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IMPROVING EDUCATION THROUGH DIGITALIZATION.
A SPATIAL PANEL MODEL

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Abstract

The outbreak of the COVID-19 pandemic caused major disruptions in the education environment, leading to a shift from traditional classroom learning to online education, and accelerating the ongoing digital revolution. The expansion of digital infrastructure prompted by the pandemic has the potential to facilitate long-term systemic improvements within educational institutions. Building on this perspective, our research seeks to evaluate the transformative role of digital tools in Romanian education. Additionally, accounting for large regional disparities in economic development, as well as in education, the influence of digitalization was analysed through a spatial lens. The use of specific spatial econometric methods allows for capturing spatial interactions between regions, enhancing our understanding of these mechanisms. The findings indicate that while digital resources may not inherently improve academic performance under conventional circumstances, they remain indispensable for ensuring educational continuity during disruptive periods, such as global pandemics or extreme environmental events. The insights derived from the analysis offer valuable guidance for

policymakers in designing frameworks that enhance the resilience and efficiency of digital integration in schools.

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

1. Introduction

Education is a structured and deliberate process of accessing knowledge, based on scientifically validated teaching strategies and methods. Education may be understood simultaneously as an outcome, a process, and a set of deliberate actions. Above all, the educational system - regardless of the country in which it operates - constitutes a fundamental pillar of society, with the essential role of shaping individuals and fostering communal progress. It must promote a core set of moral values, such as respect, responsibility, and empathy, thereby contributing to the creation of a stable future. For these outcomes to be realized, individuals must be granted free and equitable access to education, irrespective of gender, age, or social background. Hence, equality of opportunity and the absence of discrimination represent fundamental prerequisites for the proper functioning of any educational system. Once these conditions are ensured, it becomes imperative that teachers be thoroughly trained and capable of integrating both traditional and modern methods of teaching and assessment into their professional practice.

The COVID-19 pandemic has undeniably transformed the educational landscape, compelling students and teachers to adopt greater flexibility and accept changes to navigate the new challenges they faced (Schmidt, 2020). Within this complex context, all stakeholders encountered both obstacles and opportunities that are set to redefine the future of teaching, learning, and assessment. From the onset of the pandemic, educational institutions were either closed, suspended their courses, or operated under hybrid arrangements depending on the prevailing epidemiological conditions. The quality of education worldwide was inevitably affected, to varying degrees, by factors such as school infrastructure, internet connectivity, and teachers' digital competencies (Wahab, 2020). In Romania, for instance, there was a four-week period (April 2020) during which classes were conducted based on teachers' individual choices, often constrained by very limited access to digital resources. Two forms of learning were employed: synchronous and asynchronous. The former closely resembled traditional teaching through real-time communication platforms (e.g., Zoom, Teams, Webex), yet posed additional challenges for educators, who found it difficult to deliver content while simultaneously monitoring students' engagement via cameras. Conversely, asynchronous learning offered greater flexibility in scheduling (Mladenova, Kalmukov, & Valova, 2020). Understanding the teaching and learning practices of that period is therefore essential to design the future of education in the aftermath of COVID-19 (Daniel, 2020).

Although technology had already been predominantly employed in other fields, education had only marginally intersected with digital tools. The global closure of schools during the pandemic meant that learning could continue solely in online environments. For the first time, teachers and students found themselves separated not only by screens but also by their varying levels of digital competence. From that moment onward, the educational system embarked on an irreversible trajectory of change. The magnitude of these transformations is such that a reversion to pre-pandemic educational models is no longer feasible. Within this framework, the present study contributes to the existing literature in several key respects. First, it explains the role of digital adoption in restructuring the Romanian educational system. Second, it quantifies the efficiency gains resulting from the integration of digital tools into educational activities. Third, it identifies territorial interactions within the educational process by employing spatial econometric techniques designed to capture spatial dependence. By integrating spatial and temporal dimensions through spatial panel models, this research provides a granular perspective, demonstrating how regional heterogeneities, temporal trends, and spatial interactions influence the nexus between education and digitalization. Finally, it provides suggestions concerning potential future directions that could be pursued to alleviate regional gaps in education and to enhance the contribution of digitalization to this process.

