Theoretical and Applied Economics
Volume XXXIII (2026), No. 2(647), Summer, pp. 17-32

Regional inequalities and human capital adaptability in Romania

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Abstract. *Regional disparities still impact education, employment, and access to technology in Romania. The analysis of the evolution of these discrepancies over the 2018-2023 period is carried out based on regional variables on education, labour market conditions, and digital access. GIS mapping, Moran's I, LISA cluster analysis, and PCA are used for the determination of territorial patterns and regional adaptation. The results reveal important differences between Bucharest-Ilfov and less developed regions, especially as regards the link between education, digitalization, and chances of employment. The results suggest that skill difference and technology access differences are still crucial determinants of regional development and long-term change.*

Keywords: regional disparities, human capital, adaptability, digital inclusion, spatial analysis.

JEL Classification: R11, J24.

Introduction

Even at the European level, regional disparities remain a difficult problem to address. They show how much access to education, well-paid jobs and technology matters. Research in recent years has shown that these gaps do not disappear on their own. Regions that start with a disadvantage tend to lag behind and accumulate problems that affect both the economy and people's daily lives (Rodríguez-Pose, 2018). At the same time, other studies show that where people live directly influences their perceptions and development opportunities (Dijkstra, et al., 2020).

Human capital is a central factor in these disparities. Classical theories show that investments in education lead to higher productivity and can create different economic developments from one region to another (Becker, 1993). However, it is not only the number of years of schooling that matters, but also the quality of skills (Hanushek & Woessmann, 2012). Nowadays, with digitalization, access to the internet and technology is becoming essential for a region to adapt. Territorial disparities appear consistently in the European Commission's DESI reports (2020–2023). The literature on the knowledge economy also shows that large cities attract well-trained people and generate accelerated development. This is also clearly seen in Romania, where Bucharest–Ilfov stands out strongly from other regions.

This study analyses how these disparities evolved in Romania between 2018 and 2023, with a focus on education, employment and digitalization - all related to regional adaptability. We combined several methods: GIS maps, global spatial autocorrelation (Moran's I), local cluster analysis (LISA) and PCA. The aim was to capture stable territorial patterns and the factors that separate dynamic regions from stagnant ones. The results provide an overview of how human capital and access to technology influence the ability of regions to respond to rapid change.

Literature review

Studies show that many regions lag behind for long periods. They do not attract investment, do not have good services and fail to catch up with more developed areas (McCann, 2020). These things are felt in people's lives. Those in weaker regions are more likely to say that they have fewer opportunities and feel less satisfied.

Romania is in much the same boat. Studies show that economic activity and development are concentrated in a small number of large cities. Many rural regions remain less competitive, with poorer infrastructure and weaker investment (Benedek & Kurkó, 2011)

An important factor is education. Regions where people have better skills adapt more easily and attract more jobs (Gennaioli, et al., 2013). It is not just the years of schooling that count, but what people actually know how to do. The quality of skills makes the difference (Acemoglu & Autor, 2011).

Digitalisation is also changing the situation. Areas with good internet and access to technology grow faster. Where technology is lacking, the differences deepen (Jan, 2020).

Similar empirical studies also examine digital disparities through indicators related to internet access and internet use. Vicente and López (Vicente & López, 2011), for example, showed that weaker digital connectivity is associated with lower regional development across European regions.

The literature also shows something important: big cities have a clear advantage. They attract companies, skilled people, and innovation, which helps them grow even more over time (Duranton & Puga, 2020). Societal implications of regional disparities are also identified in studies. People in less-developed areas could be excluded. They may be more skeptical of institutions. Such inequalities are often the product of a slower adaptation by some areas to economic and technological progress (Simona, et al., 2019).

In general, research shows that a place's education, technology, and economic structure strongly influence regional development. These elements explain why some areas advance rapidly while others lag behind. Previous studies focused on separately economic inequalities or digital and educational differences. The interaction of these dimensions at the regional level in Romania was studied less. This paper contributes to the literature by integrating spatial analysis and PCA. The objective is to learn more about the regional adaptability through education, employment and digitalization indicators.

Methods

The analysis began with the creation of GIS maps. These were used to show how the indicators were distributed in each region of Romania between 2018 and 2023. These maps provided a much easier visual interpretation of the differences between regions. Based on these, the first hypotheses regarding possible spatial patterns could also be identified. GIS mapping was particularly useful for identifying territorial inequalities and observing regional changes over time.

The research continued with Moran's I analysis, a widely used measure of global spatial autocorrelation (Moran, 1950). The method evaluates whether regions with similar values tend to be spatially clustered or randomly distributed. Positive Moran's I values indicate clustering, while negative values suggest spatial dispersion. The next step was the Local Indicators of Spatial Association (LISA) analysis developed by Anselin (Anselin, 1995). Unlike global Moran's I, LISA identifies local spatial clusters and spatial outliers. The method highlights high–high, low–low and asymmetric spatial combinations, helping identify regions with similar or contrasting development patterns.

After completing the spatial analysis, the study continued with the principal components analysis. PCA aimed to understand the internal structure of the data. PCA did not take geographical location into account but showed how the indicators were related to each other and which common components best described the differences between regions. This resulted in dimensions such as economic development, digitalization or social vulnerability. PCA was useful for reducing the complexity of multiple socio-economic indicators and identifying the main dimensions underlying regional disparities.

Finally, the sequence GIS - Moran's I - LISA - PCA provided a complete analysis. The maps showed the situation, Moran's I confirmed the global pattern, LISA located the

critical areas, and PCA explained the factors that underpinned these differences. Together, these methods allowed both the spatial visualization of disparities and the identification of the main socio-economic dimensions associated with regional adaptability.

