ISSN-L: 1220-5567, eISSN: 2344-4657, (62), 1/2026, www.revecon.ro

Digitalization and education: modelling spatial interactions in Romania

Irina-Denisa Munteanu[1*] and Zizi Goschin[2]

To cite this article:
Munteanu, I.-D., & Goschin, Z. (2026) Digitalization and education: modelling spatial interactions in Romania. Romanian Journal of Economics, (62), 1/2026, 5-16.

Abstract*. *Objective*:** *Education is a key factor for both short-term and long-term economic and social development of a country. Not only does human progress depend largely on the advancement of education, but improvements in education have a significant impact on a country's economic growth and affect resilience to crises, as well as balanced regional development and the reduction of disparities. On the other hand, digitalization is also an important factor of progress, playing a significant role in promoting innovation, economic growth and sustainable development. Given that the education system in Romania has undergone significant changes during the COVID-19 pandemic due to intensive interaction with digital technologies, our goal is to illustrate the spatial effects that digitalization has had on education.* ***Method*: The purpose of this paper is to analyse from a territorial perspective, at the level of development regions, the factors that contribute to the improvement of the educational system in Romania, with a focus on digitalization. To this end, a database was built including specific indicators relevant for both the educational and socio-economic sectors and the appropriate spatial analysis methods were applied. Spatial econometric models highlight regional connections impossible to identify with classical econometric methods.* ***Results****: The results obtained from the econometric models indicate statistically significant spatial effects, the spatial lag of the dependent variable education being positive and strongly significant. It means that there are strong interdependencies in the field of education between neighbouring regions: a region with a high educational index tends to be surrounded by regions that also have a high level of education. Conversely, a region with a low educational index tends to be surrounded by regions that also have a low level of education. In other words, groups of neighbouring regions exhibiting similarities in terms of education level tend to form throughout the country.* ***Originality****: The research uses advanced spatial methods that incorporate spatial interactions between neighbouring regions, thus providing a better and more complex image of territorial socio-economic processes, compared to traditional analyses. Results are useful for both the members of the education system, or any other person interested in this subject.*

Keywords: *education, digitalization, spatial econometric models, COVID-19, Romania*
JEL classification: *I21, I29, C19*

1. Introduction

It is largely acknowledged that a country's education system is an indicator of its future prosperity. In poor regions, the lack of material and financial resources affects the ability to develop the education sector and limits the possibility of capitalizing on such services. The failure to adequately meet essential requirements for the effective operation of educational institutions can be a significant

[1] Institute of National Economy, Bucharest, Romania and Bucharest University of Economic Studies, Bucharest, Romania, e-mail address: irinadmunteanu@gmail.com.
[2] Institute of National Economy, Bucharest, Romania.

factor for explaining the low quality of education. It is essential to identify such influencing elements to develop action plans for improving the quality of the educational system. Moreover, education has a direct impact on labour productivity. An educated workforce is more efficient and better able to use advanced technologies, improve production processes and generate added value. Higher productivity translates into increased GDP and, at the same time, enables a more efficient use of available resources. Education also contributes to promoting entrepreneurship, as educated people are better equipped to identify business opportunities and create innovative companies.

Digitalization is another major economic factor, with a strong impact on economic development at all territorial levels. Digitalization is currently an essential element in promoting sustainable economic development. It involves the integration of digital technologies into all aspects of economic life, from the automation of production processes to the expansion of markets through e-commerce.

One of the main contributions of digitalization to economic growth is the acceleration of innovation. Through digitalization, companies can reduce operational costs, increase efficiency and improve the quality of services. Digital technologies facilitate the development of new products and services, creating opportunities for small and medium-sized enterprises to access global markets. In addition, digitalization improves the economic competitiveness of countries by enabling rapid access to information, reducing trade barriers and promoting cross-border collaboration.

Digitalization also means transforming the workforce, by creating new jobs in areas such as IT, digital marketing or data analysis. However, digitalization can also bring challenges, such as the disappearance of certain traditional jobs and the need to retrain employees.

The COVID-19 pandemic has drastically accelerated the digitalization process in education, forcing institutions to rapidly adopt digital technologies to continue the learning process (Passantino, 2021). Before the pandemic, the education system only marginally interacted with digitalization, more as an emerging trend than a strict necessity. After school closures and the imposition of social distancing measures, the transition to online learning became the only viable solution to maintain teaching activities. Thus, digitalization became a necessity, and this had a profound impact on all educational levels (Reimer & Schleicher, 2020).

