Paradigm

The Role of Renewable Energy and Emerging Technologies in Reducing Energy Poverty and Supporting Regional Sustainable Development

Maria-Magdolna MACULA*
Romanian Academy, National Institute for Economic Research "Costin C.Kirițescu", Institute of Economic Forecasting
**Corresponding author, magdamacula@gmail.com*

Georgiana Anamaria DUNĂ
Romanian Academy, National Institute for Economic Research "Costin C.Kirițescu", Institute of Economic Forecasting
anamaria.georgiana.duna@gmail.com

Sorin Alin OPREA
Romanian Academy, *National Institute for Economic Research "Costin C. Kirițescu", Institute of Economic Forecasting*
sorin-alin.oprea@ince.ro

Abstract. *Energy poverty in Romania is not just a problem of income, but also of access to modern infrastructure. This paper analyzes how the expansion of 5G technology and the quality of the electricity grid directly influence the ability of households to become prosumers. The research is based on an econometric model applied to the NUTS3 regions, for the period 2021-2025.*
The research builds an Instability Index, which was calculated using the SAIDI and SAIFI indicators. This index measures the technical resistance of old networks, which act as a brake on green energy. The data show that an unstable network with a high INI has a severe negative impact on the installed power of prosumers (coefficient -1.27; p -value - 0.0000).

The results of the Panel Least Squares model highlight the critical role of 5G coverage. Although the geographical expansion of the 5G signal is essential for smart monitoring, the final success depends on the balancing of the network. Moreover, it has been observed that economic development and the concentration of the population in urban areas function as supporting factors for the adoption of new energy technologies. The conclusion is that the simple installation of photovoltaic panels does not solve the problem without a stable digital and energy infrastructure. Our model, with an R^2 of 0.84, confirms that in order to reduce energy poverty, investments in 5G Coverage must go hand in hand with the modernization of the electricity networks, the decrease of the Instability Index, otherwise the gaps between counties will deepen.

Keywords: *energy poverty, sustainable development, renewable energy, emerging technologies, digital energy system.*

Introduction

The urgent need for decarbonization, in line with the European Union's 2023 goals, is transforming the prosumer from a mere end consumer into an active agent of change in the energy transition. Romania has seen a rapid expansion of decentralized production capacities in the period 2021-2025, but this phenomenon has not been uniform at the national level.

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This research explores how the synergy between emerging digital infrastructure and regional economic capital influences the transition to clean energy. Although digitalization, through 5G technology, may be a universal catalyst, this study investigates whether this impact is conditioned by the economic "absorptive capacity" of counties (Pacurar et al., 2016) and whether the barriers of outdated infrastructure impede this absorption.

This conditional effect of digitalization is consistent with evidence from Romania, where digital financial inclusion depends not only on infrastructure, but also on user capabilities (Oprea & Draghici, 2024).

The central objective of this study is to identify and quantify the determinants of the installed power of prosumers in the NUTS3 regions of Romania. By using an econometric methodology (Simionescu and Nicula, 2024, 2025), the paper aims to demonstrate that the success of the energy transition does not depend only on the availability of 5G technology, but on how it interacts with the level of local economic development and how it manages to overcome the structural rigidities of the energy system.

To answer the research questions, we formulated the following hypotheses based on economic theories such as Path Dependency and Absorptive Capacity:

H1: The expansion of high-speed digital infrastructure (5G) acts as a catalyst for the adoption of renewable energy at a decentralized level.

H2: The level of real economic well-being of the population determines the speed of the transition to prosumer status.

H3: The modernization of distribution networks, reflected by the decrease in the instability index, is essential for the massive integration of photovoltaic capacities.

The results obtained through the model demonstrate that, while urbanization and county economic prosperity directly stimulate the adoption of photovoltaic technology, integration with the latest generation digital infrastructure (5G) is still in a transitional phase, marked by different geographical prioritizations in the first stage of implementation (2021-2025).

