level of indicator j in unit i ;

a_j^{min} – level of indicator j in territorial unit with minimum performance;

a_j^{max} – level of indicator j in territorial unit with maximum performance;

Based on these indicators, the aggregate Human Development Index was calculated at the level of primary units (Table 2).

Table 2. Human Development Index, by components, year 2023.

Localities	Education	Economy	Infrastructure	Health	Demography	HDI
Ștefan Voda	0.716	0.589	1.000	0.759	0.716	0.756
Alava	0.001	0.077	0.020	0.810	0.001	0.182
Antonești	0.503	0.311	0.691	0.571	0.503	0.516
Brezoaia	0.658	0.276	0.061	0.414	0.658	0.413
Carahasani	0.427	0.366	0.271	0.212	0.427	0.340
Caplani	0.460	0.346	0.222	0.286	0.460	0.355
Cioburciu	0.449	0.249	0.382	0.484	0.449	0.402
Copceac	0.427	0.084	0.356	0.689	0.427	0.397
Crocmaș	0.437	0.301	0.352	0.565	0.437	0.419
Ermoclia	0.656	0.335	0.317	0.416	0.656	0.476
Feștești	0.740	0.455	0.219	0.481	0.740	0.527
Marianca de Jos	0.646	0.112	0.330	0.815	0.646	0.510
Olănești	0.591	0.482	0.382	0.529	0.591	0.515
Palanca	0.515	0.590	0.272	0.399	0.515	0.458
Popeasca	0.466	0.259	0.313	0.445	0.466	0.390
Purcari	0.477	0.974	0.292	0.520	0.477	0.548
Răscăiești	0.570	0.171	0.235	0.507	0.570	0.411
Semionovca	0.416	0.436	0.141	0.270	0.416	0.336
Slobozia	0.578	0.308	0.127	0.715	0.578	0.461
Ștefănești	0.633	0.142	0.187	0.729	0.633	0.465
Talmază	0.518	0.569	0.195	1.000	0.518	0.560
Tudora	0.693	0.228	0.211	0.457	0.693	0.456
Volintiri	0.656	0.371	0.070	0.881	0.656	0.527

Source: Calculated based on the standardization of primary statistical indicators.

4.4. Entropy-Based Weighting and HDI Correction

To correct the aggregate Human Development Index at the level of the localities within Ștefan Vodă rayon, the specific weight (w_j) of each structural component was calculated, according to the information entropy formula, used in the mathematical modeling of geographical systems (Neguț, 1997): where:

$$w_j = 1 - E_j / \sum_{i=1}^n (1 - E_j) \quad (2)$$

E_j – entropy value;

w_j – specific weight of each HDI component.

The selection of this entropy measure is strongly supported in regional analysis, where it is recognized as a significant instrument for analyzing spatial differences and transforming it into an objective measure of inequality. This approach is particularly valuable as it allows for the decomposition of total inequality into inter- and intra-regional components, which is crucial for precisely revealing local disparities (Czyż & Hauke, 2015).

Table 3. Specific weight (w_j) of the components in the HDI structure for the localities in the Ștefan Vodă rayon.

Coefficients	Education	Economy	Infrastructure	Health	Demography
E_j	0.980573	0.951029	0.931750	0.979592	0.980573
$1-E_j$	0.019427	0.048971	0.068250	0.020408	0.019427
	0.110077	0.277485	0.386725	0.115636	0.110077
w_j	11.0	27.7	38.7	11.6	11.0

Source: calculated by the authors.

Table 4. Adjusting the Human Development Index through the Entropy Method, year 2023.

Localities	HDI rev.	HDI init.	Abs.Var.	Var (%)
Ștefan Voda	0.747	0.756	-0.01	-1.15
Alava	0.136	0.182	-0.05	-25.13
Antonești	0.492	0.516	-0.02	-4.62
Brezoaia	0.350	0.413	-0.06	-15.25
Carahasani	0.340	0.340	0.00	-0.06
Caplani	0.340	0.355	-0.01	-4.02
Cioburciu	0.369	0.402	-0.03	-8.39
Copceac	0.326	0.397	-0.07	-17.74
Crocmaș	0.386	0.419	-0.03	-7.66
Ermoclia	0.433	0.476	-0.04	-9.11
Feștești	0.482	0.527	-0.04	-8.51
Marianca de Jos	0.408	0.510	-0.10	-19.93
Olănești	0.495	0.515	-0.02	-3.94
Palanca	0.466	0.458	0.01	1.80
Popeasca	0.355	0.390	-0.03	-8.89
Purcari	0.608	0.548	0.06	10.87
Răscăiești	0.344	0.411	-0.07	-16.31
Semionovca	0.337	0.336	0.00	0.36
Slobozia	0.394	0.461	-0.07	-14.67
Ștefănești	0.369	0.465	-0.10	-20.67
Talmază	0.519	0.560	-0.04	-7.31
Tudora	0.386	0.456	-0.07	-15.41
Volintiri	0.445	0.527	-0.08	-15.56

Source: calculated by the authors by adjusting the component indicators of the initial HDI.

The results of the values (w_j) are presented in Table 3. Moreover, the data in the table indicate that the infrastructure component has the greatest weight in the HDI structure calculated for the localities in the Ștefan Vodă rayon (38.7%), followed by the HDI components with a lower weight.

Following the steps of the entropic methodology, we determined the objective weights (w_j) for each of the five dimensions of the HDI within the context of the Ștefan Vodă rayon. These weights reflect the actual contribution of each indicator to the overall disparity and are essential for the final index adjustment. Table 4 presents the final results of the process of adjusting the Human Development Index using the Entropy method for the year 2023, highlighting the objectively determined weights and the final adjusted HDI value for each locality

5. Results

For a deeper understanding of the factors influencing Human Development, the present analysis was focused on each of the five main components of the HDI.

Economic component of the HDI. Primary statistical data and standardized indices for the economic component reveal a variety of performances and contributions to local development. Administrative expenses, own revenues, and the own revenues rate provide a complex framework of the financial and economic situation of the localities in the Ștefan Vodă rayon (Figures 2 and 3). Based on the final index calculated for the economic component of the HDI, the commune of Purcari recorded the maximum value among all localities (including the city) (0.974). This performance is sustained by the high contribution of own revenues within the local budget (45.8%), suggesting increased financial autonomy. The Ștefan Vodă city records a final economic index of 0.589 (Figure 4).