The study also has limitations. The analysis only uses regional-level indicators. In this respect no regional differentiation is recorded. Additionally, the factors considered and the study timeframe limited the availability of data. PCA simplifies complex socio-economic interactions to a smaller number of components. Such simplifications may hide some particularities of an area. The results are regional generalizations, not local reality.

Results and discussions

Exploratory data analysis

The data used for this work were taken from the Eurostat database. The indicators used are explained in the table below along with the units of measurement.

The indicators were selected based on the main features of regional adjustment and socio-economic development. GDP per capita and employment indicators are used to measure economic performance and labor market conditions. Internet connectivity and internet usage are indicators for the adoption of technology and digitalization. Tertiary education and R&D people are proxies for the human capital and innovative capacity. The index of social vulnerability is the poverty index.

Table 1. *Variable code, variable names of indicators and units of measurement*

Variable code	Variable name	Unit of measurement
X_1	GDP per capita	Euro per inhabitant
X_2	R&D personnel	Full-time equivalent
X_3	Employment rate	Percentage
X_4	Unemployment rate	Percentage
X_5	Internet-access households	Percentage of households
X_6	Internet users	Percentage of individuals
X_7	At risk of poverty	Percentage
X_8	Tertiary students	Number

Source: Author's own research

For this analysis, only these basic indicators were selected for this paper. The basis for their selection was to take into account that they should be from various fields such as economic, educational and social. The analysis period was 2018-2023 and included the 8 regions of Romania. The table below includes the region codes and their corresponding names.

Table 2. *Region code and name*

Region code	Region name
RO11	North-West
RO12	Centre
RO21	North-East
RO22	South-East
RO31	South-Muntenia
RO32	Bucharest-Ilfov
RO41	South-West Oltenia
RO42	West

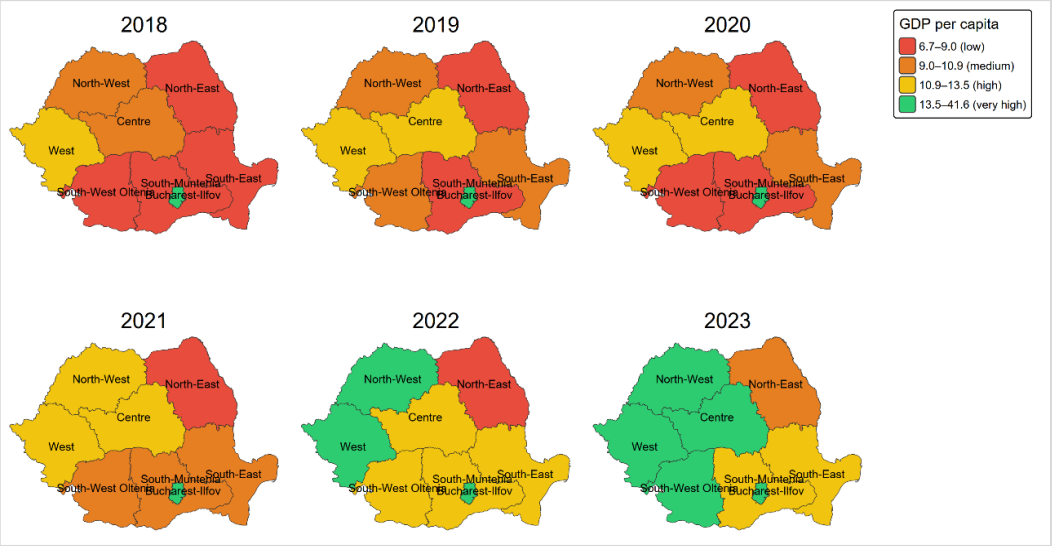
Source: Author's own research

Geographic Information System (GIS) maps

GIS maps are created for each indicator and for each year. Depending on the values of each indicator, the regions of Romania were classified each year in a certain number of classes. Similarly, considering the effect produced by that indicator, each class was represented with a certain colour. For example, for indicators that are to be maximized, in the sense of reaching a higher value, regions with low values are highlighted in red, with medium values in orange and so on until the highest values are reached, which are represented in green. The same convention was applied for indicators that are to be minimized, in the sense of reducing their values. This time, low values are represented in green, medium values in yellow up to the highest values, which are represented in red.

Regarding GDP per capita, it is observed that only in the last 2 years considered in the analysis for the North-West region are the values the highest and considered to be good. The Centre region only in 2023 ended up being green. The North-East region until 2022 had low values, with red, and only in 2023 did it move into a slightly better area, orange. The South-East and South-Muntenia regions reached an area with almost good values because it is represented with yellow in 2022 and 2023. The South-West Oltenia region in 2023 ends up having high values. The West region in the last 2 years is represented with green, and Bucharest-Ilfov throughout was the most optimal. These results are consistent with previous studies showing that Bucharest–Ilfov concentrates economic activity, infrastructure and development opportunities, while many eastern and southern regions continue to lag behind (Benedek & Kurkó, 2011).