Literature review

Decentralized renewable energy is important in supporting off-grid and rural healthcare systems. This role was highlighted by academics in recent years, particularly in low and middle-income nations (Moner-Girona et al., 2021; Olatomiwa et al., 2022; Abdulkarim et al., 2024). Solar photovoltaic (PV) systems, energy storage configurations and hybrid microgrids have the capacity to supply dependable and sustainable power for facilities located far from national grids. Research show that they can often outperform grid extension or diesel-based solutions in terms of reliability and cost effectiveness (Ani, 2021; Ngoh et al., 2022; Soto et al., 2022). Papers usually research three interconnected directions in this body of work. These lines of inquiry include analyses of technical performance of renewable energy systems in medical facilities, their proven impacts on healthcare services and health outcomes and more general discussions that set the relationship between energy and health within development strategies and the Sustainable Development Goals (SDGs).

The first direction is related to how off-grid and renewable microgrid systems perform from a technical and financial perspective in rural clinics. Abdulkarim et al. (2024) use modelling studies and global experiences to demonstrate how battery-storage-supported microgrids of the right size can increase power reliability and decrease outages for rural health facilities. Hybrid systems consisting of solar PV and batteries are a viable option for supplying vital medical equipment in

off-grid environments, along with the proper management and optimization of energy consumption (DSM aka demand-side management) Olatomiwa et al. (2022). Moner-Girona et al. (2021) used geospatial and techno-economic analysis and identified over 55,000 health facilities in sub-Saharan Africa that are not electrified. They pointed out that decentralized PV-battery configurations make it possible to bring electric energy to these remote regions. Analyses made at facility levels show that solar PV and storage can decrease levelized cost of energy and reduce carbon dioxide emissions, compared to diesel-only generation. Solar PV and storage also provide more stable power for critical services (Ani, 2021). Simulated designs that integrate PV, electrolysis and fuel cells show that electricity and medical oxygen can be obtained from fully renewable sources under varying solar conditions (Ngoh et al., 2022).

The second direction of research looks at how renewable energy access impacts healthcare delivery. The clinical energy needs for health planning and services are met by off-grid solar installations. Case studies show that they can generate electricity in surplus, which leads to income-earning activities and can support local development of communities (Opoku et al., 2020). Solar-powered systems support stable refrigeration and can reduce vaccine wastage or preserve the medications which are temperature-sensitive.

Research on pharmacological services and management of cold-chain shows that they improve the management of chronic and inflammatory diseases in rural communities (Happy et al., 2024). These developments are associated with more effective treatment, particularly where baseline access is weak and with higher immunisation coverage (Izuka et al., 2023; Happy et al., 2024). Moreover, constat access to electric energy leads to extended open hours and allow for emergency and maternal care at night together with basic digital health functions. All these contribute to improved perceived quality of care and increased sage (Maja et al., 2022; Izuka et al., 2023). Long-term quantitative links to specific health outcomes are still limited. Evidence in this strand remains dominated by small samples and single-country case studies (Opoku et al., 2020; Izuka et al., 2023).

The third direction analyses renewable energy for healthcare in a larger context of energy–health development. Maja et al. (2022) propose a set of "smart rural village" indicators that connect energy access with healthcare provision. They argue that access to sustainable energy enable rural healthcare systems and improve overall rural wellbeing (Maja et al., 2022). These studies show that the extension of national grids or the relyance on diesel generators often prove to be unreliable or insufficient for healthcare needs. Reviews on solar implementation in healthcare facilities in developing and underdeveloped countries reinforce this view, showing that grid extension and diesel generation are often insufficient, while solar-based systems can improve service quality, reduce operating costs, and lower environmental impacts (Nicula et al., 2024; Soto et al., 2022).