2. Literature review

Since ancient times, the national educational system has been shaped by international ideologies. Over the course of its evolution, education has undergone numerous reforms, each aiming to generate a positive impact on its participants. Among the most significant influences were the French School (1877–1939), the German School (1930–1947), and the Soviet School (1948–1989). Nowadays, the range of external influences has become too extensive to be clearly defined (Anghelache et al., 2018). Following Romania's accession to the European Union in 2007, the educational system was increasingly aligned with European directives, particularly with respect to learner-centered approaches and digitalization. Another notable shift has been the recognition that learning does not end with compulsory education, as a wide variety of continuing education programs for adults are now available. Nevertheless, the Romanian educational system has faced, and continues to face, persistent challenges, including rural–urban disparities (Zamfir et al., 2024), high dropout rates (Petre et al., 2024), and a shortage of skills required by the labour market (Rogoz, 2024). To function effectively, educational institutions rely on a wide range of resources, the most significant being human resources, financial, informational, and technological resources, school infrastructure, and curricula. While all of these are essential for the proper functioning of the system, their relative importance varies, as some contribute more actively than others to the overall quality of education. Research on the effects of technology in education began approximately twenty years ago, and studies have highlighted that technology can yield positive outcomes compared to traditional learning in certain subject areas by enabling content personalization, increasing student engagement, and facilitating access to resources (Meza-Fregoso et al., 2024). However, the same studies emphasize the crucial role of the teacher and the way instructional materials are designed and implemented (Diaz-Barriga, 2013). Technological resources in pre-university education primarily include computers and similar devices available within schools. They also encompass software solutions such as Google Classroom, Microsoft Teams, or Zoom, as well as emerging technologies including virtual reality headsets, augmented reality tools, and artificial intelligence devices. Like many other European countries, Romania did not, prior to the pandemic, possess an extensive network of technological resources for teaching and learning. Classrooms were not equipped with computers and smart boards, and lacked access to educational platforms, leaving both teachers and students with minimal exposure to digitalization. A specialized study concluded that, as of 2018, even economically developed countries such as Germany, Italy, and France were lagging in terms of access to educational technology (Fraillon et al., 2019).

The COVID-19 pandemic represents an unprecedented event that fundamentally transformed the world as we knew it. All sectors experienced significant changes, and individuals adopted habits and behaviours that persist to this day. The most significant change resulting from the state of emergency and ceasing of physical presence in schools and universities was the rapid transition to online classes. At the peak of the pandemic, more than 190 countries temporarily closed schools as a preventive measure to curb the virus's spread (Jones et al., 2021), leaving approximately 91% of the school-age population at home (UNESCO, 2020). In Romania, there was a four-week period in April 2020 during which classes were conducted according to teachers' individual choices, largely constrained by limited access to digital resources. Until that point, teachers had generally been hesitant to integrate technology into their teaching; however, the circumstances compelled them to adopt it as a necessary solution (Dhawan, 2020).

By March 2020, global lockdown measures were implemented, confining people to their homes, and schools transitioned entirely to online learning. Both universities and pre-university educational institutions closed their doors, requiring teachers and students to interact virtually. This shift entailed both advantages and disadvantages.

Numerous digital resources were made available for use by both teachers and students, the latter being naturally attracted to this mode of learning due to its autonomy and convenience. Over the years, educational platforms, interactive games, and online libraries have been developed. These resources can be accessed from virtually anywhere, at any time, and by nearly anyone. Although they existed prior to the pandemic and had been gradually developed over the past two decades, their utilization accelerated beginning in 2020 (Serdyukov, 2021). Consequently, the pandemic context is closely linked to the digitalization of the educational system, which offered a wide range of benefits.

However, it must be noted that the closure of schools and universities had adverse effects on students from vulnerable backgrounds. Young people living in impoverished areas with limited or no internet access, as well as restricted access to electronic devices, were particularly affected. For example, in disadvantaged families with multiple children, difficult choices had to be made regarding which child could participate in online classes when devices were insufficient. Larger access to the internet and technological resources can help mitigate such inequalities (Korkaz et al., 2022). Due to a lack of resources, some children experienced significant educational losses. Moreover, the absence of personal space at home and unfavorable external conditions (e.g., cold, noise) further disrupted online learning. Consequently, students from developing countries, as well as those from impoverished or special-needs contexts, suffered disproportionately during online education. Factors such as gender, poverty, and disabilities contributed to deepening social inequalities.

A UNICEF report (UNICEF, 2020) concluded that 31% of children were unable to engage in online learning due to lack of access to technology. Non-participation in classes, particularly among primary school students, risked the loss of foundational skills such as reading and arithmetic. Additionally, some children missed access to nutritious meals and protection from domestic violence that schools had previously provided. A telephone survey conducted in Peru, India, Vietnam, and Ethiopia found that, compared to 2016, students experienced significant learning losses and an increase in school dropout rates due to the COVID-19 pandemic (Favara et al., 2022). In Ethiopia, only one in ten surveyed students maintained contact with their teachers during the pandemic. This is largely attributable to the limited and uneven access to internet and technological tools necessary for remote learning in low- and middle-income countries. Nevertheless, 86% of respondents made efforts to continue learning during the suspension of in-person classes. In Jordan, 96% of surveyed students participated in learning activities during the pandemic, primarily using online educational resources, whereas in Bangladesh and Ethiopia, students relied on pre-owned text-books or educational programs delivered via radio and television (Bangladesh).