2. Literature review

Over time, several scholars have identified a variety of problems associated with the low quality of the education system in different parts of the world. The main obstacles to achieving an equitable education service include population distribution, socio-economic issues, and geographical characteristics. In this context, He and Huang (2021) proposed a method to assess the difficulties in the education system, as well as their social consequences, considering socio-economic and geographical factors.

In China, Gao et al. (2016) and Wan et al. (2018) assessed the sustainability and imbalance related to education in terms of accessibility to primary and middle schools and the development of primary education, respectively. Most of these studies focus on specific locations and analyse specific influencing factors. The results showed not only that there is a deficit in large-scale evaluations of the education system, but also that integrated evaluation that considers regional distributions, patterns, and key governance factors is also rare. Consequently, more research is needed in this area not only to reduce the knowledge gap but also to promote the provision of high-quality educational services.

The way schools allocate their resources can be another way to influence a region’s well-being. Walsemann et al. (2021) conducted a spatial analysis of regional educational contexts and population well-being in the US, and the results showed that regions with high-quality public education systems are more likely to develop factors that enhance population health and well-being, such as a civically engaged population, a strong economy, a low unemployment rate, and a stable tax base. According to some authors, traditional university education is insufficient, and lectures are ineffective techniques for learning values and skills (Abeysekera and Dawson, 2014) since they “cannot reliably express a sustainable point of view” because they are not cooperative (Kwon and Woo, 2018). Cotton and Winter (2010) argue that it is essential to avoid a purely transmissive approach to shaping key ESD concepts such as participation, cooperation and openness to other ideas (Goodman and Richardson, 2010). It is also important to identify the nature of the obstacles that hinder the improvement of educational attainment in a country. The uneven distribution of funding and facilities, gender parity and the rural or urban structure of locations, for example, have an impact on inter-regional educational variations (Queiroz et al., 2020).

The COVID-19 pandemic has strongly accelerated the process of digitalization in education, forcing institutions to rapidly adopt digital technologies to continue the learning process (Passantino, 2021). A major effect of this transition was the urgent need for investment in digital infrastructure and in the technological skills of teachers. According to Azorin (2020), a large part of teachers and school administration were not prepared to manage a fully digital educational process. The lack of necessary equipment, reluctance to adopt new technologies and insufficient digital pedagogical training were significant barriers in the first phase of this process. On the other hand, online learning also brought important opportunities. For example, it allowed for increased flexibility in programming and access to diversified educational resources, but also the development of students' digital skills, which have become essential in the new global context.

Thus, digitalization has become a necessity, and this has had a profound impact on all educational levels (Reimer & Schleicher, 2020). One of the main reasons why digitalization is seen as a necessity in modern education is the impact it has on preparing young people for today’s society, which is strongly influenced by technology. In this increasingly interconnected world, young people need to learn to use digital technologies effectively and productively, which will allow them to take advantage of the numerous opportunities offered by the digital environment (Areshonkov, 2020). Therefore, digital skills are no longer just optional but are becoming essential for professional and personal success in the context of an increasingly digitalized global economy. In this sense, the digitalization of education not only facilitates access to varied and innovative educational resources but also contributes to the development of essential skills for today’s young people. Digitalization can be seen as one of the forces contributing to the preparation of future specialists, competent in the use of technology in everyday life and in the professional environment. This training is crucial, especially in the context of the rapidly developing digital economy, where technological knowledge and skills are often basic requirements for employment and success.

Digitalization can be viewed through three major dimensions: people management, data analysis, and external engagement (Safonov et al., 2022). In education, these three directions are fundamental to building an efficient and sustainable system. In education, digitalization has a broad impact not only on teaching methods, but also on the curricular structure. Brunetti et al. (2020) suggest that an effective digital educational ecosystem must integrate culture, skills, and technological infrastructure. This requires not only access to technology, but also the development of coherent educational policies, supported by education and IT experts. Safonov et al. (2022) emphasize that the implementation of a solid digital infrastructure must be accompanied by rigorous cybersecurity measures and clear policies to protect user rights.