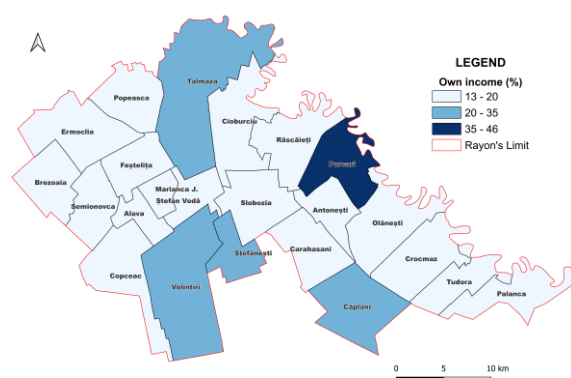


Figure 2. Own income, 2023 (%)

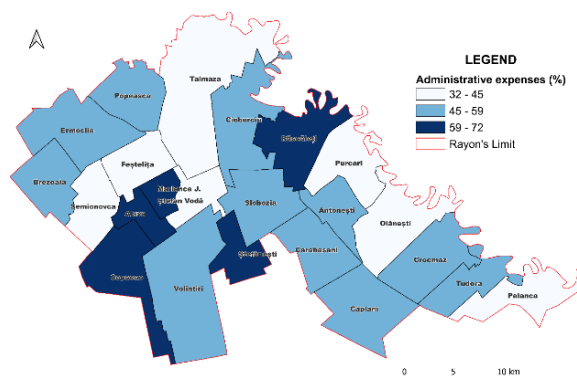


Figure 3. Administrative expenses, 2023 (%)

At the other extreme, localities such as Alava (0.077), Copceac (0.084), and Marianca de Jos (0.112) record the lowest final economic indices, indicating substantial challenges in terms of economic development. Another outstanding aspect is the share of administrative expenses. Alava (71.6%) and Marianca de Jos (71.3%) record the highest shares, which could limit investment in development. This trend is also reflected in their relatively low final economic indices. The share of own revenues in the budget varies from a minimum of 14.1% in Popeasca to a maximum of 45.8% in Purcari, highlighting various degrees of financial autonomy.

Overall, the analysis highlights the vital importance of generating own revenues and efficiently managing administrative expenses for sustainable economic development at the locality level. It is observed that localities with higher economic indices are generally those that manage to generate significant revenues per capita and keep administrative expenses under control.

Infrastructure component of the HDI. Analysis of data on the provision of housing stock with own and centralized sewage systems and the volume of public investments for the maintenance of local roads highlights significant disparities (Figures 5 - 7).

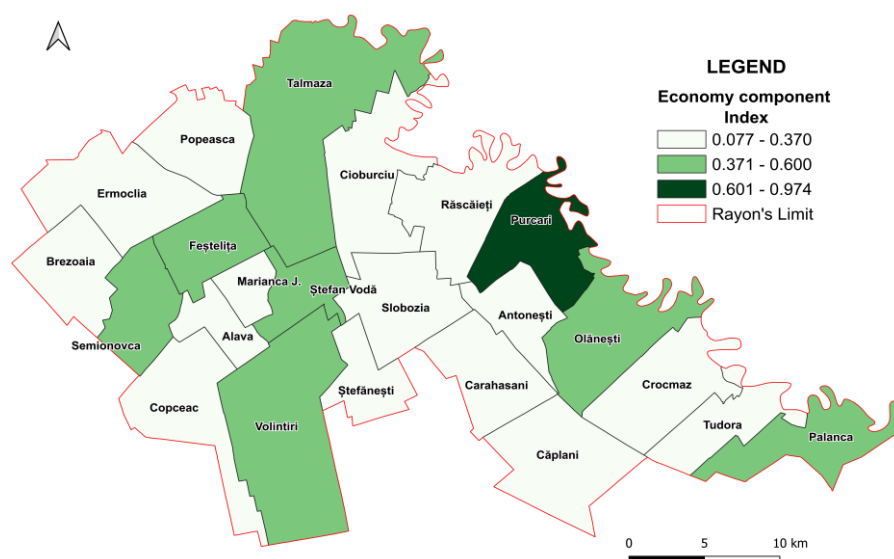


Figure 4. Economy component Index, 2023

The Ștefan Vodă city clearly stands out as having the most developed infrastructure, with a final score of (1.000), reaching the maximum value. This performance is supported by a very high degree of coverage of the locality with sewage systems (94.8%). The high amount of financial transfers allocated for local road maintenance suggests increased interconnectivity across the rayon (Figure 6).

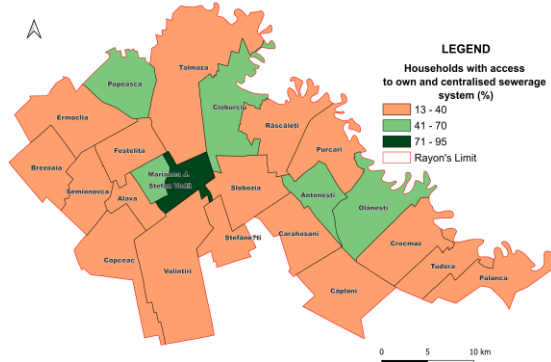


Figure 5. Households with access to own and centralized sewerage system, 2023 (%)

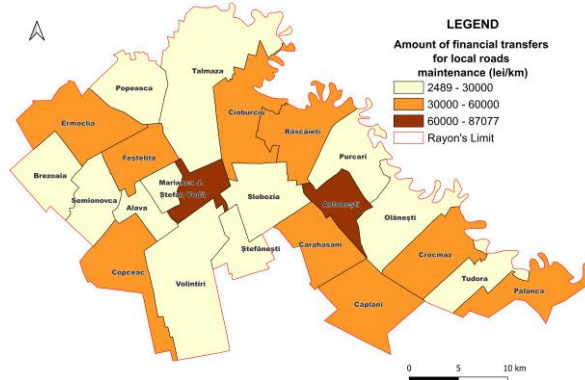


Figure 6. Amount of financial transfers for local road maintenance, 2023 (lei/km)

At the opposite pole, localities Alava (0.020), Brezoaia (0.061), Volintiri (0.070), and Semionovca (0.141) record the lowest final infrastructure scores (Figure 7). These localities generally face low coverage rates with sewage systems, highlighting the persistence of major challenges in ensuring basic infrastructure services. Also, the low volume of transfers for local road maintenance in these localities significantly influences the level of local economic development. These gaps highlight the persistence of major challenges in ensuring basic infrastructure services.

This critical importance of infrastructure is supported by theories of Socio-Ecological Systems (SEs), which recognize "engineered works" as essential "physical capital"

whose provision and maintenance are vital for the long-term robustness and persistence of the entire social system (Anderies et al., 2004).

The demographic component of the HDI reflects the population dynamics and structure, being influenced by the total population balance and the demographic dependency ratio (Figures 8 - 10). The total population balance is negative for all localities in the rayon, though with varying degrees of severity, reflecting a generalized demographic problem. The data analysis highlights a variety of demographic situations, with direct implications for local development.