The use of digital tools within the teaching–learning–assessment process can provide a personalized learning experience, leading to increased productivity, while also raising ethical concerns. In the post-pandemic period, artificial intelligence has experienced significant growth, and AI-based applications, such as ChatGPT, are increasingly utilized by students, thereby impacting the integrity of the assessment process in education. Academic dishonesty has always been a serious issue, and the COVID-19 pandemic has only exacerbated it. Studies indicate that students were more likely to engage in cheating during examinations conducted through digital platforms compared to traditional in-person exams (Janke et al., 2021; Flores et al., 2022; Newton & Essex, 2023).

Online availability of textbooks in Romania slowly increased since 2018, but the widespread use of digital tools speeded up with the onset of the COVID-19 pandemic. In March 2025, six years after the initial announcement of the project, the Ministry of Education launched the Edulib platform, which provides access to all textbooks in digital format, as well as specially designed learning sheets for both students and teachers. This demonstrates that the authorities continue striving for the comprehensive digital transformation of the education sector in the wake of pandemic, although the process seems to have lost momentum.

In recent years, specifically 2023 and 2024, Romania has benefited from several projects funded through the National Recovery and Resilience Plan (PNRR), enabling schools to acquire state-of-the-art technology to support the educational process. For example, under the program aimed at equipping schools with smart laboratories, institutions across the country received advanced PCs, smart boards, educational content platforms, virtual reality headsets, 3D printers, and other specialized technological equipment tailored to their study profiles. These investments are intended to enhance the degree of digitalization within the educational system while simultaneously improving the quality of instruction. Unfortunately, there is no centralized database documenting the number of devices and their distribution across counties. Nonetheless, it is expected that in the coming years, once the implementation of these projects is finalized, such data will become publicly available.

Currently, although online examinations are no longer as prevalent, students continue to use digital tools to circumvent assessments and employ artificial intelligence software to complete assigned tasks. AI can generate content tailored to individual learners; however, this raises important ethical considerations (Lam & Khare, 2016). For instance, tools such as ChatGPT can help bridge the gap between students and teachers by supporting diverse learning styles and providing materials adapted to each learner’s needs (Ollivier et al., 2023). Furthermore, in higher education, the use of such software facilitates the research process, particularly in reviewing existing literature (Bin Arif et al., 2023). Nevertheless, it is essential to ensure that any content produced through these tools is carefully verified for accuracy to prevent the dissemination of misinformation (Fijačko et al., 2023).

This paper contributes to the existing literature by addressing a significant research gap: prior studies have generally examined digitalization, the COVID-19 pandemic, educational resources and school performance in isolation, while overlooking the spatial dependencies and interconnections among these factors. Using a specific methodology, this paper contributes to a more detailed and in-depth analysis for Romania which can be replicated for other countries.

3. Method

The present study undertakes a comprehensive investigation into the interrelationship between education and digital transformation at the Romanian county level. Its principal aim is to evaluate how technological infrastructure modulates educational outcomes within a spatial-temporal framework.

3.1. Data

The analysis includes a set of relevant variables from 41 counties and the municipality of Bucharest, corresponding to the NUTS3 territorial level, over the period 2001–2023. To obtain a comprehensive understanding of the relationship between education and digitalization, the study employs advanced econometric methods, such as spatial panel econometric models. This econometric approach enables the assessment of spatial interactions among counties, considering both temporal and spatial effects. Consequently, it is possible to measure the extent to which the degree of digitalization in one county influences neighbouring counties. The results of this analysis can inform public policy aimed at implementing and optimizing the use of digital infrastructure in educational institutions at the national level.

Our spatial econometric analysis aims to address the following research questions:

(a) Which factors influence education in Romania?

(b) What are the temporal and spatial effects of these influencing factors?

(c) Are there significant spatial interactions between counties with respect to educational outcomes?

The literature warns that traditional regression models yield inaccurate results when interactions exist between neighbouring regions (Anselin, Le Gallo, & Jayet, 2008; LeSage & Pace, 2009). The fallacy arises because the spatial distribution of regressors is usually unbalanced due to local characteristics. In such cases, spatial econometric modelling is an appropriate alternative, as it captures spatial dependencies between territorial units and provides more relevant and precise estimates. Furthermore, to account not only for territorial variations but also for temporal dynamics, this study employs a spatial panel econometric model. By combining spatial and temporal dimensions, this approach extends the analytical horizon and offers a more detailed perspective, highlighting how regional disparities and temporal trends influence the relationship between education and the degree of digitalization within the educational system.

To collect the necessary data, the official database of the National Institute of Statistics was thoroughly examined. Considering all available options within the database, the following variables were selected.

Table 1. Variables

Variable Type	Name	Description
Dependent Variable	Education	Annual number of graduates relative to the school-age population (own calculations)
Independent Variables	Digitalization	Number of computers available in educational institutions relative to the school-age population (own calculations)
	Teachers	Number of teachers per 100 students (own calculations)
	Income	GDP per capita at constant prices (own calculations)
	Health	Average life expectancy (years)
	COVID	Dummy variable: 0 = 2001–2019; 1 = 2020–2023

Source: Own representation.