However, we must understand that the digitalization of education is not just about introducing new technological tools into classrooms. It is a profound change that affects the structure, objectives and personnel of the education system. The change cannot be achieved effectively without proper training of teachers, who are the ones who will ultimately implement these technologies and guide students in their use. Bessarab et al. (2022) conclude that one of the most important actions in the process of digitalizing education is the development of teachers' digital skills, since they are the ones who prepare future decision-makers to face the challenges that an increasingly digitalized world will bring. For this reason, it is essential that teachers are properly prepared to use modern technologies in the educational process. Continuous training of teaching staff thus becomes an essential component of the digitalization process, and investments in this area must be a priority for education authorities. Only through adequate training and continuous adaptation to new technologies will teachers be able to provide students with the necessary skills to face the future challenges of the digital society.

Although the digitalization of education brings advantages such as wider access to resources and flexibility of the study program, there are numerous studies that suggest that many students and teachers continue to prefer face-to-face interaction to strictly online learning. Walker et al. (2021) emphasize that digital education, especially when fully implemented, comes with several significant challenges for teachers, who must quickly adapt to new technologies, but also face the difficulties of maintaining students' attention and interest.

Bozkurt (2020) and Toquero (2021) also emphasize that the shift to online education has exacerbated existing social inequalities, especially among vulnerable groups. These inequalities are more evident in the case of students from disadvantaged backgrounds, who do not always have access to quality technology or an adequate space for learning. Thus, the lack of access to modern digital equipment and a stable internet connection has considerably affected their academic performance. Faturoti (2022) argues that students from immigrant families or disadvantaged backgrounds feel these educational inequities the most. Unequal access to digital resources can amplify educational gaps between different social groups, negatively affecting the future of these young people.

3. Methodology and data

The purpose of this paper is to analyse from a territorial perspective, at the level of development regions, the factors that contribute to the improvement of the Romanian educational system, with a focus on digitalization. For this purpose, a database was built including specific indicators for both the educational and socio-economic sectors and methods of spatial analysis were applied to reveal regional connections that classical econometric methods normally elude.

Based on these considerations, our research uses advanced spatial analysis methods to incorporate economic interdependencies between neighbouring regions. Thus, we can provide a better and more complex picture of territorial socio-economic processes, compared to traditional analyses. The goal is to reveal the interconnections between territorial units (development regions) and to gauge their impact on the relationship between digitalisation and education in Romania. To this end we start from the available statistical data and further apply specific spatial analysis techniques.

Placed on the principles and methods of spatial analysis, various types of spatial econometric models using panel data have been built and estimated. Finally, relying on the analysis and interpretation of the results provided by the methods of spatial empirical analysis, we formulated recommendations for regional economic development strategies and policies using education and digitalization as key factors for accelerating economic growth and reducing regional inequalities.

Panel data is a data structure commonly used in statistical and econometric analyses that consists of two dimensions: a cross-sectional dimension and a time dimension. This type of data is preferred to separate cross-sectional or time series analyses because it allows for better estimation of relationships in an econometric model by increasing the number of observations. It also offers the ability to control for individual fixed effects, which are common to an entity over time but may differ across entities, and it is more efficient in estimating regression models due to sample size, reducing collinearity and increasing heterogeneity, which are problems in traditional regression models because they affect the final results.

Conventional regression models commonly used to analyse cross-sectional and panel data assume that observations are independent of each other. In the case of spatial data samples, where each observation represents a point or region in space, this means that neighbouring regions are as independent as distant regions. Spatial models introduce a new perspective, integrating the principle that regions situated in geographical proximity can influence each other through direct interactions, knowledge sharing and spillover effects.

Since it is not possible to know with certainty the type of dependence between regions, alternative ways of testing the data have been found. The most common are the methods based on the Lagrange multiplier test, as follows:

Lagrange Multiplier for spatial lag dependence
H0: no spatial lag dependence
H1: spatial lag dependence

Lagrange Multiplier for spatial error dependence
H0: no spatial error dependence
H1: spatial error dependence

ISSN-L: 1220-5567, eISSN: 2344-4657, (62), 1/2026, www.revecon.ro

Robust Lagrange Multiplier test for spatial lag dependence and Robust Lagrange Multiplier test for spatial error dependence might also be considered to confirm the results obtained from the standard tests.