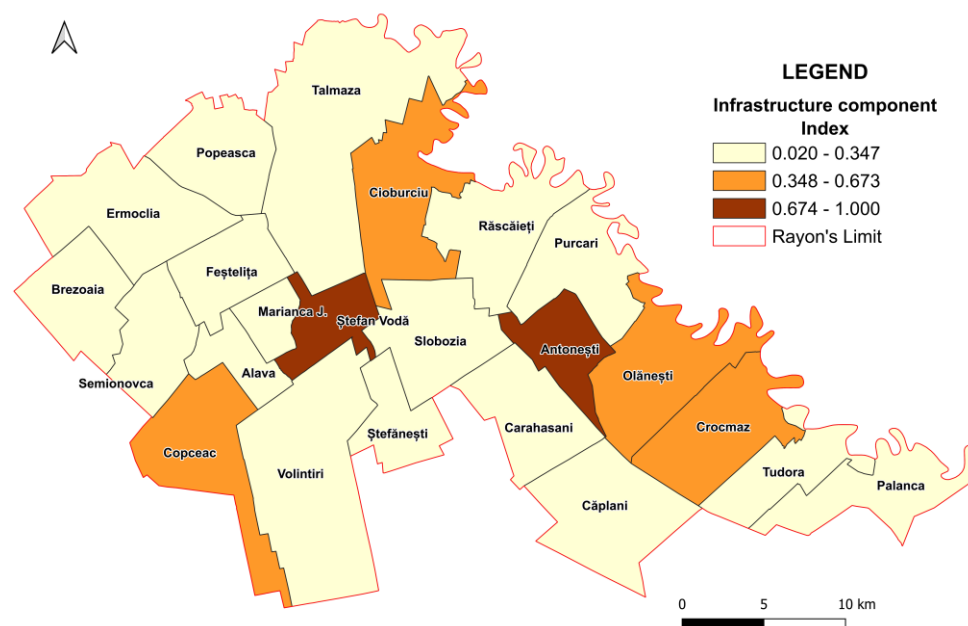


Figure 7. Infrastructure component Index, 2023

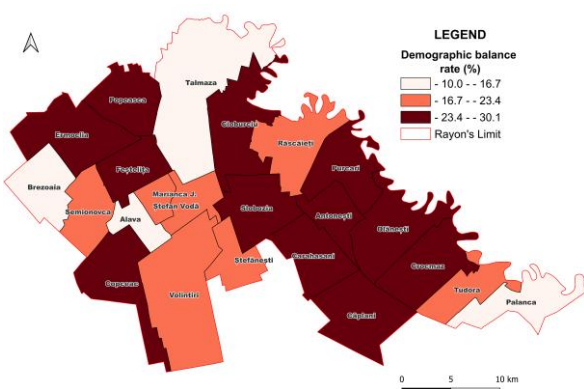


Figure 8. Demographic balance rate, 2023 (%)

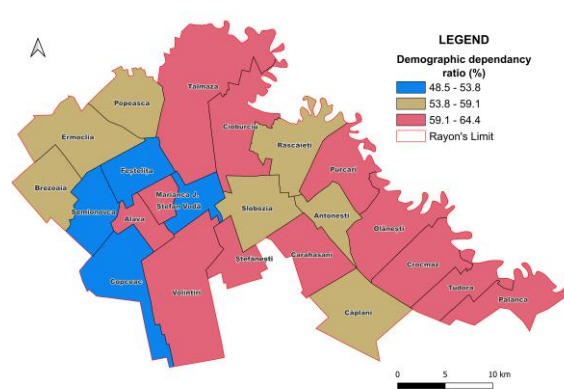


Figure 9. Population aging coefficient, 2023 (%)

The Ștefan Vodă city records the highest Demographic component Index of 0.716 (Figure 10). This score is supported by a relatively low demographic dependency rate (48.5%). Among rural localities, Tudora (0.693) registers the highest score, followed by Brezoaia (0.658) and Volintiri (0.656), which also stand out with high values. At the opposite pole, Alava (0.001), Carahasani (0.427), Purcari (0.477), and Căplani (0.460) record the lowest final scores for the demographic component (Figure 10).

This weak position is often associated with high demographic dependency rates (Palanca with 64.1%, Răscăieți with 62.0%), reflecting significant pressures on the active population. Localities such as Alava (0.001) and Marianca de Jos (0.646) present

below-average demographic scores, where the population balance is marked by significant losses (Alava with -10.0% and Marianca de Jos with -18.2%).

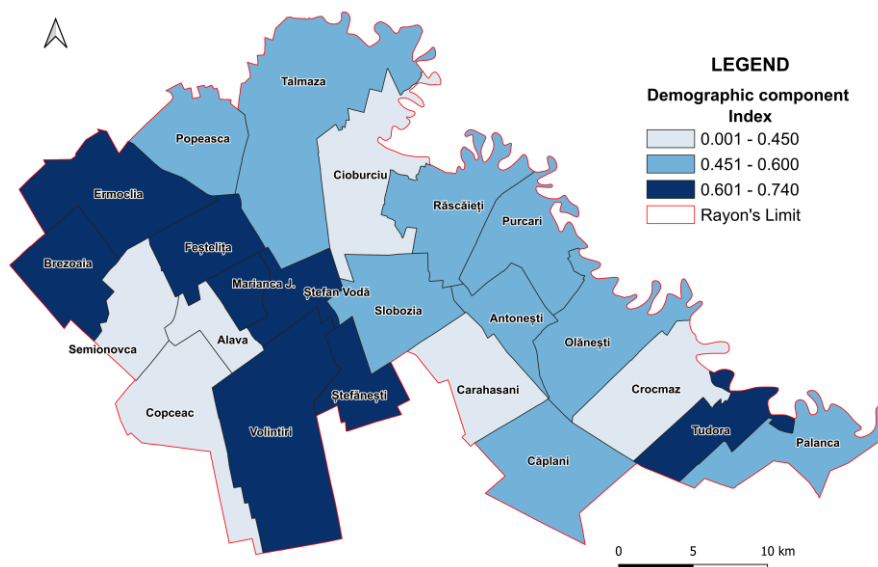


Figure 10. Demographic component Index, 2023

The education component of the HDI provides insight into the dynamics and performance of the local education system (Figures 11-13). The final scores of this component vary significantly between localities, reflecting disparities regarding access and use of educational resources. Feștelîța commune records the highest final score for the education component (0.740), slightly surpassing Ștefan Vodă city (0.716). This top performance is supported by two key favorable indicators: a high school occupancy rate (Feștelîța: 51.6%; Ștefan Vodă: 68.2%) and a positive replacement coefficient of school generations (Feștelîța: 5.7; Ștefan Vodă: 3.4).