Figure 1. *GDP per capita GIS map*

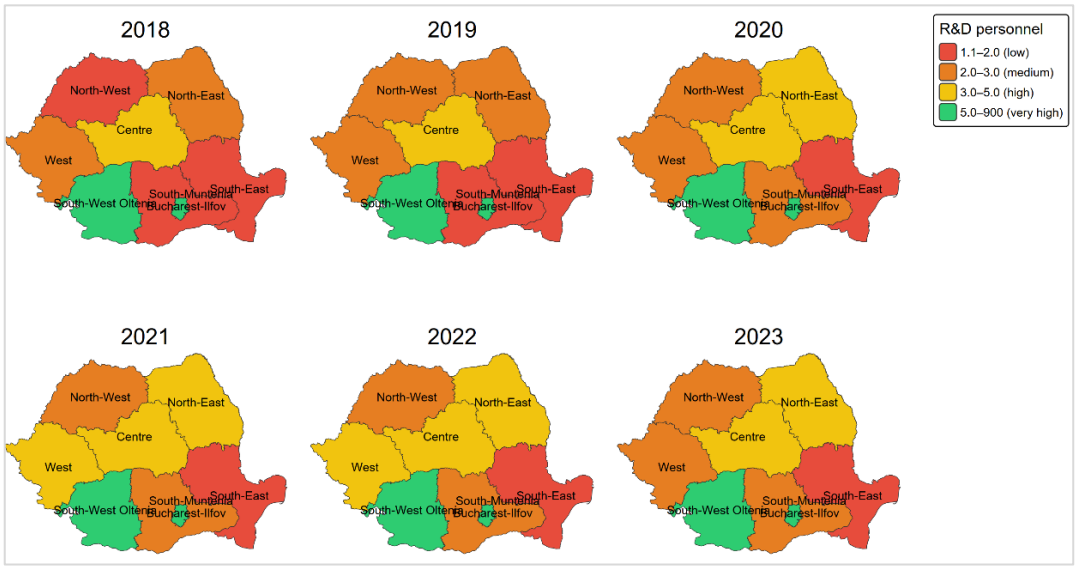


Source: Author's own research

Figure 2 illustrates the indicator regarding R&D personnel. In the first year, the North-West region had very low values, represented in red, which only increased slightly, reaching orange, even by the end of the analysed period. The North-East region was considered more

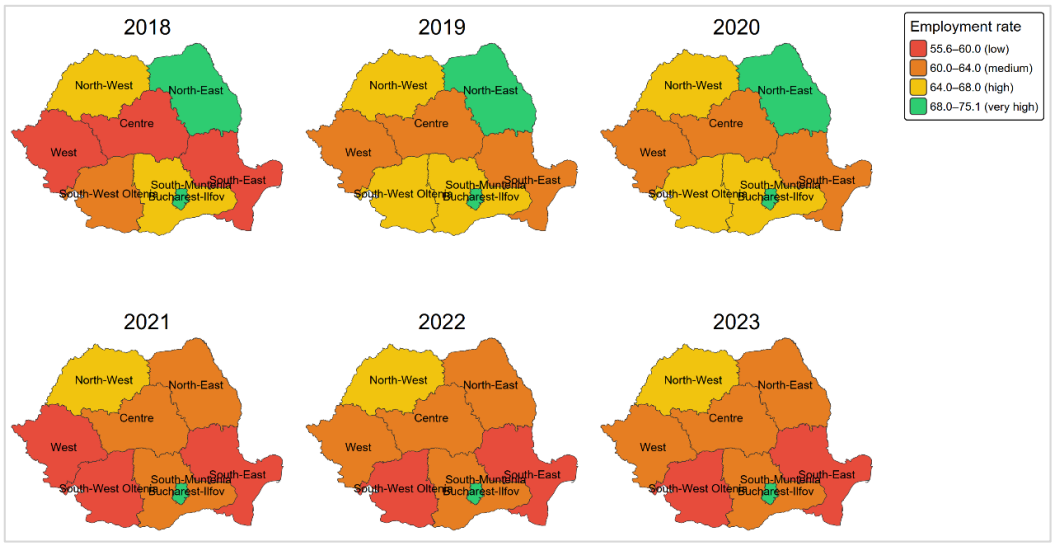
opportune because even from 2018 it had higher values, but even this did not reach the best values until 2023. The Centre region was constant over time and had quite high values. In the first 2 years, the South-Muntenia region recorded very low values and reached average values. The West region had periods when it had average values as well as quite high values. Only the 2 regions, Bucharest-Ilfov and South-West Oltenia had the highest values, and which were represented in green throughout the analysed period.