The approach to spatial panel data is similar to classical panel. Depending on how the unobserved heterogeneity is modelled (fixed or random effects), specifications involving one or two of the spatial terms presented previously lead to the following spatial econometric models:

a. Models with fixed effects: spatial autoregressive model (SAR), spatial error model (SEM) and spatial lag model with spatial error (SARAR)

a.1. SAR: $Y_{it} = \rho \sum_{i \neq j} W_{ij} Y_{jt} + X_{it}\beta + \alpha_i + u_{it}$
Where:
Y_{it} – dependent variable for unit *i* at time t
ρ – spatial autoregressive coefficient (measures how much neighbours' values influence *i*)
W_{ij} – element of the spatial weight matrix W (represents the link between unit *i* and unit *j*)
$X_{it}\beta$ – explanatory variables and their coefficients
α_i – individual fixed effect (specific to unit *i*, constant over time)
μ_{it} – error term

a.2. SEM: $Y_{it} = X_{it}\beta + \alpha_i + u_{it}$, $u_{it} = \lambda \sum_{i \neq j} W_{ij} u_{jt} + \varepsilon_{it}$
Where:
Y_{it} – dependent variable for unit *i* at time t
$X_{it}\beta$ – explanatory variables and their coefficients
α_i – individual fixed effect (specific to unit *i*, constant over time)
μ_{it} – error term, but spatially correlated
λ – spatial autocorrelation coefficient of the error
$W_{ij}\mu_{jt}$– weighted average of the errors of neighbours
ε_{it} – pure error term

a.3. SARAR: $Y_{it} = \rho \sum_{i \neq j} W_{ij} Y_{jt} + X_{it}\beta + \alpha_i + u_{it}, u_{it} = \lambda \sum_{i \neq j} M_{ij} u_{jt} + \varepsilon_{it}$
Where:
Y_{it} – dependent variable for unit *i* at time t
ρ – spatial autoregressive coefficient (measures how much neighbours' values influence *i*)
W_{ij} – element of the spatial weight matrix W (represents the link between unit *i* and unit *j*)
$X_{it}\beta$ – explanatory variables and their coefficients
α_i – individual fixed effect (specific to unit *i*, constant over time)
μ_{it} – error term, but spatially correlated
λ – spatial autocorrelation coefficient of the error
$M_{ij}\mu_{jt}$– another spatial weight matrix
ε_{it} – pure error term

b. Models with random effects: spatial lag model (SAR), spatial error model (SEM) and spatial error model with spatial lag (SARAR)

b.1. SAR: $Y_{it} = \rho \sum_{i \neq j} W_{ij} Y_{jt} + X_{it}\beta + u_{it}, u_{it} = \alpha_i + \varepsilon_{it}$
Where:
Y_{it} – dependent variable for unit *i* at time t
ρ – spatial autoregressive coefficient (measures how much neighbours' values influence *i*)
W_{ij} – element of the spatial weight matrix W (represents the link between unit *i* and unit *j*)
$W_{ij}Y_{jt}$ – spatial lag of the dependent variable
$X_{it}\beta$ – explanatory variables and their coefficients
μ_{it} – composite error term

α_i – random effect (individual-specific component, treated as a random variable)
ε_{it} – pure error term

b.2. SEM: $Y_{it} = X_{it}\beta + u_{it}, u_{it} = \alpha_i + \lambda \sum_{i \neq j} W_{ij} u_{jt} + v_{it}$
Where:
Y_{it} – dependent variable for unit *i* at time t
$X_{it}\beta$ – explanatory variables and their coefficients
μ_{it} – error term with spatial dependence and random effects
α_i – random effect
λ – spatial autocorrelation coefficient of the error
$W_{ij}\mu_{jt}$– spatial lag of the error term

ν_{it} – idiosyncratic error term

b.3. SARAR: $Y_{it} = \rho \sum_{i \neq j} W_{ij} Y_{jt} + X_{it}\beta + u_{it}, u_{it} = \alpha_i + \lambda \sum_{i \neq j} W_{ij} u_{jt} + \varepsilon_{it}$
Where:
Y_{it} – dependent variable for unit *i* at time t
ρ – spatial autoregressive coefficient (effect of the neighbours' Y)
W_{ij} – spatial weight matrix
$X_{it}\beta$ – explanatory variables and their coefficients
μ_{it} – error term, but spatially correlated
α_i – random effect
λ – spatial autocorrelation coefficient of the error
$W_{ij}\mu_{jt}$– spatial lag of the error term
ε_{it} – pure error term

Two main categories of methods are used to estimate spatial models using panel data: the Maximum Likelihood (MLE) method and the Generalized Method of Moments (GMM). In general, maximum likelihood estimators are more efficient but require stricter conditions on the normal distribution of the error term. The Generalized Method of Moments is often preferred because it is faster and easier to implement. In addition, since the estimators do not rely on the assumption of normality, those obtained by this method are more tolerant of heteroscedasticity. To decide which model is more suitable for the analysis, there are several methods that can be applied, the main ones being:

a. The Hausman Test

H0: the random effects estimator is consistent
H1: the random effects estimator is inconsistent

If we reject the null hypothesis, one or both estimators are inconsistent. However, since empirical experience has shown that fixed effects are more suitable for spatial data, we will choose this type of effects as being suitable for the analysed model.

b. Baltagi, Song and Koh marginal test

SLM1 hypotheses:
H0: fixed effects model
H1: random effects model

SLM2 hypotheses:
H0: there is no spatial autocorrelation in the spatial model errors
H1: there is spatial autocorrelation in the spatial model errors.