All variables were obtained from the TEMPO online database of the National Institute of Statistics and have been processed through own calculations into indicators suitable and relevant for the analysis. The dataset comprises county-level observations for Romania from 2001 to 2023, representing the maximum available timeframe for this research.

3.2. Method

To select the most appropriate spatial model for analysing the relationship between education and digitalization across counties, it is essential to consider the general methodology of spatial econometric models. This serves as the starting point for the present analysis, with the goal of identifying a model that provides an accurate assessment of territorial characteristics and yields high-precision results.

The first consideration is that territorial units, namely counties, do not operate as independent entities. Interactions between neighbouring counties, whether social or economic, are significant and create spatial dependencies that cannot be ignored. Consequently, the use of a classical regression model would produce distorted results, as territorial influences would not be accounted for. To ensure accurate analysis, a spatial regression model should be employed, and various econometric specifications need be tested, with the final model selection guided by statistical testing.

Irrespective of the specific spatial model employed, the construction of a spatial weight matrix (W) is indispensable, as it serves as the mechanism through which all spatial lags are integrated into the model. The spatial weight matrix depicts the relative spatial positions of territorial units. Its role is to explicitly model and account for spatial dependence among the territorial units within the regression framework. Alternative spatial weight matrices must be tested until a valid model is achieved.

Next, we specify the spatial regression models by considering the different modalities through which territorial units exhibit interaction with their geographical neighbors. The literature discusses the following three types of territorial interactions (e.g., Burkey, 2018):

(a) The value of the dependent variable y in one region may influence or be associated with the value of y in neighbouring regions. In this case, a spatial lag model of the dependent variable y (Spatial Lag Model), denoted as Wy, is employed.

(b) The value of an independent variable X in one region may affect (or be correlated with) the value of y in a neighbouring region (common factors of influence). Here, a spatial lag model of the independent variable X (Spatially Lagged X Model), denoted as Wx, is applied.

(c) Residuals may affect (or be correlated with) residuals in a neighbouring region (spatial correlation of omitted variables). In this case, a spatial error model, denoted as We, is used.

However, these three models limit spatial interactions to a single type:

(a) Wx – captures exogenous interaction effects in explanatory variables;

(b) Wy – captures endogenous interaction effects in the dependent variable;

(c) We – captures spatial interaction effects among the error terms.

To overcome this limitation, it is necessary to develop more complex models that incorporate combinations of these spatial effects.

Spatial regression models have been extended to panel data models, which account for dependencies created by the temporal lag of a time series. Observations are thus analysed cross-sectionally across multiple time periods. Significant contributors to this field include Kapoor (2007), Baltagi (2007), and Lee and Yu (2010), who developed and theorized models incorporating both spatial dependencies and spatial error terms, alongside fixed or random effects. These authors also proposed various tests to determine the most appropriate model for forecasting purposes (e.g., the Hausman test). One of the most widely used spatial panel data models is that of Baltagi and Li (2004), originally developed in a study on cigarette demand from 1963 to 1992 across 46 U.S. states.

A key advantage of panel data regression models is the ability to contain the unique characteristics of the observations, significantly reducing aggregation bias and loss of relevant information. Panel regression models can capture individual variability. Since panel data consist of the same observations over multiple periods, they allow for the identification of unit-specific differences. This additional information enhances the accuracy of econometric analysis and facilitates the detection of relationships that might otherwise remain hidden. Furthermore, the use of panel data reduces multicollinearity among independent variables, resulting in robust econometric estimates.

The spatial panel model builds upon the classical panel data regression model, which is expressed as:

$$y_{it} = \alpha + \beta X_{it} + \mu_{it} + \gamma_{it} + \varepsilon_{it} \qquad (1)$$

where:

i = territorial units; t = time

Y_{it} and X_{ij} - dependent and explanatory variables in region i, at time t

α and β – parameters

ε_{it} – error terms

μ_i - individual fixed effects (specific to each region i)

γ_t - temporal fixed effects (specific to each time period t).

Individual fixed effects capture the unique characteristics of each observation, remaining invariant over time, thereby reflecting individual heterogeneity. Temporal fixed effects are common across all observations and vary over time.

Panel data models with random effects are also available. In this case, individual heterogeneity accounts for effects that remain constant over time. Random effects are associated with stochastic causes and are suitable when more precise estimates are desired to generalize from a sample to the entire population. The random effects model is represented as:

$$y_{it} = \alpha + \beta X_{it} + \mu_{it},\ \mu_{it} = \alpha_i + \varepsilon_{it} \ (2)$$