Figure 2. *R&D personnel GIS map*



Source: Author's own research

Figure 3. *Employment rate GIS map*

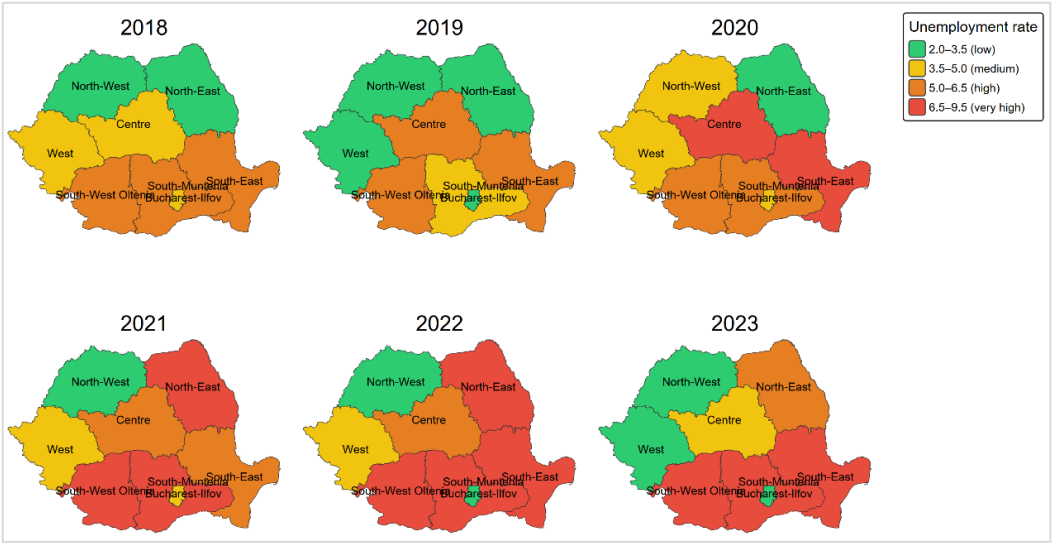


Source: Author's own research

Figure 3 contains the economic indicator regarding the employment rate. The map shows us that the North-West region has remained constant over time with quite high values. In contrast, in the first 3 years of analysis, the North-East region had very high values for this indicator and was represented in green, but then it recorded decreases that reached average values. The Centre region had low values only for 2018, in the following years it recorded average values, represented in orange on the map. The South-East region indicated average values only for 2019 and 2020, in the remaining years it had very low values, illustrated in red. The South-Muntenia region started from low values to average values. The South-West Oltenia region had both average values and quite high values, but in recent years it has reached very low values. The West region also had periods with very low but also average values. And for this indicator, the Bucharest-Ilfov region was the only one to record the highest values.

The following figure shows the unemployment rate indicator for the entire analyzed period and for each region separately. The North-West region had among the lowest values for this indicator except for 2020. The North-East region recorded low values for the first 3 years of the analysis, and then these began to gradually increase, reaching even very high values for the years 2021 and 2022. The Centre region also presented fluctuations, from very high values to average values for this indicator. Throughout the analysis period, the South-East region presented only high and very high values. The South-Muntenia region started in the first 3 years with average and high values, and in the last 3 years it had very high values. The South-West Oltenia region in the first 3 years had quite high values, and in the last 3 years very high values. The West region only for the years 2019 and 2023 recorded low values, represented in green, in the rest of the years it had average values. Even the Bucharest-Ilfov region this time for this indicator had low values only for the years 2019, 2022 and 2023, in the rest of the years the values were average.

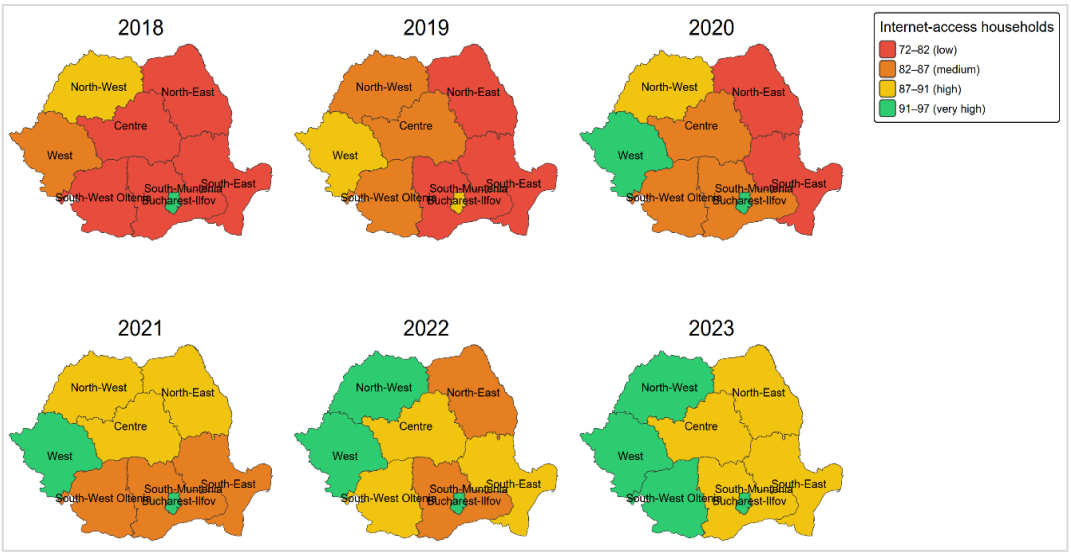
Figure 4. *Unemployment rate GIS map*



Source: Author's own research

The figure below illustrates the map related to the internet access household's indicator. For the North-West region, only in the last 2 years of analysis, very high values were recorded for this indicator. The North-East region demonstrated quite high values only for the years 2021 and 2023. The Centre region started from very low values for this indicator and reached quite high values for the last 3 years of the analysed period. The South-East region recorded very low values to quite high values. The South-Muntenia region had quite high regions only for the year 2023. The South-West Oltenia region had low values at the beginning of the period, represented in red, which increased along the way and reached very high values in 2023, represented in green. In the last 3 years considered in the analysis, the West region recorded very high values for this indicator. The Bucharest-Ilfov region, apart from 2019, recorded the highest values for this indicator.

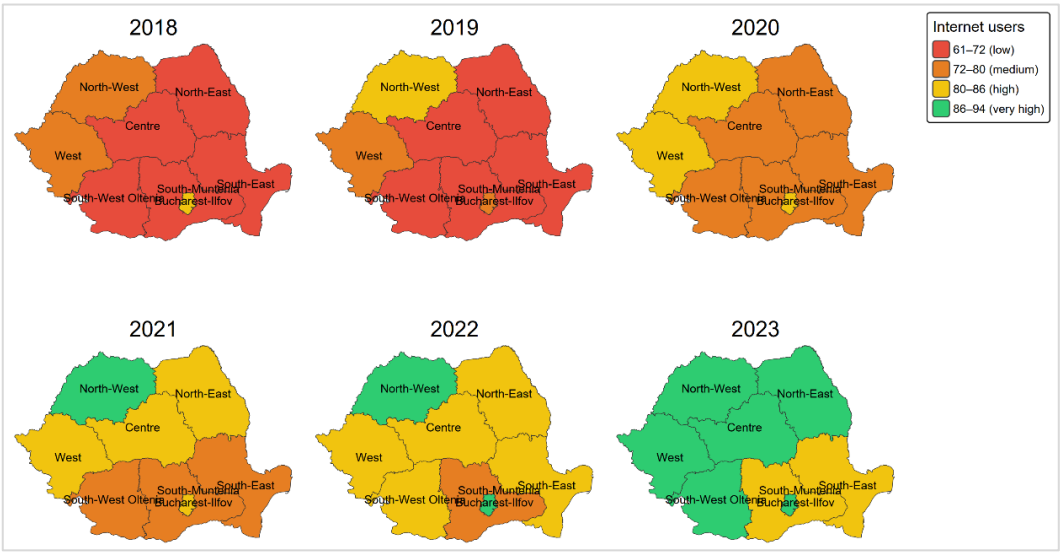
Figure 5. *Internet-access households GIS map*