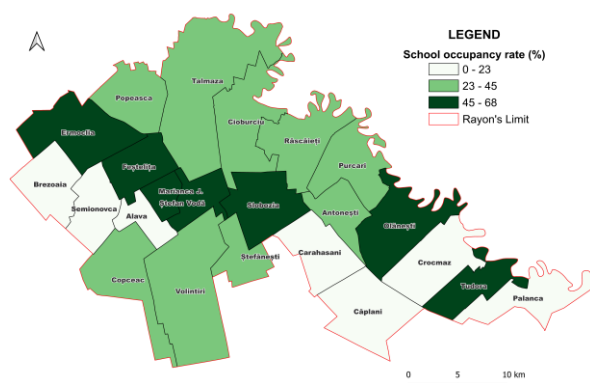


Figure 11. School occupancy rate, 2023 (%)

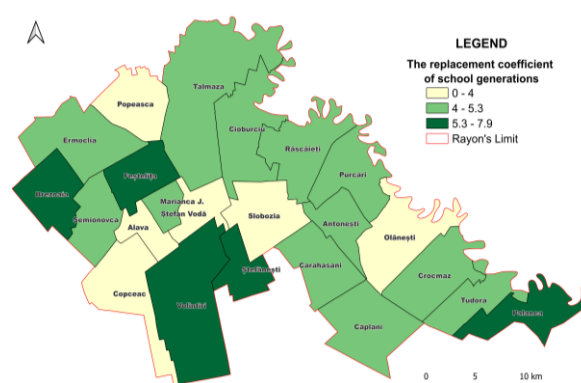


Figure 12. Occupancy rate of places in preschool institutions, 2023 (%)

The city's higher occupancy rate in schools (68.2%) primarily drives its overall high score. Tudora (0.693), Brezoaia (0.658), and Ermoclia (0.656) also stand out with high scores. At the opposite end, Alava village (0.001) is at the bottom of the ranking (Figure 13).

This score primarily reflects the absence of primary and secondary education institutions in the locality, which results in a 0.0% school occupancy rate and a zero generation replacement coefficient (0.0). Other localities with low scores include Semionovca (0.416), Carahasani (0.427), and Copceac (0.427), which generally have

low rates of pupil occupancy (14.8%, 19.8%, and 28.8%, respectively). These low rates, alongside the reduced values of the generation replacement coefficient (e.g., Copceac 3.4), indicate severe problems with the accessibility or attractiveness of local educational institutions.

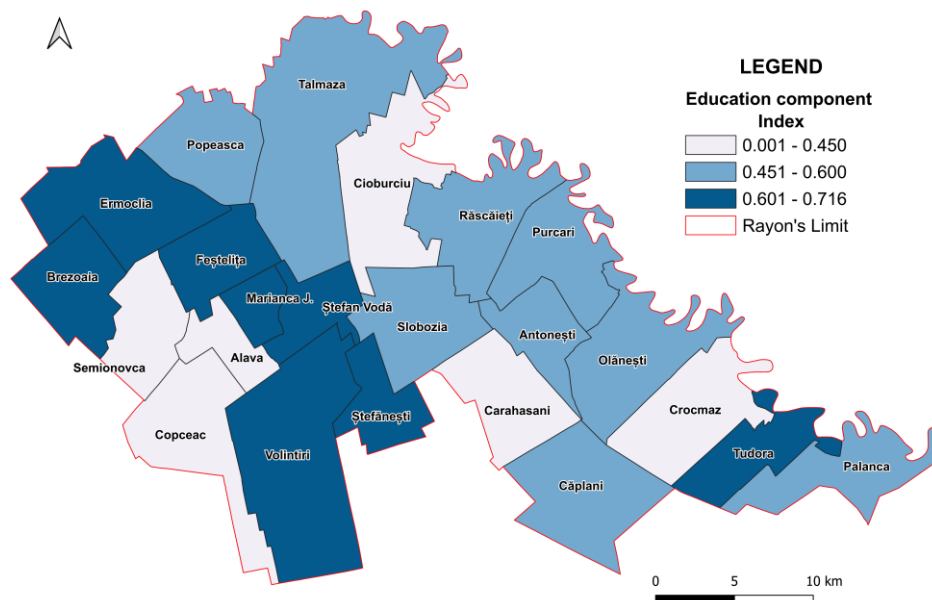


Figure 13. Education component Index, 2023

The health component of the HDI, reflected in the incidence of malign tumors and access to emergency medical services, provides an essential overview of the population's health status in the localities of the Ștefan Vodă rayon. This component is directly influenced by the accessibility and effectiveness of the primary health care network (Figures 14 - 15).

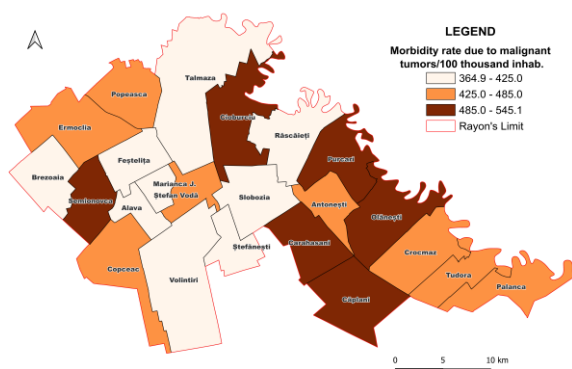


Figure 14. Morbidity rate from malignant tumors, 2023

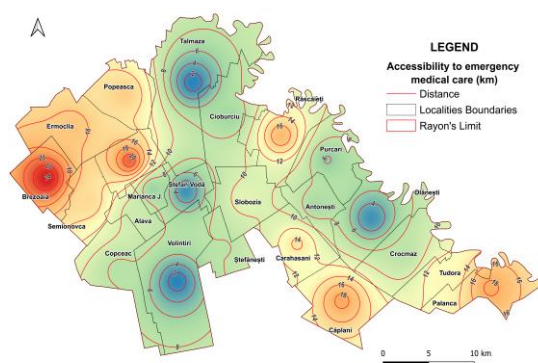


Figure 15. Accessibility to emergency medical care (km), 2023

Talmază commune is prominent with the highest final score for the health component (1.000), reaching the maximum value. This result is obtained despite a malignant tumor incidence of 364.9 per 100,000 inhabitants, suggesting that proximity to medical services (1.0 km distance to the hospital) is a major compensating factor (Figures 14-15). Volintiri (0.881) and Alava (0.810) villages also register high final scores, indicating a relatively favorable health situation, influenced by easy access to emergency medical services. At the opposite end, rural mayoralties such as Carahasani (0.212), Căplani (0.286), Feștelita (0.481), and Antonești (0.571) indicate the lowest final scores for the health component (Figure 16). These localities face very high incidences of malignant tumors combined with long distances to the nearest hospital

(Feștești 21.1 km and Brezoaia 24.1 km), which aggravates public health problems and access to treatment (Figure 15).