The specification of the spatial panel model builds upon the classical panel model described above. Key contributions in this area have been made by Anselin et al. 366 (2008), Baltagi, Song, & Koh (2003), and Elhorst (2010). The modelling process begins with a specification that incorporates both spatial lag and spatial error effects, as follows:

$$y_{it} = \rho \sum_j w_{ij} y_{jit} + \sum_k \beta_k X_{kit} + \mu_i + \gamma t + \varepsilon_{it} \qquad (3)$$

$$\varepsilon_{it} = \lambda \sum_j w_{ij} \varepsilon_{jit} + \nu_{it} \qquad (4)$$

where:

i = regions; t = time;

w_{ij} = spatial weights

μ_i and γ_t – fixed effects

$\sum_j w_{ij} y_{jit}$ – spatial lag for dependent variable

$\sum_j w_{ij} \varepsilon_{jit}$ – spatial lag for errors

This specification represents a fixed effects spatial model, where μ_i estimates the individual-specific effect, invariant over time, on the endogenous variable y (spatial fixed effect), while γ_t estimates the time-specific effect, constant across cross-sectional units (i.e., the same for all regions), expressing the influence at time t on the endogenous variable y (temporal fixed effect).

A random effects spatial model is represented as follows:

$$y_{it} = \rho \sum_j w_{ij} y_{jit} + \sum_k \beta_k X_{kit} + \mu_{it} \qquad (5)$$

$$\mu_{it} = \alpha_i + \lambda \sum_j w_{ij} \mu_{jit} + \nu_{it} \qquad (6)$$

This model is used when a sample is drawn from a large population. The effects are captured by the variable μ_{it}, representing unobserved, unit-specific effect of variables not included in the model.

The spatial models employed in this analysis are as follows.

(1) The Spatial Autoregressive Panel Model (SAR) incorporates spatial dependence only in the dependent variable:

$$Y_{it} = \lambda \sum_j W_{ij} Y_{jit} + \sum_k \beta_k X_{kit} + \mu_i + \gamma_t + \varepsilon_{it} \qquad (7)$$

(2) The Spatial Error Panel Model (SEM) includes spatial dependence only in the error term:

$$Y_{it} = \sum_k \beta_k X_{kit} + \mu_i + \gamma_t + \varepsilon_{it} \qquad (8)$$

where: $\varepsilon_{it} = \rho \sum_j W_{ij} \varepsilon_{jit} + \nu_{it}$ (9)

(3) The Spatial Durbin Panel Model (SDM) inserts spatial dependence both in the dependent variable Y and in the independent variables X, as follows:

$$Y_{it} = \lambda \sum_j W_{ij} Y_{jit} + \sum_k \beta_k X_{kit} + \sum_l \theta W_{ij} X_{lit} + \mu_i + \gamma_t + \varepsilon_{it} \qquad (10)$$

(4) The Dynamic Spatial Panel Model incorporates a spatial-temporal lag, specifically defined as the spatial lag of the lagged dependent variable (WY_{t-1}). This specification accounts for a broad range of spatial and temporal dependencies, including contemporaneous spatial effects, serial persistence from past values, and the delayed impact of neighbouring regions. By capturing these simultaneous dynamics, the model provides a highly flexible framework for analysing panel data, typically estimated within the Spatial Durbin (SDM) or Spatial Autoregressive (SAR) structures.

After downloading the data and computing the relevant indicators, data processing was carried out in accordance with the methodology described above. The first step involved calculating descriptive statistics, which are presented in Table 2.

Table 2. Descriptive Statistics of the Variables

Variable	Average	Mean squared deviation	Minimum value	Maximum value	Number of observations
Education overall	0.228066	0.3490405	0.0086162	3.418684	966
between		0.3450759	0.0113685	2.254871	n = 42
within		0.0739365	0.4085875	1.391879	T = 23
Digitalization overall	8.832338	6.079089	0.2927954	39.54861	966
between		1.909573	6.646457	18.873	n = 42
within		5.77858	7.269134	39.58846	T = 23
Teachers overall	6.736923	0.6229393	4.445991	8.865538	966
between		0.5226743	5.676108	7.8127	n = 42
within		0.3479844	5.493084	7.953907	T = 23
GDP/capita overall	5184.03	2473.815	1867.721	21592.95	966
between		2148.872	2578.8	14743.01	n = 42
within		1267.826	1840.246	12033.97	T = 23
Health overall	73.72494	2.001708	67.36	81.51	966
between		1.010921	71.42087	76.5013	n = 42
within		1.734409	69.44363	78.73363	T = 23

Source: Own representation.

The total number of observations in the panel is 966, comprising 42 cross-sectional units (counties) and 23 time periods (2001–2023). For each variable, the statistical indicators presented in the table are calculated in three ways:

•Between: captures the spatial distribution (variation across counties) of each variable.

•Within: captures the temporal distribution (variation over the 23-year period).

•Overall: captures the total variation across both space and time.

The results in Table 2 indicate that the analysed variables exhibit variation both temporally and spatially, justifying the further use of a panel data model.

The next step involved testing the stationarity of each variable. Using the Levin-Lin-Chu test, it was concluded that only the variable Health is stationary, while the others are non-stationary.

Table 3. Panel unit root test

Variable	p-value Levin–Lin–Chu unit-root test
Education	0.3761
Teachers	0.9720
Digitalization	0.9999
Health	0.0000
GDP/capita	0.4663

Source: Own representation.