Sometimes the two tests commonly used for selecting fixed or random effects (namely Baltagi, Song and Koh SLM1 marginal test and Spatial Hausman test) indicate different results. In this case, fixed effects are preferred since empirical experience has shown that they are more suitable for spatial data.

To achieve the objective of analysing regional inequalities regarding the education index in Romania in relation to the digitalization of the educational process, we estimated different types of spatial models, using panel data for the 8 development regions of Romania, during the period 2001-2022.

The dependent variable for the estimated models is the education index, taken from the Global Data Lab. The indicator represents the educational dimension of the human development index and is determined using two indicators. The first indicator estimates the average years of schooling of adults over 25 years of age and reflects the current situation regarding education in a region. The second indicator estimates the expected years of schooling and indicates the probable level of education of the population in the future. It is defined as the number of years of schooling that a child of school-going age can expect to receive, if the prevailing patterns of age-specific enrolment rates persist throughout the child's schooling life. Finally, the education index is calculated as the geometric mean of the separate indices for expected years of schooling and average years of schooling.

The main variable of interest in all models to be estimated is digitalization. The proxy variable used for this purpose is the number of computers in the administration of educational units, and the data source is the National Institute of Statistics. According to the literature, we expect this influencing factor to exert a positive impact on the dependent variable - education index.

Our choice for this proxy is motivated by several considerations. First, computers are widely adopted as digital infrastructure in schools and universities. They are fundamental for any other digital technologies. Second, this variable ensures comparability over time as it is systematically reported by the National Institute of Statistics. Finally, while other indicators (e.g. internet connectivity) might be more relevant, they are not available at the level of development regions. Therefore, the chosen variable offers an accessible proxy that captures a fundamental aspect of digitalization.

Other explanatory variables to be included in the different specifications of the panel estimation models are the human development index (HDI) calculated at regional level, the income index and the health index. The data source is Global Data Lab. These additional factors should also positively influence the synthetic education index.

4. Research results and comments

Prior to econometric models' estimation the first step was to identify the correlations that exist between the indicators. For this purpose, a correlation matrix was created for all the variables of the models. According to the correlation matrix, the dependent variable education is strongly and positively influenced by the independent variables: digitalization (number of computers), income and health.

Next, we checked whether the errors of the classical model are spatially correlated, which would justify estimating a spatial panel model instead of the classical (non-spatial) one. For this purpose, we first estimated the classical panel and then used the Pesaran test for cross-sectional independence of observations. As it turned out, the Pesaran test strongly rejects (Pr = 0.0000) the null hypothesis of independence of the territorial distribution of the values of the variables in the classical model, which justifies the further use of the spatial model.

Consequently, panel spatial regression models were estimated, according to the methodology presented above: spatial autoregressive model (SAR), spatial error model (SEM), spatial Durbin (SDM). Both fixed and random effects were estimated, but since fixed effects proved to be better (as expected based on the spatial data literature), only these were further reported. The synthetic results are presented in Table 1.

Table 1. Education index by digitalization, income and health, 2001-2022

	Models			
Variables	**OLS**	**SDM fixed effects**	**SAR fixed effects**	**SEM fixed effects**
Constant	-0.8868922***	-	-	-
Spatial lag (Education index)	-	0.7547102***	0.8849915***	-
Digitalization (Computers)	0.0625578***	0.0007959*	-0.0144687***	0.0553945***
Income	0.0256798	0.0886358	0.1415547***	-0.1128259
Health index	0.249506**	0.1194605	-0.0310759***	0.5521695***
Spatial effects of independent variables				
W Digitalization	-	-0.0054889***	-	-
W Income	-	0.0727525***	-	-
W Health index	-	-0.0988469***	-	-
Global spatial effects				
Rho	-	0.0818293***	0.0309901*	-
Lambda	-	-	-	0.2131994***
Selection criterion				
Loglikelihood		589.1170	566.5616	566.5616
Akaike		-1164.655	-1123.098	-949.3741
Schwartz		-1142.787	-1104.354	-933.5217

Source: Authors' computations in Stata.