The Ștefan Vodă city, despite its administrative function, obtains a final score of 0.759 for the health component. This is due to a significant incidence of malignant tumors (441.8), suggesting that the urban environment does not automatically guarantee a better state of health, due to population density or other risk factors. Thus, the analyzed data highlight the presence of critical disparities in the health status of the population and in access to health services in the Ștefan Vodă rayon. The incidence of serious diseases (malignant tumors), combined with limited access to medical infrastructure, especially in remote rural areas, represents a major challenge. It is imperative to develop and implement targeted public health policies aimed at reducing the incidence of diseases and improving the accessibility of health services, especially in the lowest performing localities.

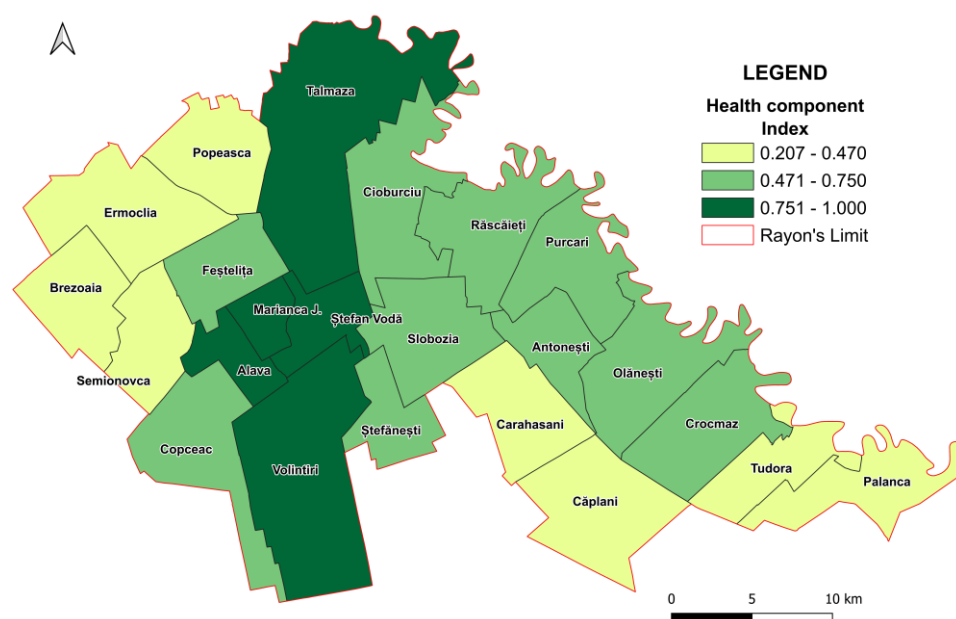


Figure 16. Health component Index, 2023

Euclidean Distance Matrix. The analysis of the Euclidean Distance Matrix for HDI values at the level of the mayoralties in the Ștefan Vodă rayon provides a quantitative perspective on the similarities and differences between them. Each value in the matrix represents the Euclidean distance between the HDI of the locality (i) and the HDI of the locality (j). Therefore, low values indicate high similarity, while high values signal significant differences in the level of the human development index (Table 5).

The city of Ștefan Vodă demonstrates a distinct position within the matrix, having relatively large distances from most rural settlements. For instance, the distance to the Alava commune is considerable (0.420), reflecting a pronounced development gap. Nevertheless, its distance to the Antonești commune is significantly smaller (0.148), suggesting a relative similarity, even though, at a general level, the city is more developed. At the other end of the spectrum, a very high similarity among certain localities is noteworthy. For example, the Carahasani and Căplani localities have an extremely small distance between them (0.022), indicating a nearly identical development profile. Similarly, the Cioburciu and Crocmaz localities (0.021) or Tudora and Râșcăieți (0.027) present minimal dissimilarity, being the first ones to merge in the dendrogram. Concurrently, within the matrix, it is observed that the Purcari commune generally has larger distances from most other rural localities compared to the city of Ștefan Vodă. This is visible through its large distance from Copceac (0.249) and Alava (0.282). This observation supports the idea that the development profile of the Purcari commune is more distinct or less "average" in relation to the other communes in the

district, often being an isolated case defined by singular economic variables (e.g., very high own revenues).