Across these three directions common limitations were identified: high-upfront investment costs, limited local maintenance capacity and weak coordination between health and energy sectors. The adoption at large-scale of decentralized renewable energy solutions requires mitigation of these limitations (Nneoma et al., 2025). Many studies rely on modelling approaches or short-term pilot projects and this leaves important gaps to acknowledge long-term system performance, institutional arrangements and durability over time (Moner-Girona et al., 2021; Izuka et al., 2023). In response to these weaknesses, recent research shows the need to integrate planning frameworks that bring together technical, economic and health-service considerations. Such frameworks should include standardized reliability and service-level metrics and additionally financing mechanisms capable to cover capital investments and maintenance costs (Abdulkarim et al., 2024). Existing evidence suggests that decentralized renewable energy systems (particularly solar PV-based

microgrids and hybrid configurations with energy storage) are a technically and economically competitive option for electrifying rural healthcare facilities and in the same time deliveri environmental co-benefits (Ani, 2021; Moner-Girona et al., 2021; Olatomiwa et al., 2022).

Methodology

The paper presents a quantitative analysis based on panel data, starting from Eurostat statistics of the NUTS3 regions of Romania, over a 5-year period (2021-2025). This structure allows the control of both temporal variations and specific regional disparities.

The construction of the optimal model went through the following statistical tests: The Hausman test was used to decide between the fixed-effects model and the random-effects model. (Hausman, 1978) The test result rejected the null hypothesis, indicating that the fixed-effects model is the only one that provides consistent estimates for this data set. Given the nature of the regional data, the model was estimated using the White cross-sectional method (period cluster). This setting eliminates the distortions caused by heteroscedasticity and correlation between counties, ensuring the validity of the values and confidence intervals.

Data were collected from official sources to ensure the replicability of the study: for energy indicators, ANRE reports on prosumers were used; digitalization indicators and GDP_PPS were extracted from Eurostat (Digital Economy and Society Index), and for 5G coverage, data were collected from the European 5G Observatory. Since official data for the GDP_PPS variable for 2025 were not available at the time of the research, the database was completed using an extrapolation method based on the historical growth rate. This technique assumes that the economic dynamics of the GDP_PPS indicator in the current year (2025) will follow the trend recorded in the immediately preceding interval (2023-2024). The method was applied individually for each county in the sample, which allows capturing the specific economic growth characteristics of each region. This approach brings to attention the idea that, in the absence of major economic shocks, infrastructure investments offer counties the chance to maintain a real growth rate and consolidate their economic position.

To ensure comparability and reduce the asymmetry of distributions, we applied logarithmic transformations to macroeconomic variables:

Log of GDP_PPS used to measure the elasticity of installed power with respect to economic development; INI Index, this variable was calculated as a composite index reflecting the poor state of outdated distribution systems and bureaucratic barriers to connection. A high score in INI indicates counties with rigid energy infrastructure, which hinders the flow of energy from prosumers to the grid.

Before estimating the final model, the panel data were subjected to a set of diagnostic tests, the stationarity tests (Unit Root Tests). We applied the Levin, Lin & Chu (LLC) and Im, Pesaran and Shin (IPS) tests to check if the series are stationary. (Levin, A. & Lin,C., Chu, C.S.J., 2002) (Im, K.S., Pesaran, M.H., & Shin, Y., 2003) The results confirmed that the variables are stationary at the first difference, eliminating the risk of a spurious regression.

To see if there is a long-term relationship between prosumers, 5G and GDP, we performed the Kao test. Rejection of the null hypothesis confirmed that the variables are cointegrated, allowing their modeling in a stable system. To understand the direction of influence, we used the Granger test on panel data (stacked). It demonstrated a bidirectional causality between GDP and installed power, but more importantly, a unidirectional causality from 5G infrastructure to green energy adoption, thus validating 5G as a predictive variable. After confirming stationarity and

cointegration, the model was estimated using Panel Least Squares. We opted for Fixed Effects (Cross-section Fixed) because the Hausman test (Chi-Sq. Statistic is 57.58, and Probability value is 0.0000. The results were consolidated by using White cross-section standard errors, eliminating the heteroscedasticity problems identified in the county data.