Comparing the results in Table 1 stemming from the various models - classic OLS, spatial autoregressive model (SAR), spatial error model (SEM), and spatial Durbin (SDM) - the econometric criteria for choosing the best model indicate the Spatial Durbin Model with fixed effects as the most appropriate for our data. The results obtained based on the SDM model indicate statistically significant spatial effects, the spatial lag of the dependent variable education being positive and strongly significant, which means that there are strong interdependencies in the field of education between neighbouring regions: a region with a high educational index tends to be surrounded by regions that have, in turn, a high level of education.

Conversely, a region characterized by a low educational index is often geographically surrounded by other regions that similarly exhibit low levels of education. This pattern suggests the formation of clusters or groups of neighbouring regions sharing comparable educational outcomes, highlighting the spatial clustering of educational disparities across the country. Such clustering may be driven by shared socio-economic conditions, cultural factors, or infrastructural limitations that affect educational access and quality. For example, regions with limited investment in schools or a lack of qualified teachers may perpetuate low educational standards, which in turn influence adjacent regions through migration patterns, resource allocation, and regional policies.

These global interdependencies are captured by the lagged dependent variable — education — indicating that the educational status of one region is influenced not only by its own characteristics but also by the education levels of its neighbours. This spatial autocorrelation underscores the importance of considering geographic context in educational policymaking, as isolated interventions may be less effective without addressing the broader regional dynamics.

These spatial patterns are further reinforced when examining the spatial effects of key independent variables. Specifically, the three independent factors considered in the model — digitalization, income, and health— demonstrate significant spatial spillover effects. This means that the levels of these variables in neighbouring regions play a crucial role in shaping the educational index of the reference region. For instance, a region surrounded by neighbours with high digital connectivity may benefit indirectly through shared access to online educational resources or regional digital initiatives. Similarly, higher income levels in neighbouring regions can translate into greater overall investment in education infrastructure or community support, which may have positive ripple effects across borders.

Health, as another independent variable, influences educational outcomes by affecting students' ability to attend and perform well in school; healthier populations in nearby regions can lead to better health awareness and services that transcend administrative boundaries. These interconnected socio-economic factors highlight how education is embedded in a wider system of regional development and well-being.

The fixed-effects Spatial Durbin Model (SDM) applied in this study reveals several important findings. Foremost among them is the strong positive influence of digitalization on the education index, emphasizing that the integration of digital technologies—such as high-speed internet access, digital learning platforms, and e-government services—plays a vital role in enhancing educational opportunities. Digitalization not only facilitates remote learning and access to global knowledge but also helps reduce disparities caused by geographical isolation or lack of physical infrastructure. Moreover, the model uncovers clear spatial interdependencies between neighbouring regions, supporting the notion that education does not develop in isolation but rather benefits from regional collaboration and the diffusion of resources, expertise, and policies. This spatial interconnectedness suggests that regions that invest collectively in education and digital infrastructure may achieve synergistic effects, elevating the overall educational performance beyond what isolated efforts could accomplish.

Together, these results validate our initial hypotheses: first, that digitalization is essential to modern educational processes, enabling better access to information, innovative teaching methods, and lifelong learning opportunities; and second, that fostering regional cooperation in education leads to mutually reinforcing benefits, promoting more balanced educational development across the territory. From a policy perspective, this underscores the need to design coordinated regional strategies that leverage digital tools and encourage inter-regional partnerships. Such approaches can help bridge educational gaps, reduce inequalities, and support sustainable development goals by empowering learners and educators alike.

In conclusion, understanding and harnessing the spatial dimensions of education, alongside socio-economic drivers, is crucial for building resilient and inclusive educational systems in the 21st century.

5. Conclusion

In this paper, we analysed the relationship between digitalization and education in Romania from a territorial perspective, at the level of development regions, using panel spatial models. For this purpose, specific spatial analysis methods were applied to facilitate the highlighting of regional connections impossible to identify with classical econometric methods. Our research therefore used appropriate methods of spatial analysis to incorporate economic interdependencies between neighbouring regions, thus providing a better and more complex picture of territorial socio-economic processes, compared to traditional analyses.