Another step involved testing the hypothesis of spatial correlation in the errors of the classical regression model. If this hypothesis is confirmed, estimating a spatial model is more appropriate than using a traditional regression model. Pesaran's test for cross-sectional independence rejected the null hypothesis, indicating the presence of spatial dependence (Table 3), justifying the use of a spatial model.

Table 4. Pesaran Test

Pesaran's test of cross sectional independence = 54,299, Pr = 0.0000
Average absolute value of the off-diagonal elements = 0.481

Source: Own representation.

The next step involved testing the normality of the errors. This assesses the asymmetry of the frequency distribution curve in comparison to a normal distribution. Regarding the random component of the errors, the null hypothesis of normality is not rejected; however, when testing the normality of the individual-specific error component, the null hypothesis is rejected.

Following these preliminary analyses, the classical (non-spatial) panel regression model was estimated. This model serves as a baseline, after which, in accordance with the methodology outlined at the beginning of the paper, the spatial models were estimated, and the most appropriate model was selected.

The spatial models were estimated using Stata BE18 with the econometric package xsmle (Belotti, Hughes, & Mortari, 2017). The first step in the estimation process involved defining the neighbourhood relationships between territorial units. Several types of spatial matrices were generated in GeoDa to determine the most appropriate specification. Initially, a first-order Queen contiguity matrix was used, but it did not yield satisfactory results. The analysis was then continued with a distance-based neighbourhood matrix, which produced better outcomes. Once the type of matrix was established, spatial panel regression models were estimated. Following the strategy proposed by LeSage and Pace (2009), the first model estimated was the Spatial Durbin Model (SDM). Subsequently, two tests were conducted to assess whether the SDM could be simplified to either a SAR or SEM model. This simplification was not possible. Therefore, the SAC model was also estimated and compared to the SDM based on information criteria (AIC and BIC) and the Likelihood statistic. Finaly, three dynamic SDM models were estimated. Dynamic models can only be estimated for SAR and SDM specifications. Since the initial tests indicated that the SDM could not be reduced to a SAR model, dynamic models were estimated solely for the SDM. The first SDM model incorporates a temporal lag of the dependent variable, the second includes a lag for the spatially lagged dependent variable, and the third combines both types of lags.

4. Results and Discussion

Initial estimations were performed using a classical panel data framework; the corresponding empirical results are presented in Table 5.

Table 5. Results for the Classic Panel Model

Variable	Coefficient	Standard error	Z	P>z
Digitalization	0,0873301	0,0121247	7,20	0,000
Teachers	0,7290148	0,0836119	8,72	0,000
GDP/capita	0,0226419	0,364588	0,62	0,535
Health	-0,0658836	0,0043561	-15,12	0,000
Covid	0,4839007	0,3947141	1,23	0,220
Covid.Digitalization	-0,984452	0,0311449	-3,16	0,002
Covid.Teachers	0,4247098	0,114054	3,72	0,000
Covid.GDP/capita	-0,1325535	0,307415	-4,31	0,000
Constant	1,184616	0,3840151	3,08	0,002
Statistics				
Sigma_u	0,69902107			
Sigma_e	0,1064081			

Source: Own representation.

The model includes interaction variables between COVID-19 and several variables: Digitalization (Covid.Digitalization), Teachers (Covid.Teachers), and GDP per capita (Covid.GDP/capita). The coefficients of the classic panel model are statistically significant, except for GDP/capita and COVID-19.

Subsequently, the spatial panel models were estimated and the resulting outputs are documented in Table 6.

Table 6. Results for spatial models

Variables	SDM		SAC	
	Coefficient	**P>z**	**Coefficient**	**P>z**
Digitalization	0,506387	0,047	0,0450739	0,000
Teachers	1,00743	0,000	0,5120521	0,000
GDP/capita	-0,542113	0,764	-0,0277933	0,469
Health	-0,0176589	0,051	-0,0239302	0,003
Covid	2,356417	0,000	0,5777786	0,365
Covid.Digitalization	-0,563742	0,240	-0,078018	0,011
Covid.Teachers	-0,0684482	0,670	0,3575568	0,091
Covid.GDP	-0,2489721	0,240	-0,1270113	0,006
W Digitalization	-0,0232636	0,001		
W Teachers	-0,1995685	0,001		
W GDP/capita	-0,0401374	0,106		
W Health	0,0187339	0,000		
W Covid	-0,40544	0,237		
W Covid.Digitalization	0,0528088	0,011		
W Covid.Teachers	-0,1020512	0,266		
W Covid.GDP	0,0568809	0,059		
Rho	0,2862009	0,000	0,0863928	0,000
Lambda	-	-	-0,1102887	0,000
Statistics				
Sigma2_e	0,206408	0,000	0,0079284	0,000
AIC	-613,3097		-1774,668	
BIC	-525,5928		-1721,063	
Log-likelihood	324,6549		898,3341	

Based on the information criteria, the most suitable model is the SAC model with fixed effects since the Log-Likelihood statistic is higher for the SAC model (898.3341) compared to the SDM model (324.6549), the Akaike Information Criterion (AIC) is lower for the SAC model (-1774.668) compared to the SDM model (-613.3097) and the Bayesian Information Criterion (BIC) is lower for the SDM model (-1721.063) compared to the SAC model (-525.5928).