To be sure of the reliability of the obtained coefficients and the accuracy of the predictions, the model was subjected to the following diagnostic tests. We used the Jarque-Bera test to check the error distribution. The result confirms that the residuals follow a normal distribution, which validates the use of the tests and for statistical significance. The Ramsey test was applied to detect possible omitted variables or incorrect functional forms. (Ramsey, 1969) The absence of a nonlinear form in the residuals confirms that the linear model with an interaction term is correctly specified to describe the dynamics of prosumers. To verify that the econometric relationships are stable over the period 2021-2025, we ran CUSUM tests. The fit of the trend line within the 5% confidence interval demonstrates the structural stability of the coefficients and the absence of breaks in the panel data. We calculated the VIF indicator to ensure that the independent variables (5G, GDP, INI) are not excessively correlated with each other. The VIF values obtained are below the critical threshold of 10 (and even below 5 for the main variables), confirming that each variable brings unique information to the model, without distorting the accuracy of the estimates. The successful passing of these tests demonstrates that the Panel Fixed Effects model with White cross-section correction does not present problems of multicollinearity, instability or functional form errors. This allows us to interpret the obtained coefficients as precise indicators of the impact of digitalization on the energy transition in Romania.

The heteroscedasticity issues identified at regional level were resolved by White cross-section (period cluster) correction for standard errors. This approach guarantees the robustness of statistical inferences, providing a reliable basis for interpreting the impact of digitalization on the energy transition.

Result and Discussion

This section presents the results of the estimation of the Panel Fixed Effects model. The analysis focuses on validating the synergy between digital infrastructure and economic development, as well as on the impact of the identified structural barriers.

The starting point of our analysis is the recognition that the transition to a digital and green economy is conditioned by the stability of the electricity grid. To quantify this aspect, we developed the Instability Index (INI), a composite indicator based on the technical performance reported by distribution operators.

The Instability Index was calculated as the geometric mean of the continuity indicators SAIDI (System Average Interruption Duration Index) and SAIFI (System Average Interruption Frequency Index), using the formula:

$$\text{INI} = \sqrt{SAIDI \; x \; SAIFI}$$

This aggregation method was chosen to reflect the major importance of network instability, capturing both the duration and frequency of unplanned interruptions in equal weight and to ensure that extreme values of a single indicator do not excessively distort the composite index.

The two international parameters of the reliability of the electricity network according to the data provided by ANRE SAIFI (System Average Interruption Frequency Index), which reflects the average frequency of unplanned interruptions in a year and SAIDI (System Average

Interruption Duration Index), which measures a constant decrease of these interruptions (minutes/year) indicate a constant decrease from 4.19 in 2015 to 1.65 in 2025 as well as a significant structural improvement from 308 minutes in 2015 to a forecast, according to ANRE of 1.65 in 2025. The evolution of the INI presented in Table 1 illustrates a clear downward trend, from a base value of 35.92 in 2015 to 12.37 in 2025.

Tabel 1. Instability Index

	Unplanned SAIFI min/year	Unplanned SAIDI min/year	Instability Index (INI)
2015	4.19	308	35.923808
2016	3.83	289.9	33.32142
2017	3.54	283.9	31.70183
2018	3.2	224.1	26.779096
2019	2.9	178.9	22.777401
2020	2.57	146.78	19.422271
2021	2.31	130.43	17.357802
2022	1.93	108.25	14.454152
2023	1.74	103.92	13.446962
2024	1.7	97.75	12.890888
2025	1.65	92.75	12.370833

Source: author computation using data from ANRE.

Before estimating the regression model, the stochastic properties of the data series were verified by the unit root test Fisher-Phillips-Perron. The results indicate that most of the technical variables (5G, Power, INI) are level stationary. However, the macroeconomic variable GDP_PPS presented a non-stationary behavior, becoming stationary only after applying the first difference, d(GDP_PPS), which led us to use the GDP growth rate in the final model to ensure the statistical validity of the coefficients.