The specified models linked the synthetic education index (taken from Global Data Lab), as a dependent variable, with the explanatory variables: digitalization (using the number of computers in the administration of educational units as a proxy variable), the human development index (HDI) calculated at the regional level, the income index and health.

The correlation matrix, which measures the links between the model variables, showed that the dependent variable education is strongly and positively influenced by the independent variables: digitalization (number of computers), income and health. The descriptive statistics for the model variables indicated a significant variation between regions in their values, and the Pesaran test strongly rejects the null hypothesis of independence of the territorial distribution of the variable values in the classical model, both showing the opportunity of spatial analysis instead of the classical one.

Different types of spatial panel regression models were estimated and compared and the criteria for choosing the best model indicated the fixed effects spatial panel Spatial Durbin Model (SDM) as the most appropriate for our data.

The results revealed statistically significant spatial effects, the spatial lag of the dependent variable education being positive and strongly significant. This means there are strong interdependencies between neighbouring regions in the field of education. A region with a high educational index tends to be surrounded by regions that also have a high level of education. Conversely, a region with a low educational index tends to be surrounded by regions that also have a low level of education. Moreover, all three independent variables (digitalization, income and health) exert spatial influences: their level in neighbouring regions significantly influences the level in the reference region.

The results obtained from this study hold significant relevance for a wide range of stakeholders engaged in the economic and education activities. In particular, policymakers who design and implement educational and economic strategies stand to benefit from these insights. For example, a solution might be increasing investments in digital infrastructure (computers, smart boards or high-speed internet) in regions with low digitalization. In already digitalised regions, policies might focus on fostering regional cooperation, sharing best practices and providing continuous professional development for teachers. In this case, in addition to policies that address the transformation of digital infrastructure, teacher training in this direction is needed (Mystakidis, et al., 2022).

The empirical evidence clearly indicates that digitalization is not merely a complementary tool but a central element that must be integrated thoughtfully into educational frameworks. This highlights the need for effective use of technologies so that they become a real factor of progress (Sadjadi, 2023). However, beyond the mere adoption of digital technologies, it is equally crucial to establish effective mechanisms for monitoring and controlling their use to ensure that they contribute positively to the education system. This includes addressing challenges such as digital literacy gaps, equitable access to technology, data privacy concerns, and the prevention of misuse or over-reliance on digital tools. In the absence of developed digital skills, the positive effect turns into a contribution with unwanted effects (Feldman & Czerniewicz, 2023). By doing so, policymakers can harness the full potential of digitalization to foster a more inclusive, efficient, and adaptive educational environment that meets the evolving needs of students and educators alike.

While this study provides valuable initial insights into the relationship between education and digitalization within Romania’s regional context, it represents only a foundational step in understanding this complex dynamic. The current analysis opens several avenues for future research that could deepen and broaden our comprehension of the factors shaping educational outcomes. For instance, subsequent studies could explore additional determinants of the education index, such as cultural influences, quality of educational institutions, teacher qualifications, and socio-political factors, which may also play critical roles in shaping regional educational disparities. Moreover, extending the temporal scope of the research to cover a longer period would allow for the observation of new trends over time and the assessment of long-term impacts of digitalization and other socio-economic variables.

Another important direction for future work involves refining the spatial granularity of analysis by examining smaller territorial units, such as municipalities or school districts, rather than broader regions. This finer scale could reveal more nuanced patterns and localized interactions that remain obscured at higher levels of aggregation.

Ultimately, such detailed investigations can inform targeted interventions and policies that address specific local needs while complementing broader regional or national strategies. Together, these efforts will contribute to building a more comprehensive and actionable knowledge base to support the continuous improvement of the Romanian education system in an increasingly digital and interconnected world.

***Authors contribution**: Introduction, M.I.-D., G.Z.; Literature review, M.I.-D., G.Z.; Methodology and data, M.I.-D., G.Z.; Research results and comments, M.I.-D., G.Z.; Conclusion, M.I.-D., G.Z.*

References

Abeysekera, L., & Dawson, P. (2014). Motivation and cognitive load in the flipped classroom: Definition, rationale and a call for research. *Higher Education Research & Development*, *34*.

Areshonkov, V. (2020). Digitization of higher education: Challenges and answers. *Visnyk NAPN Ukrainy - Bulletin of the National Academy of Sciences in Ukraine*, 2, 2.

Azorín, C. (2020). Beyond COVID-19 supernova: Is another education coming? *Journal of Professional Capital and Community*, *5*(3–4), 381–390.