Source: Author's own research

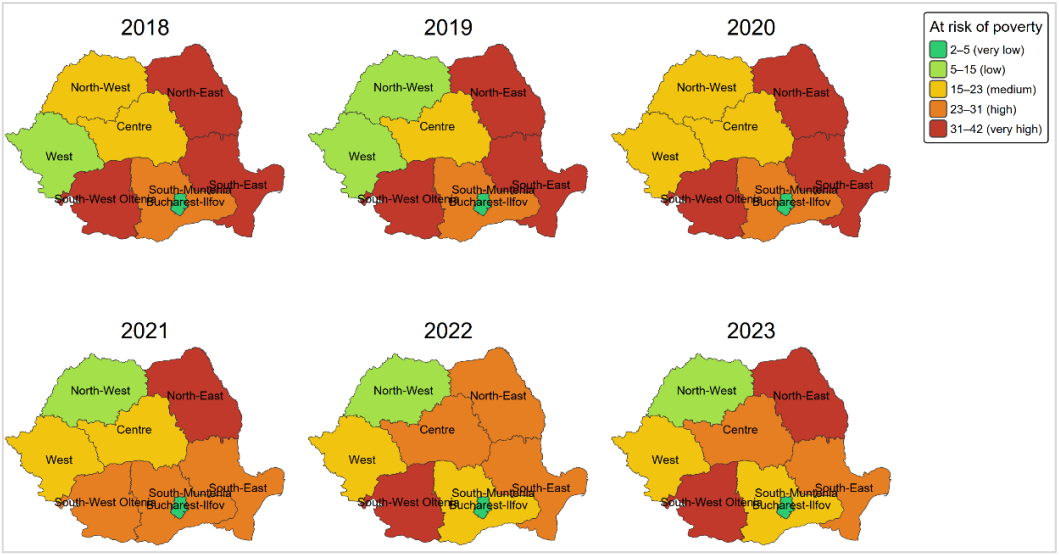
Figure 6 shows the users who use the internet. The North-West region had very high values in the last 3 years of the analysis. The North-East region only in 2023 had very high values for this indicator. The Centre region started from very low values for this indicator for the years 2018 and 2019 and reached very high values only for the year 2023. The South-East region recorded quite high values only for the years 2022 and 2023. The South-Muntenia region illustrated quite high values for this indicator only for the year 2023, otherwise it had medium or low values. The West region had very high values also only for the year 2023. The Bucharest-Ilfov region recorded very high values only for the years 2022 and 2023.

Figure 6. *Internet users GIS map*



Source: Author's own research

Figure 7. *At risk of poverty GIS map*



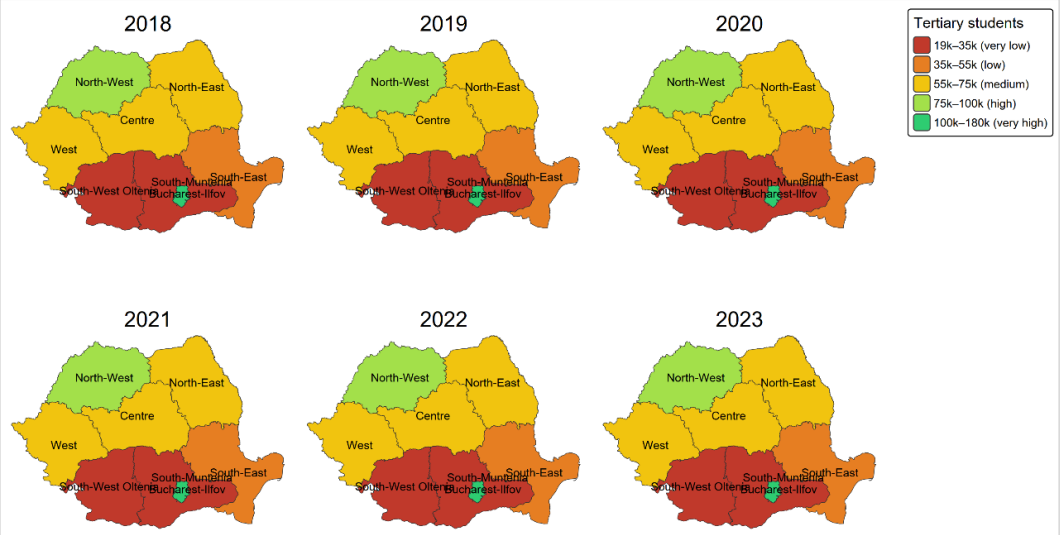
Source: Author's own research

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had medium or low values. The West region had very high values also only for the year 2023. The Bucharest-Ilfov region recorded very high values only for the years 2022 and 2023.