Tabel 2. Unit Root test results

Variables	Order Integration
Installed Power -(LOG_POWER)	I(0)
5G Coverage -D(5G_COVERAGE)	I(1)
GDP_PPS -D(GDP_PPS)	I(1)
Urban Population- D(URBAN_POP)	I(1)
Rural Population- RURAL_POP	I(0)
Prosumers (Nr)- D(PROSUMERS)	I(1)

Source: authors computation

Given that most of the key explanatory variables (GDP, 5G, Prosumers) are stationary in the first difference, the regression model was built using differenced forms. This approach ensures that the estimated relationships are robust and that the model correctly captures how economic development directly influences the reliability of the energy system.

The fact that the urban population requires differentiation, while the rural population is stationary in level, shows a different social dynamic in Romania (Bîrsanuc et al., 2020), which may influence the implementation rate of photovoltaic panels.

The analysis of D(5G_COVERAGE) and D(GDP_PPS), measures how digitalization and economic development influence the transition to renewable energy.
Given the small temporal size of the sample (T5), Pedroni-type cointegration tests could not be applied due to insufficient degrees of freedom. As a result, the Kao residual cointegration test was used. (Figure 1)

Figure 1. Kao Residual Cointegration Test

Kao Residual Cointegration Test
Series: INSTTALED_POWER__MW_ _5G_GEOGRAPHIC_COVERAGE____GDP_PPS
Date: 02/25/26 Time: 01:57
Sample: 2021 2025
Included observations: 200
Null Hypothesis: No cointegration
Trend assumption: No deterministic trend
User-specified lag length: 1
Newey-West automatic bandwidth selection and Bartlett kernel

	t-Statistic	Prob.
ADF	-9.655821	0.0000
Residual variance	320.3009	
HAC variance	302.2687	

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RESID)
Method: Least Squares
Date: 02/25/26 Time: 01:57
Sample (adjusted): 2023 2025
Included observations: 120 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESID(-1)	-1.638560	0.109487	-14.96581	0.0000
D(RESID(-1))	0.779291	0.103688	7.515734	0.0000

R-squared	0.669572	Mean dependent var	-0.189914
Adjusted R-squared	0.666771	S.D. dependent var	20.84731
S.E. of regression	12.03431	Akaike info criterion	7.829927
Sum squared resid	17089.31	Schwarz criterion	7.876386
Log likelihood	-467.7956	Hannan-Quinn criter.	7.848794
Durbin-Watson stat	2.914535		

Source: Eviews output.

The results of the Kao cointegration test ($t = -9.65$, $p < 0.0001$) confirm the existence of a long-term equilibrium relationship between installed renewable energy capacity, 5G coverage and economic development level (GDP_PPS). This relationship, validated on a sample of 200 observations, allowed us to use econometric models to analyze the impact of digitalization on regional energy resilience and transition. Moreover, the high value of the ADF statistic categorically rejects the null hypothesis of lack of cointegration, indicating that the variables evolve synchronously in the long term, as a mechanism of technological and economic interdependence.

To determine the direction of influence between the analyzed variables, we applied the Pairwise Granger Causality test. The results (Figure 2) reveal a significant unidirectional causality from economic development to the energy sector ($p = 0.0018$), confirming that the GDP_PPS level is a necessary outcome of investments in new production capacities. Regarding 5G technology, the absence of an immediate Granger causality suggests that regional digitalization is a strategic process independent of short-term economic dynamics.