Table 5. Euclidean distance indicator matrix

Localities	Ștefan Voda	Alava	Antonești	Brezoaia	Carahasani	Caplani	Cioburciu	Copceac	Crocmaș	Ermoclia	Festelița	Marianca de Jos	Olănești	Palanca	Popeasca	Purcari	Răscăieți	Semionovca	Slobozia	Ștefănești	Talmaza	Tudora	Volintiri
Ștefan Voda	0.000	0.420	0.148	0.376	0.299	0.316	0.262	0.289	0.267	0.276	0.306	0.291	0.243	0.286	0.286	0.298	0.320	0.343	0.347	0.338	0.314	0.323	0.365
Alava	0.420	0.000	0.280	0.126	0.158	0.143	0.168	0.147	0.161	0.175	0.178	0.157	0.204	0.196	0.150	0.282	0.129	0.142	0.118	0.119	0.174	0.143	0.132
Antonești	0.148	0.280	0.000	0.246	0.169	0.184	0.121	0.145	0.131	0.148	0.191	0.154	0.129	0.181	0.148	0.240	0.181	0.218	0.219	0.202	0.210	0.190	0.245
Brezoaia	0.376	0.126	0.246	0.000	0.095	0.074	0.129	0.135	0.119	0.100	0.080	0.123	0.138	0.121	0.102	0.216	0.075	0.068	0.046	0.071	0.120	0.060	0.060
Carahasani	0.299	0.158	0.169	0.095	0.000	0.022	0.063	0.101	0.055	0.047	0.066	0.107	0.070	0.067	0.044	0.173	0.069	0.054	0.085	0.098	0.112	0.067	0.115
Caplani	0.316	0.143	0.184	0.074	0.022	0.000	0.071	0.101	0.061	0.050	0.058	0.103	0.080	0.072	0.046	0.179	0.058	0.041	0.065	0.082	0.104	0.053	0.096
Cioburciu	0.262	0.168	0.121	0.129	0.063	0.071	0.000	0.053	0.021	0.048	0.096	0.065	0.068	0.105	0.027	0.204	0.064	0.110	0.105	0.091	0.130	0.077	0.138
Copceac	0.289	0.147	0.145	0.135	0.101	0.101	0.053	0.000	0.062	0.086	0.128	0.039	0.115	0.148	0.059	0.249	0.061	0.137	0.111	0.075	0.153	0.085	0.143
Crocmaș	0.267	0.161	0.131	0.119	0.055	0.061	0.021	0.062	0.000	0.042	0.082	0.069	0.057	0.089	0.024	0.188	0.062	0.096	0.091	0.086	0.109	0.072	0.122
Ermoclia	0.276	0.175	0.148	0.100	0.047	0.050	0.048	0.086	0.042	0.000	0.053	0.077	0.051	0.076	0.037	0.180	0.058	0.084	0.082	0.082	0.107	0.051	0.110
Festelița	0.306	0.178	0.191	0.080	0.066	0.058	0.096	0.128	0.082	0.053	0.000	0.112	0.068	0.056	0.078	0.152	0.084	0.064	0.066	0.094	0.077	0.063	0.079
Marianca de Jos	0.291	0.157	0.154	0.123	0.107	0.103	0.065	0.039	0.069	0.077	0.112	0.000	0.110	0.144	0.066	0.244	0.055	0.137	0.097	0.057	0.140	0.070	0.124
Olănești	0.243	0.204	0.129	0.138	0.070	0.080	0.068	0.115	0.057	0.051	0.068	0.110	0.000	0.055	0.071	0.142	0.103	0.102	0.112	0.123	0.094	0.098	0.131
Palanca	0.286	0.196	0.181	0.121	0.067	0.072	0.105	0.148	0.089	0.076	0.056	0.144	0.055	0.000	0.094	0.108	0.118	0.069	0.103	0.135	0.076	0.107	0.116
Popeasca	0.286	0.150	0.148	0.102	0.044	0.046	0.027	0.059	0.024	0.037	0.078	0.066	0.071	0.094	0.000	0.199	0.043	0.085	0.081	0.072	0.117	0.054	0.115
Purcari	0.298	0.282	0.240	0.216	0.173	0.179	0.204	0.249	0.188	0.180	0.152	0.244	0.142	0.108	0.199	0.000	0.225	0.163	0.197	0.237	0.131	0.212	0.195
Răscăieți	0.320	0.129	0.181	0.075	0.069	0.058	0.064	0.061	0.062	0.058	0.084	0.055	0.103	0.118	0.043	0.225	0.000	0.090	0.061	0.034	0.126	0.027	0.096
Semionovca	0.343	0.142	0.218	0.068	0.054	0.041	0.110	0.137	0.096	0.084	0.064	0.137	0.102	0.069	0.085	0.163	0.090	0.000	0.068	0.105	0.096	0.080	0.086
Slobozia	0.347	0.118	0.219	0.046	0.085	0.065	0.105	0.111	0.091	0.082	0.066	0.097	0.112	0.103	0.081	0.197	0.061	0.068	0.000	0.052	0.084	0.052	0.036
Ștefănești	0.338	0.119	0.202	0.071	0.098	0.082	0.091	0.075	0.086	0.082	0.094	0.057	0.123	0.135	0.072	0.237	0.034	0.105	0.052	0.000	0.124	0.042	0.080
Talmaza	0.314	0.174	0.210	0.120	0.112	0.104	0.130	0.153	0.109	0.107	0.077	0.140	0.094	0.076	0.117	0.131	0.126	0.096	0.084	0.124	0.000	0.117	0.078
Tudora	0.323	0.143	0.190	0.060	0.067	0.053	0.077	0.085	0.072	0.051	0.063	0.070	0.098	0.107	0.054	0.212	0.027	0.080	0.052	0.042	0.117	0.000	0.084
Volintiri	0.365	0.132	0.245	0.060	0.115	0.096	0.138	0.143	0.122	0.110	0.079	0.124	0.131	0.116	0.115	0.195	0.096	0.086	0.036	0.080	0.078	0.084	0.000

Source: author's calculations.

The matrix of Euclidean Distances provides the numerical basis on which the dendrogram is built, visualizing groups of localities with similar profiles of the Human Development Index (Figure 17). The dendrogram illustrates how the localities combine into successive clusters, with the length of the horizontal line indicating the distance at which the union is made, i.e. the degree of dissimilarity. The shorter the horizontal line, the more similar the united localities or clusters are.

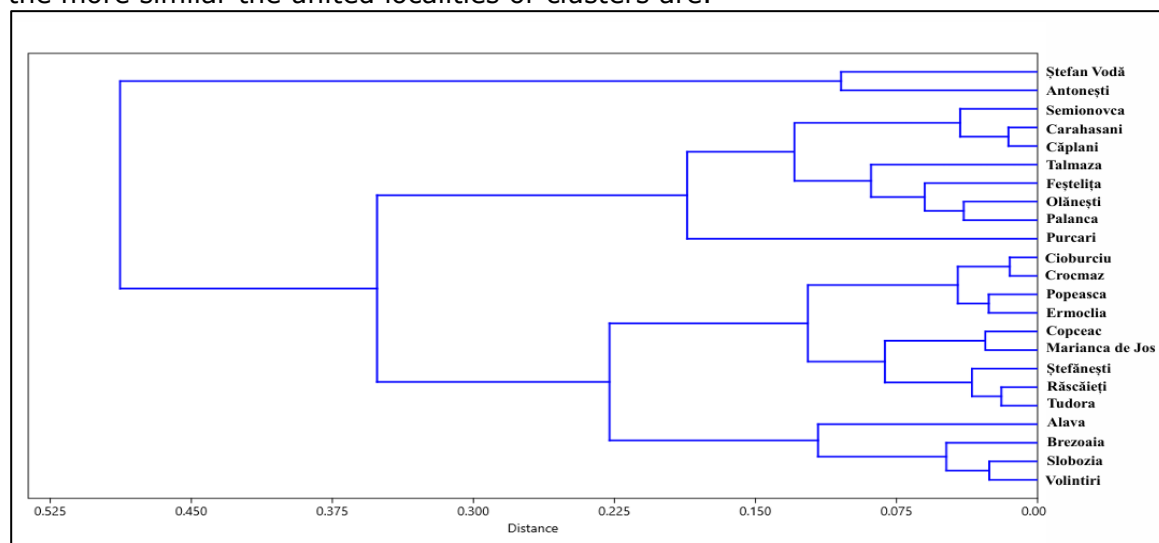


Figure 17. Dendrogram of hierarchical clustering of the localities in the Ștefan Vodă rayon based on the similarity of the Human Development Index (HDI) (Source: developed by the authors based on the Euclidean Distance Matrix).