The map regarding students enrolled in tertiary education is illustrated in the graph below. For the North-West region, it was observed that there are high values throughout the analyzed period. The North-East, Centre and West regions remained constant for all years with average values, represented in yellow. The South-West Oltenia and South-Muntenia regions recorded very low values regarding this indicator. Bucharest-Ilfov was the only region with very high values for this indicator. The results also support the literature emphasizing the role of education and human capital in regional adaptability and labor market performance (Gennaioli, et al., 2013).

Figure 8. *Tertiary students GIS map*



Source: Author's own research

Moran's I and LISA analysis

The results for the Moran's I analysis can be seen in the appendix in table 3. The Moran's I analysis revealed that most of the socio-economic indicators have very low values. Even most of the time close to zero. Also, the p-values were not significant. This meant that there is no clear spatial pattern between the NUTS2 regions in Romania. The regions do not cluster into "high-high" or "low-low" areas, they vary quite independently of each other. It was also observed that for certain years, the Moran's I values increased slightly towards zero or positive values. This could suggest a very weak tendency of convergence between the regions, but it was not strong enough to be considered statistically significant.

Table 4 in the annexes shows the LISA results for the significant regions. The LISA results confirm what was also observed at the global level. Most regions appear as “insignificant”, so they do not form clear clusters. There are certain causes for which isolated areas appear that are significant. These are of the high-high or high-low type. It is also worth mentioning

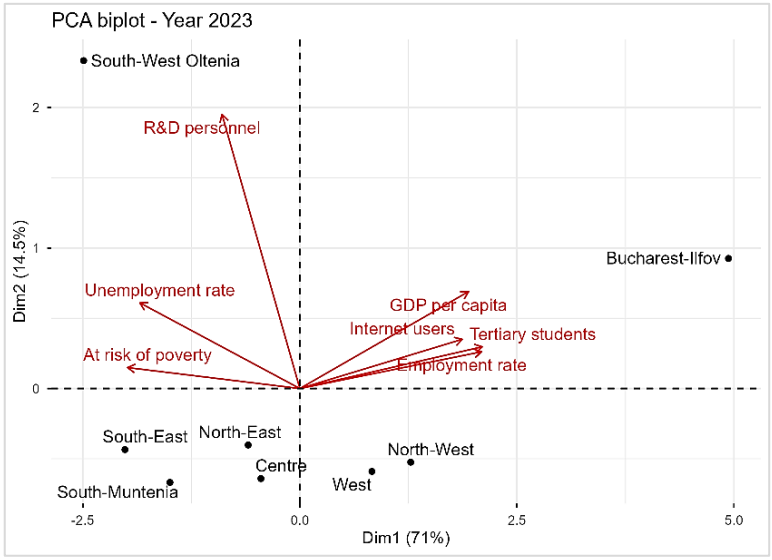
that they do not persist over time and therefore do not have a stable pattern. It was also observed that the indicators change a lot from one year to the next, and this variation makes the differences between regions difficult to put into a simple or constant pattern.

Principal component analysis

After applying the principal components analysis for all years, it was observed that the first 2 principal components could be retained. In this case, Component 1 explains about 55–76% of the total variation, and Component 2 explains between 14–21%, depending on the year. Together, the two components capture about 70–90% of the variation, which is large enough to provide a clear picture of differences between regions. Principal component 1 (Dim1) represents economic and human capital development. This structure is in line with previous studies showing that economic performance, education and digitalization tend to evolve together and shape regional competitiveness (Hanushek & Woessmann, 2012; Duranton & Puga, 2020). Principal component 2 (Dim2) captures the social and vulnerability dimension, as well as a part related to the structure of the research workforce. Also, the indicator internet access households was not considered because it was redundant. That is why the indicator internet users was kept. To illustrate this analysis, the year 2023 was selected, the rest of the graphs can be found in the appendix.

Figure 9 below shows how the regions of Romania differ in 2023 following the application of principal component analysis. It was observed that the Bucharest-Ilfov region was the most different of all because it had high values for the economy, students enrolled in university education and the internet. The eastern and southern regions appeared to be comparatively weaker, with lower values for GDP and employment rate. The South-West Oltenia region stood out with an atypical profile related to social problems but also presented very high values for R&D personnel. In contrast, the central and western regions were close to the average. Overall, the differences between the regions remained quite large.

Figure 9. *PCA biplot – Year 2023*



Source: Author's own research

In 2018 (figure 10), the differences between the regions were evident from the first year considered in the analysis. The Bucharest-Ilfov region was much more advanced in terms of economy, education and internet use. The North-West and West regions also presented quite good values, but more moderate compared to Bucharest-Ilfov. The regions in the South and East lagged behind because they presented lower values for GDP per capita, employment rate. They also presented high values for the poverty risk rate. Also, for this year, the South-West Oltenia region was atypical due to the high number for R&D.

In 2019 (figure 11), the structure of the regions was maintained. The Bucharest-Ilfov region remained far ahead compared to the others. The North-West region continued to have a relatively good profile. The East and South of the country lagged behind, with low values for GDP, students and employment. The North-East region continued to present a high risk of poverty.

In 2020 (figure 12), the Bucharest-Ilfov region continued to be the best of all. The North-West and West regions remained considered quite balanced. The South and East continued to be in the area with weaker performances. The North-East region remained sensitive to vulnerability indicators. This supports the broader literature arguing that weaker regions often face persistent socio-economic vulnerability and slower adaptation to structural change (Simona, et al., 2019).