To capture the temporal persistence of the phenomena, dynamic spatial specifications were subsequently estimated and are presented in Table 7.

Table 7. Results for the Dynamic Spatial Panel Models

Variables	SDM lag(1)		SDM lag(2)		SDM lag(3)	
	Coefficient	P>z	Coefficient	P>z	Coefficient	P>z
Education_t-1	0,8239942	0,000			0,8852147	0,000
W Education_t-1			-0,0070558	0,510	-0,077186	0,000
Digitalization	-0,057091	0,013	0,0368638	0,508	-0,0545443	0,003
Teachers	0,413883	0,000	0,727273	0,001	0,3162617	0,000
GDP/capita	0,0297082	0,571	-0,0165991	0,908	0,02645	0,423
Health	0,0026534	0,700	-0,0239633	0,282	0,0017334	0,716
Covid	1,111062	0,000	1,044453	0,101	0,1991339	0,333
Covid.Digitalization	0,0848403	0,002	-0,0531139	0,323	0,069627	0,002
Covid.Teachers	-0,213037	0,014	0,2911449	0,153	-0,0188528	0,762
Covid.GDP	-0,106935	0,000	-0,1744397	0,002	-0,0392983	0,017
W Digitalization	-0,010455	0,000	0,0015543	0,843	0,0047915	0,093
W Teachers	-0,040585	0,109	-0,0965926	0,016	-0,0369128	0,070
W GDP/capita	0,0065809	0,406	0,0233351	0,229	0,0069447	0,230
W Health	0,0047166	0,000	-0,0037238	0,171	-0,0015564	0,045
W Covid	0,0187941	0,842	-0,3406062	0,143	-0,0111763	0,861
W Covid.Digitalization	0,0420987	0,000	-0,0125639	0,537	-0,0017536	0,782
W Covid.Teachers	-0,075447	0,002	0,0432517	0,519	0,0008545	0,964
W Covid.GDP	0,0022298	0,780	0,0330621	0,099	0,0012875	0,810
Rho	0,057295	0,000	0,0397356	0,000	0,0704478	0,000
Statistics						
Sigma2_e	0,00418	0,000	0,0093721	0,000	0,0031729	0,000
AIC	-2419,526		-1683,005		-2648,541	
BIC	-2327,781		-1591,259		-2551,967	
Log-likelihood	1193,8704		860,0483		1335,54	

Source: Own representation.

Based on the information criteria, the dynamic SDM model with lags —for both the dependent variable and the spatially lagged variables— is the most appropriate. Moreover, when compared to the previously estimated SAC model, this dynamic SDM model demonstrates stronger explanatory power.

Examining the coefficients, those associated with the lags are statistically significant, as are the spatial dependence coefficients (rho), the variables Digitalization, Teachers, Covid × Digitalization, Covid × GDP per capita, the spatial dependence associated with Digitalization (W Digitalization), Teachers (W Teachers), and Health (W Health). The remaining coefficients do not significantly explain variations in the Education variable.

The variation in statistical significance across model specifications suggests that the estimated relationships are sensitive to the inclusion of spatial and temporal dynamics. Once spatial spillovers and higher-order lags are introduced, part of the explanatory power of several variables is redistributed to the interaction and lagged terms. This indicates that simpler specifications may overestimate direct effects while more complex structures provide a more detailed representation of interdependencies.

The rho coefficient associated with the spatial lag is positive and highly significant across all models, indicating that the educational system in one region is correlated with that in neighbouring regions. Similarly, the coefficient for the lag of Education is positive and strongly significant, suggesting that the current level of Education depends on its previous level. Conversely, the coefficient for the spatially lagged Education variable (W Education) is negative and highly significant, implying that neighbouring regions exert an inverse effect on Education, most likely due to the redistribution of educational resources among close regions.

Regarding the standard explanatory variables, Digitalization has a negative impact on Education, as does the interaction between GDP and Covid, whereas Teachers exert a positive influence, as does the interaction between Covid and Digitalization. In other words, technology proved to be extremely valuable during periods of crisis.

This selected model highlights the importance of both temporal persistence and spatial interdependencies in explaining education performance. Firstly, the positive and highly significant coefficient of Education_t-1 confirms that educational outcomes are strongly path-dependent. At the same time, the negative and significant coefficient of the W Education_t-1 suggests the existence of competitive effects between neighbouring regions indicating that educational advantages in surrounding areas may reduce the relative performance of a given region. Moreover, the findings reveal a complex relationship between digitalization and education performance. The negative coefficient suggests that technological expansion alone does not automatically improve educational outcomes. However, it has a positive impact when it interacts with the effects of COVID-19.