A detailed analysis of the dendrogram structure allows for the visual identification of four distinct groups, each characterized by a similar Human Development Index (HDI) profile (Figure 18). These clusters provide a solid basis for targeted interventions, as each represents a unique combination of strengths and vulnerabilities:

Cluster I: Localities with superior administrative capacity and high demographic dependency. This cluster defines the capability for revenue generation and administrative efficiency. It functions as the economic anchor of the district. However, even the most developed areas are not immune to the region's health and demographic challenges.

Cluster II: Localities with adequate basic infrastructure and severe demographic decline. This cluster signals imminent demographic risk, demonstrating that possessing essential infrastructure does not guarantee population retention and highlighting the urgency of interventions aimed at labor force stabilization.

Cluster III: Localities with moderate income and a deficit in sanitation services. This group highlights a critical material need—insufficient sewerage and water supply. It is a cluster where a single major investment could unlock development, improving both the quality of life and the attractiveness of the areas.

Cluster IV: Localities with low demographic dependency and high administrative expenditures. This cluster represents the lowest level of governance and development, manifesting in the combination of limited financial resources and inefficient budget allocation, as evidenced by high administrative expenditures. Addressing these issues requires a comprehensive approach that targets both funding optimization and local administrative reform.

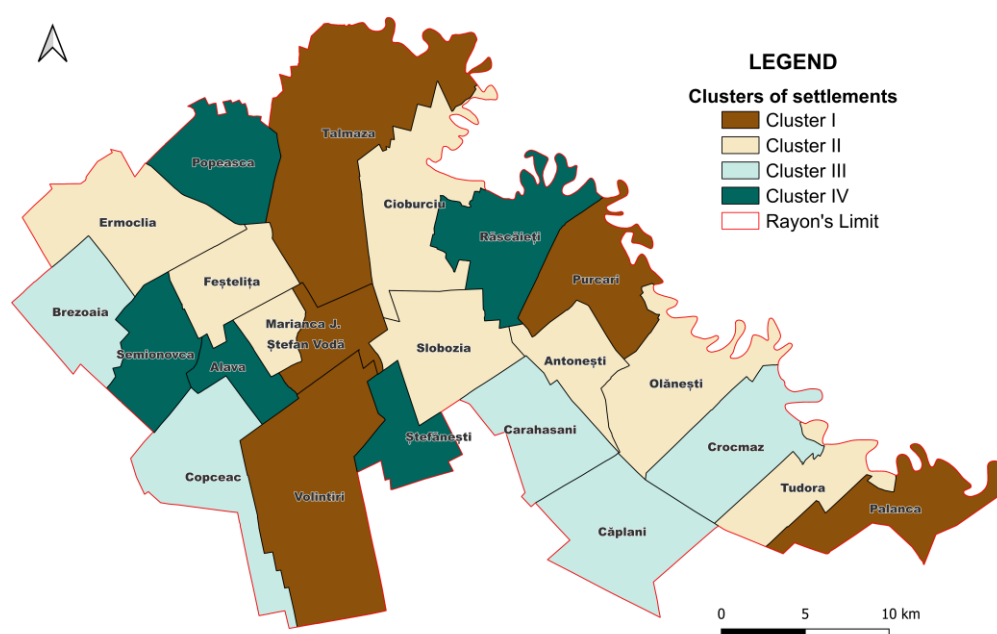


Figure 18. Clusters of settlements

Entropy analysis and dendrogram visualization have confirmed the existence of significant human development disparities in the Ştefan Vodă rayon. The results highlighted clear clusters of localities with similar profiles, from those with high performance (Ştefan Vodă city and Purcari commune) to those with major gaps (such as Carahasani and Căplani). These findings highlight the vital importance of a personalized approach in the development policy-making, which takes into account the specific needs of each cluster of localities.

Furthermore, the identification of these clusters allows for an assessment of regional resilience. As resilience is widely recognized as a key, multidimensional factor in regional development, its comprehensive analysis necessitates a composite index approach (Stanickova & Melecký, 2018). Consequently, the substantial development gaps identified between clusters (e.g., between Ştefan Vodă/Purcari and Carahasani/Căplani) reflect significant differences in the ability of these localities to withstand economic and social shocks, underscoring the urgency of targeted policy intervention to enhance the resilience of the most vulnerable clusters.

Moreover, the use of the entropic approach to determine the objective weights of the HDI components can be understood as a form of territorial innovation. Torre (2023) maintains that territorial innovation encompasses social, organizational, and institutional changes, not just technological ones, serving as a tool for more efficient governance.

Therefore, our methodology provides a superior analytical foundation for decision-making, contributing to more informed local governance and strategies better adapted to the real needs of these distinct territorial clusters.

6. Discussion

The application of the information entropy method, by objectively assigning weights based on the intrinsic variability of the development components, leads to a profound re-evaluation of the Human Development Index (HDI) at the local level. This section interprets the objective weighting structure, analyzes the resulting variations in the HDI scores, and connects the findings to existing academic literature and policy relevance.

6.1. Interpretation of Objective Weights and Core Disparities

The entropy analysis resulted in a clear differentiation of weights, contrasting sharply with the restrictive assumption of equal weights utilized by the standard HDI. The most critical dimensions for determining local disparities in the Ștefan Vodă rayon were identified as Infrastructure (38.7%) and Economy (27.7%). Together, these two components account for over two-thirds (66.4%) of the objective weight in the corrected HDI structure.

This finding is of paramount importance, as the high weight assigned to Infrastructure (which is nearly four times the weight of Education or Health) provides causal evidence of a profound investment deficit and a severe lack of homogeneity in the provision of essential public services across the rayon's rural communities. Such pronounced spatial disparities, particularly in relation to water supply and centralized sewage systems, are characteristic of the persistent challenges faced by post-transition economies in Eastern Europe (Kusideł, 2013; Pawlas, 2018).

The low coverage rates of basic infrastructure services act as a dominant factor contributing to overall inequality in human development. Similarly, the significant weight of the Economy component reflects marked economic inequalities between localities, emphasizing that the limited economic base is not robust enough to support balanced human development across the rayon. This underscores the need to prioritize investments that enhance local economic resilience, consistent with the theory of Territorial Capital (Perucca, 2014), which highlights the interdependence of social, economic, and infrastructural assets for achieving sustainable development. Conversely, the lower and nearly equal weights assigned to Education, Health, and Demography (all around 11%) indicate a relatively higher homogeneity in the quality or distribution of these services across the rayon, meaning these dimensions contribute less to the observed local disparities.