In the following year (figure 13), the differences between the regions started to become increasingly evident. The Bucharest-Ilfov region became increasingly distant from the rest. The North-West and West regions remained roughly the same. The South-West Oltenia region appeared to be atypical again due to indicators such as R&D personnel and the unemployment rate. The South-East and North-East regions continued to be considered weak because they presented a high risk of poverty and a low employment rate.

The same things were observed for 2022 (figure 14). There were no major differences.

Conclusions

The results show significant regional inequalities in Romania for the period 2018-2023. Bucharest-Ilfov recorded the top economic, educational, and digital indicators. Much of the South and East were falling behind. The northwest and west areas were more evenly developed. South-West Oltenia had a more atypical profile. The focus was about the social vulnerability and the structure of R&D people.

The results highlight the differences in human capital adaptability of Romanian regions. Better educated, better connected, and with improved labour market conditions, regions were better placed to respond to economic and technological change. In contrast, those with more poverty and less secure employment conditions seemed less adaptable. They also had more socio-economic vulnerability.

The results indicated that regional inequalities were largely stable over time. There were a few indications of regional convergence. The differences did not show strong consistent spatial groupings. This means that the regional differences are more dependent on internal socio-economic factors than geographical proximity.

The study concludes that there is a strong connection between human capital, digitalization, and regional adaptability. The results are consistent with previous studies. These studies point to the importance of access to education, technology, and employment opportunities for the long-term growth of the region. Filling these gaps will take continued investment in education, digital infrastructure, innovation, and labour market opportunities. This is especially important in the less developed areas of Romania.

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Appendix

Table 3. *Moran's I results*

Indicator	Year	Moran_I	Expected_I	Variance	p_value
At risk of poverty	2018	-0.09	-0.14	0.05	0.41
At risk of poverty	2019	-0.07	-0.14	0.05	0.36
At risk of poverty	2020	-0.01	-0.14	0.04	0.25
At risk of poverty	2021	-0.04	-0.14	0.04	0.31
At risk of poverty	2022	0.00	-0.14	0.04	0.24
At risk of poverty	2023	0.05	-0.14	0.04	0.18
Employment rate	2018	-0.06	-0.14	0.05	0.37
Employment rate	2019	-0.08	-0.14	0.05	0.39
Employment rate	2020	-0.10	-0.14	0.05	0.42
Employment rate	2021	-0.02	-0.14	0.03	0.25
Employment rate	2022	-0.06	-0.14	0.03	0.32
Employment rate	2023	0.02	-0.14	0.03	0.17
GDP per capita	2018	-0.10	-0.14	0.01	0.36
GDP per capita	2019	-0.11	-0.14	0.01	0.39
GDP per capita	2020	-0.12	-0.14	0.01	0.41
GDP per capita	2021	-0.11	-0.14	0.01	0.38
GDP per capita	2022	-0.08	-0.14	0.01	0.29
GDP per capita	2023	-0.08	-0.14	0.01	0.28
Internet-access households	2018	-0.05	-0.14	0.05	0.33
Internet-access households	2019	-0.07	-0.14	0.05	0.38
Internet-access households	2020	-0.04	-0.14	0.05	0.32
Internet-access households	2021	-0.15	-0.14	0.05	0.51
Internet-access households	2022	-0.21	-0.14	0.04	0.62
Internet-access households	2023	-0.02	-0.14	0.04	0.27
Internet users	2018	-0.05	-0.14	0.05	0.33
Internet users	2019	0.10	-0.14	0.05	0.13
Internet users	2020	0.03	-0.14	0.06	0.23
Internet users	2021	0.04	-0.14	0.05	0.21
Internet users	2022	-0.35	-0.14	0.05	0.83
Internet users	2023	-0.24	-0.14	0.05	0.67
R&D personnel	2018	-0.11	-0.14	0.01	0.34
R&D personnel	2019	-0.11	-0.14	0.01	0.34
R&D personnel	2020	-0.11	-0.14	0.01	0.33
R&D personnel	2021	-0.11	-0.14	0.01	0.33
R&D personnel	2022	-0.11	-0.14	0.01	0.33
R&D personnel	2023	-0.11	-0.14	0.01	0.33
Tertiary students	2018	-0.23	-0.14	0.03	0.69
Tertiary students	2019	-0.23	-0.14	0.03	0.69
Tertiary students	2020	-0.23	-0.14	0.03	0.70
Tertiary students	2021	-0.23	-0.14	0.03	0.70
Tertiary students	2022	-0.24	-0.14	0.03	0.71
Tertiary students	2023	-0.24	-0.14	0.03	0.72
Unemployment rate	2018	0.05	-0.14	0.05	0.20
Unemployment rate	2019	-0.09	-0.14	0.05	0.41
Unemployment rate	2020	-0.10	-0.14	0.05	0.43
Unemployment rate	2021	-0.13	-0.14	0.05	0.48
Unemployment rate	2022	-0.10	-0.14	0.05	0.43
Unemployment rate	2023	-0.04	-0.14	0.06	0.33