A more interesting finding is one about the variable for GDP. Although lnGDP/capita is not statistically significant, this can suggest that economic wealth alone does not directly explain differences in educational performance. GDP matters indirectly, but its direct marginal effect becomes statistically weak in this model. A similar explanation can be offered for the Health variable. Its direct effect is not statistically significant since health works mainly through spatial externalities, not direct effects. Lastly, the results for the COVID-19 proxy are mixed; whereas the standalone coefficient is statistically insignificant, the interaction effects frequently achieve significance, suggesting a conditional impact. Its direct effect is often absorbed by dynamics and fixed spatial effects, but it is structurally significant through heterogeneity. This can be observed by the significant positive effect for the interaction between Covid and Digitalization and the one between Covid and GDP. The first one indicates that technology was a crucial supporting factor during the pandemic, while the second one indicates that economically developed regions may have been more vulnerable to the disruptions generated by the pandemic.

5. Conclusion

Aiming to capture the effects of enhanced digitalization of the educational system during COVID-19 pandemic, we tested several spatial panel models and found that the most appropriate for the Romanian data is the dynamic Spatial Durbin Model (SDM) with lags for both the dependent variable and for the spatially lagged variables. It indicates the presence of a delayed temporal effect that significantly influences the evolution of the education system. The positive temporal lag points to an inertia process, meaning that the performance of a region in one period is likely to influence its performance in the subsequent period. This effect can also be interpreted as a motivational influence across different generations of students. In contrast, the negative spatial lag of the dynamic Spatial Durbin Model indicates competition between neighbouring regions. It suggests that regions adjacent to a high-performing area may experience a decline in educational achievements, potentially due to the redistribution of educational resources or migration of students toward better-performing areas. Such dynamics are natural in an educational environment, where is constant competition for resources, as well as continuous population mobility.

The key variable of interest, digitalization, is statistically significant in all spatial panel models, although the coefficient's sign might be surprising. Contrary to expectations that digitalization would positively contribute to educational performance ((Marhasova et al., 2023), (Sadjadi, 2023), the models show a negative effect. These findings underscore the imperative for a more strategic utilization of digital technology within the Romanian educational sector. The mere acquisition of hardware or digital tools proves insufficient for enhancing educational outcomes. Rather, the observed negative impact may be attributed to the heterogenous distribution of technological resources among schools and a lack of formalized pedagogical frameworks for their effective integration.

However, during periods of crisis, such as the COVID-19 pandemic, technology proved highly beneficial. In our models, the interaction between the variable Digitalization and the COVID dummy variable is statistically significant and positive, indicating that the presence of technological tools in schools supported not only educational continuity under emergency conditions, but improved learning results as well. This suggests that while digital resources alone may not enhance performance under normal conditions, they are critical in maintaining the learning process during disruptive events (Gorina et al., 2023), (Benavides et al., 2020), (Rapanta et al., 2021).

The number of teachers remains a highly significant positive factor in all models, emphasizing the central role of human resources in education. However, the interaction variable Teachers x COVID shows a negative effect, indicating that without adequate digital skills, teachers may face difficulties in adapting to emergency remote teaching. This underlines the importance of continuous professional development, particularly in digital competencies, alongside investments in infrastructure (Feldman & Czerniewicz, 2023). Moreover, the spatial interaction of the variable Teachers is significant, reflecting regional disparities in teacher distribution: areas with high teacher availability may attract resources at the expense of neighbouring regions.

Variables measuring health and wealth (proxied by life expectancy and GDP per capita) are generally not statistically significant. Nevertheless, during the pandemic, the interaction between GDP and the COVID-19 proxy exerted a negative influence on educational performance. This suggests that in regions with higher economic development, students might have deferred their schooling, potentially due to a lower perception of risk or the adoption of alternative protective strategies. Also, sometimes, having more resources than others may diminish the will for learning and the added value of school (Hamamoto et al., 2023). Similarly, the spatial lag associated with health shows significance in some models, indicating regional disparities in educational outcomes related to health infrastructure and conditions.

Overall, the results provide a significant framework for the development and formulation of educational policies. Moreover, the findings are original and contribute to the existing literature by revealing unexpected effects among the analyzed variables, as well as through the spatial approach applied at the county level (NUTS3) in Romania.

The analysis opens new avenues for research aimed at evaluating the long-term impact of technology use in education. The spatial models that we developed are valid and insightful, offering a tool for better understanding the Romanian education system both in general and in the context of crises such as the COVID-19 pandemic.

Digitalization represents a profound and meaningful change; however, its expected effects have not yet fully materialized, and there may be delayed impacts. Consequently, future research can build on this study by incorporating new data as it becomes available, as well as qualitative variables capturing digital competencies of stakeholders and the quality of teaching when these technologies are employed.

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