6.2. Analysis of Entropy-Corrected HDI Variation

The adjustment of the HDI using objective entropic weights resulted in a general downward trend: out of the 23 localities analyzed, the vast majority (20) registered a decrease in their final HDI score compared to the initial equal-weighting value. This outcome suggests that the traditional approach tended to overestimate the development of most vulnerable localities. The uneven distribution of development within the entropically weighted components has, therefore, led to a more realistic and often more critical assessment of the level of human development. The analysis of extreme cases vividly illustrates the causal impact of the entropy method:

Most Significant Decreases: The largest percentage decreases are observed in Alava commune (-25.13%), Ștefănești commune (-20.67%), and Marianca de Jos commune (-19.93%). These pronounced negative variations indicate that the localities' scores, which might have appeared acceptable in the equally-weighted model due to relatively stable indices in Education or Demography (low objective weight), masked critical deficiencies in Infrastructure and Economy (high objective weight). This aligns with the

findings that integrated metrics are necessary to overcome narrow, sector-specific development models (Moulaert & Sekia, 2003). The high share of administrative expenses (around 71% in Alava and Marianca de Jos) further suggests poor financial efficiency, which exacerbates economic deficiencies and contributes to the overall drop in the corrected HDI.

The Purcari Case: In contrast, Purcari commune experienced the highest percentage gain (+10.87%), highlighting that its development profile aligns strongly with the dimensions weighted as most critical by the entropy method (Infrastructure and Economy). This suggests a more balanced and resilient local development structure, supported by high own revenues derived from specialized economic activities (viticulture). Even the urban center, Ștefan Vodă town, registered a slight decrease (-1.15%), reflecting a more nuanced and realistic assessment of its development when objective weights emphasize deficiencies - a finding consistent with subnational studies in regions like Serbia, where even urban centers can show vulnerabilities masked by aggregate scores (UNDP Serbia, 2022).

6.3. Policy Relevance, Clustering, and Contribution

The subsequent hierarchical clustering analysis, based on the Euclidean Distance Matrix, confirmed the existence of four distinct clusters of localities, reflecting natural patterns of spatial inequality and functional proximity across the rayon. This finding underscores a profound structural heterogeneity, ranging from the high-performing Cluster I (superior administrative capacity) to the vulnerable Cluster IV (resource deficit and administrative inefficiency), alongside specific barriers identified in Clusters II and III. The substantial development gaps identified between these clusters reflect significant differences in the ability of these localities to withstand economic and social shocks, underscoring the urgency of targeted policy intervention to enhance the resilience of the most vulnerable clusters (Stanickova & Melecký, 2018).

The entropy-corrected HDI is not merely a statistical refinement; it is a powerful tool for informed public policy. By objectively identifying Infrastructure and Economy as the most critical factors of inequality, the study provides a robust analytical basis for shifting from undifferentiated policies to differentiated strategies tailored to the specific needs of each territorial cluster. Furthermore, the use of the entropic approach to determine objective weights can be understood as a form of territorial innovation. Torre (2023) argues that territorial innovation encompasses social, organizational, and institutional changes, not just technological ones, serving as a tool for more efficient governance. Therefore, our methodology provides a superior analytical foundation for decision-making, contributing to more informed local governance and strategies better adapted to the real needs of these distinct territorial clusters.

7. Limitations and future research

Although the entropic approach significantly improves the objectivity and relevance of the HDI assessment at the local level, this study contains several inherent limitations that must be acknowledged. First, the analysis is limited to a restricted geographical area (Ștefan Vodă rayon, Republic of Moldova). While this focus allows for an in-depth assessment of local disparities, the specific objective weights derived (e.g., the 38.7% for Infrastructure) are context-dependent and may not be directly translatable to regions with different specific development characteristics or policy environments.

Second, the comparability of the results must be viewed with caution. By employing variable, objectively determined weights, the final corrected HDI scores cannot be directly compared with the traditional, globally published HDI (which uses fixed, equal weights). The corrected HDI offers a more accurate reflection of internal disparities and investment priorities within the rayon, but it constitutes a relative measure of internal performance rather than an absolute measure for international comparison.

Third, the estimation of weights is static, based on a single cross-section of data (year 2023). This approach may not accurately reflect the long-term dynamics of change or the effects of external factors, such as sustained economic migration, sudden policy shifts, or climate change impacts on the agricultural sector. Future research should consider dynamic approaches, such as running the entropic model longitudinally to capture changes in priority dimensions over time.

Finally, while the clustering analysis provided a strong quantitative basis for grouping localities, future methodological refinement should focus on integrating a spatial dimension directly into the inequality measurement.

While this approach offers a measure of similarity/dissimilarity based on final HDI scores, it does not integrate the geographical context and distance directly into the core calculation of inequality. Future methodological refinement could involve the use of advanced approaches, such as the spatialized Shannon entropy, which transcends administrative boundaries and enables multiscale assessments of spatial structure by incorporating a distance-based assessment (Mucciardi & Benassi, 2025).

8. Conclusions

The results obtained through the entropic methodology offer a relevant perspective regarding the territorial patterns of human development. The entropic approach proves more sensitive in detecting internal disparities than equal weighting, which, in the case of the Ștefan Vodă rayon, concealed significant differences. The Euclidean Distance Matrix confirmed a pronounced heterogeneity and justified the identification of four distinct clusters, showing that uniform development measures are inadequate. Cluster I (economic anchor) and Cluster IV (systemic vulnerability) mark the extremes, while Cluster II (demographic decline) and Cluster III (insufficient sanitation infrastructure) highlight specific constraints. These results support a differentiated, context-based approach, in line with recent literature (Torre, 2023; UNDP, 2023–2024).

The study has several limitations. As a cross-sectional exercise, it does not account for temporal dynamics or policy effects. Due to the use of dynamic, entropy-based weights, the Human Development Index is not directly comparable with traditional indices or national values. The index is therefore more relevant for analysing internal disparities than for external benchmarking. In addition, qualitative determinants of well-being are only partially captured.

Future research should apply the methodology longitudinally (minimum three years) to observe trends and evaluate policy impact. Validation in districts with similar profiles (e.g., Leova, Cantemir) would test the stability of clusters and weights. Integrating qualitative indicators through mixed methods would provide a broader understanding of local well-being and territorial capital (Perucca, 2014). Spatialized entropy (Mucciardi & Benassi, 2025), based on Gaussian kernel and multi-scale analysis, would overcome the limitations of classical entropy and enable the assessment of disparities beyond administrative boundaries. Applying the methodology at national level, supported by appropriate public policies, may contribute to more equitable and effective territorial strategies, consistent with the principles of territorial innovation and ecosystem approaches.

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