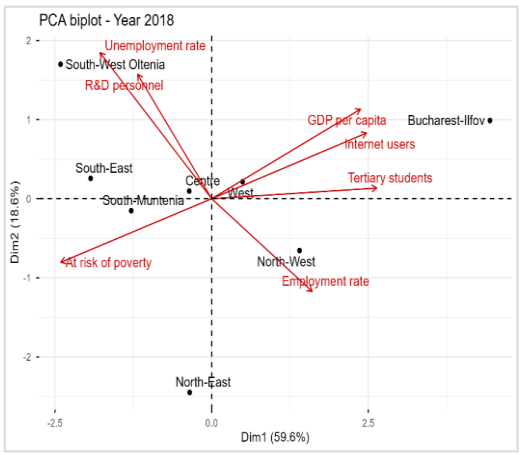
Source: Author's own research

Table 4. *LISA's results*

Indicator	Year	NUTS_ID	Name	Value	Ii	Z_Ii	P value	Lag value	cluster
Employment rate	2021	RO12	Centre	60.3	0.09	2.05	0.04	60.03	Low-Low
Employment rate	2022	RO12	Centre	61.9	0.06	2.07	0.04	60.98	Low-Low
Employment rate	2023	RO12	Centre	61	0.12	2.16	0.03	61.17	Low-Low
GDP per capita	2018	RO12	Centre	10.1	0.06	2.39	0.02	8.77	Low-Low
GDP per capita	2019	RO12	Centre	10.9	0.07	2.39	0.02	9.53	Low-Low
GDP per capita	2020	RO12	Centre	10.9	0.06	2.40	0.02	9.37	Low-Low
GDP per capita	2021	RO12	Centre	11.9	0.06	2.40	0.02	10.32	Low-Low
GDP per capita	2022	RO12	Centre	13.4	0.09	2.40	0.02	12.00	Low-Low
GDP per capita	2023	RO12	Centre	15.2	0.09	2.40	0.02	13.75	Low-Low
Internet-access households	2018	RO22	South-East	72.69	0.86	1.99	0.05	75.99	Low-Low
Internet-access households	2019	RO22	South-East	78.8	0.88	1.99	0.05	81.08	Low-Low
Internet-access households	2022	RO12	Centre	90.87	-0.15	-1.99	0.05	88.14	High-Low
Tertiary students	2018	RO12	Centre	56803	0.08	2.18	0.03	50947.17	Low-Low
Tertiary students	2019	RO12	Centre	56284	0.08	2.16	0.03	50792.67	Low-Low
Tertiary students	2020	RO12	Centre	57444	0.08	2.15	0.03	51741.33	Low-Low
Tertiary students	2021	RO12	Centre	59737	0.08	2.13	0.03	53811.50	Low-Low
Tertiary students	2022	RO12	Centre	59077	0.08	2.13	0.03	53087.00	Low-Low
Tertiary students	2023	RO12	Centre	58234	0.07	2.13	0.03	51806.33	Low-Low

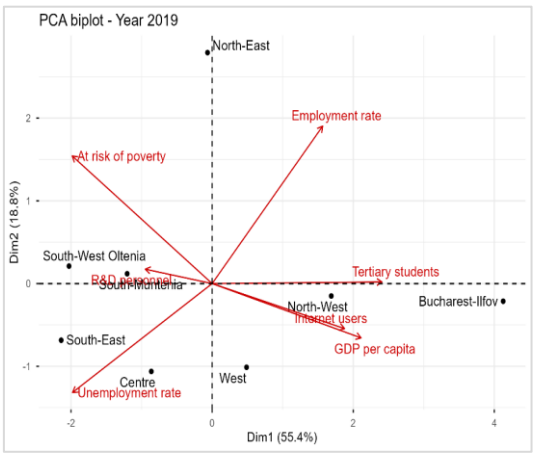
Source: Author's own research

Figure 10. *PCA biplot – Year 2018*



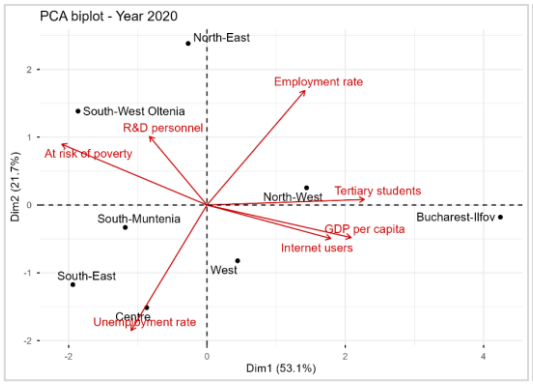
Source: Author's own research

Figure 11. *PCA biplot – Year 2019*



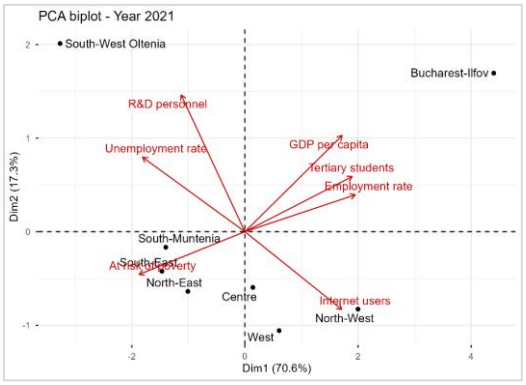
Source: Author's own research

Figure 12. *PCA biplot – Year 2020*



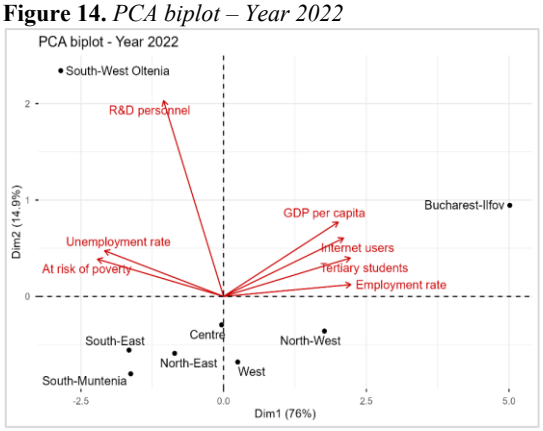
Source: Author's own research

Figure 13. *PCA biplot – Year 2021*



Source: Author's own research

Figure 14. *PCA biplot – Year 2022*



Source: Author's own research