Bessarab, A., Turubarova, A., Gorshkova, G., Antonenko, I., & Rukolyanska, N. (2022). Creating a digital institution of higher education: Theory and practice. *Eduweb*, *16*(3), 106–120.

Bozkurt, A., & Sharma, R. C. (2020). Education in normal, new normal and next normal: Observations from the past, insights from the present and projections for the future. *Asian Journal of Distance Education*, *15*(2), i-x. https://doi.org/10.5281/zenodo.4362664

Brunetti, F., Bonfanti, A., Longhi, A., Pedrini, G., & Orzes, G. (2020). Digital transformation challenges: Strategies emerging from a multi-stakeholder approach. *The TQM Journal*, *32*(4), 697–724.

Cotton, D., & Winter, J. (2010). It's not just bits of paper and light bulbs: A review of sustainability pedagogies and their potential for use in higher education. *Sustainability Education: Perspectives and Practice Across Higher Education*, 39-54.

Faturoti, B. (2022). Online learning during COVID-19 and beyond: A human rights-based approach to internet access in Africa. *International Review of Law, Computers & Technology*, *36*(1), 68–90.

Feldman, J. & Czerniewicz, L., 2023. Transitions in education: Educators, digitalisation, and datafication. Journal of Education, Vol. 92.

Gao, Y., He, Q., Liu, Y., Zhang, L., Wang, H., & Cai, E. (2016). Imbalance in spatial accessibility to primary and secondary schools in China: Guidance for education sustainability. *Sustainability*, 8(12), 1236. https://doi.org/10.3390/su8121236

Goodman, B., & Richardson, J. (2010). Climate Change, Sustainability and Health in UK Higher Education: The Challenges for Nursing. In P. Jones, D. Selby, & S. Sterling (Eds.), *Sustainability Education: Perspectives and Practice Across Higher Education* (Vol. 0)

He, G., & Huang, Q. (2021). Geospatial analysis and research on social and spatial inequality of compulsory education: A case study of Hangzhou, China. *Complexity*, 1-14.

Kwon, J. E., & Woo, H. R. (2018). The impact of flipped learning on cooperative and competitive mindsets. *Sustainability*, *10*(79). https://doi.org/10.3390/su10010079

Mystakidis, S., Christopoulos, A. & Pellas, N., 2022. A systematic mapping review of augmented reality applications to support STEM learning in higher education. Education and Information Technologies, Vol. 27, pp. 1883-1927.

Passantino, F. (2021). Reflections: Diversity, inclusion and belonging in education post-COVID. *Intercultural Education*, *32*(5), 583–589.

Queiroz, M. V. A. B., Sampaio, R. M. B., & Sampaio, L. M. B. (2020). Dynamic efficiency of primary education in Brazil: Socioeconomic and infrastructure influence on school performance. *Socio-Economic Planning Sciences*, Elsevier, vol. 70(C).

Reimer, F., & Schleicher, A. (2020). A framework to guide an education response to the COVID-19 pandemic of 2020. *OECD Publishing*. https://doi.org/10.1787/6a26b082-en

Sadjadi, E., 2023. Challenges and Opportunities for Education Systems with the Current Movement toward Digitalization at the Time of COVID-19. Mathematics, 11(2).

Safonov, Y., Vsyk, V., & Bazhenkov, I. (2022). Digital transformations of education policy. *Baltic Journal of Economic Studies*, *8*(2), 127-136. https://doi.org/10.30525/2256-0742/2022-8-2-127-136

Toquero, C. (2021). "Sana all" inclusive education amid COVID-19: Challenges, strategies and prospects of special education teachers. *International and Multidisciplinary Journal of Social Sciences*, *10*(1), 30–51.

Walker, J., Brewster, C., Fontinha, R., Haak-Saheem, W., & Lamberti, F. (2021). Examining the impact of Brexit & COVID-19 on the working lives of business, management and economics academics in the UK. *Henley Business School Report*.

Walsemann, K. M., Fisk, C. E., & Dues, A. N. (2021). A spatial analysis of county-level education context and population health and wellbeing. *Wellbeing, Space and Society*, *2*. https://doi.org/10.1016/j.wss.2021.100039

Wan, J., Liu, Y., Chen, Y., Hu, J., & Wang, Z. (2018). A tale of north and south: Balanced and sustainable development of primary education in Ningxia, China. *Sustainability*, *10*(2), 559. https://doi.org/10.3390/su10020559