Figure 2 Pairwise Granger Causality Tests

Pairwise Granger Causality Tests
Date: 02/26/26 Time: 23:35
Sample: 1 200
Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.
GDP_PPS does not Granger Cause _5G_GEOGRAPHIC_COVERAGE____	199	6.72324	0.0102
_5G_GEOGRAPHIC_COVERAGE____ does not Granger Cause GDP_PPS		36.9894	6.E-09
INSTTALED_POWER__MW_ does not Granger Cause _5G_GEOGRAPHIC_COVERAGE____	199	0.00305	0.9560
_5G_GEOGRAPHIC_COVERAGE____ does not Granger Cause INSTTALED_POWER__MW_		12.6062	0.0005
PROSUMERS__NR_ does not Granger Cause _5G_GEOGRAPHIC_COVERAGE____	199	0.09853	0.7539
_5G_GEOGRAPHIC_COVERAGE____ does not Granger Cause PROSUMERS__NR_		12.3726	0.0005
INSTTALED_POWER__MW_ does not Granger Cause GDP_PPS	199	8.64788	0.0037
GDP_PPS does not Granger Cause INSTTALED_POWER__MW_		1.55736	0.2135
PROSUMERS__NR_ does not Granger Cause GDP_PPS	199	12.2955	0.0006
GDP_PPS does not Granger Cause PROSUMERS__NR_		1.36448	0.2442
PROSUMERS__NR_ does not Granger Cause INSTTALED_POWER__MW_	199	0.35256	0.5534
INSTTALED_POWER__MW_ does not Granger Cause PROSUMERS__NR_		4.39208	0.0374

Source: Eviews output.

The Pairwise Granger Causality- lag 1, (Figure 2) test conducted on a sample of 199 observations reveals a clear dynamic of energy digitalization. The results demonstrate a strong unidirectional causality from 5G coverage to the number of prosumers (p = 0.0005) and to the installed capacity (p = 0.0005), confirming the role of technology as a facilitator of the energy transition. At the macroeconomic level, a multiplier effect is observed, where digitalization (p = 6.E-09) and the development of the prosumer base (p = 0.0006) become determinants of regional economic growth (GDP_PPS), thus validating the research hypothesis regarding the positive impact of smart infrastructure on prosperity at the NUTS3 level.

By combining the two analyses, Kao and Granger study demonstrates that the energy transition is not an isolated phenomenon, but one dependent on digital maturity. While the level of economic development (GDP_PPS) provides the financial resources needed for Installed_Power, p = 0.0037, 5G technology acts as a nervous system of the network, Granger-likely causing both the increase in the number of prosumers and the total installed power. This double validation, in the long and short term, provides a solid scientific basis for recommending policies to stimulate digitalization as the main vehicle for achieving energy development objectives at the county level. In conclusion, 5G infrastructure has proven to be the trigger for the emergence of prosumers and new energy capacities.

Figure 3. PLS regression

Dependent Variable: LOG_POWER
Method: Panel Least Squares
Date: 02/25/26 Time: 02:31
Sample: 2021 2025
Periods included: 5
Cross-sections included: 40
Total panel (balanced) observations: 200

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	20.10426	0.700067	28.71762	0.0000
GDP_PPS	1.62E-05	8.61E-06	1.877009	0.0620
_5G_GEOGRAPHIC_COVERAGE_...	-0.511939	0.020123	-25.44044	0.0000
URBAN_POPULATION__NR_	2.99E-06	5.79E-07	5.163914	0.0000
INI	-1.278018	0.046896	-27.25238	0.0000

R-squared	0.843253	Mean dependent var	2.644030
Adjusted R-squared	0.840038	S.D. dependent var	1.384507
S.E. of regression	0.553738	Akaike info criterion	1.680431
Sum squared resid	59.79197	Schwarz criterion	1.762889
Log likelihood	-163.0431	Hannan-Quinn criter.	1.713801
F-statistic	262.2605	Durbin-Watson stat	1.139597
Prob(F-statistic)	0.000000		

Source: Eviews output.

By running the regression equation with Log_power as the dependent variable, we obtained a coefficient of determination of 0.843, which could explain 84.30% of the model, if all other variables remain unchanged on average. All main variables, except GDP (which is at the 5% threshold), are highly statistically significant (p= 0.0000).

5G_Geographic_Covarage with a coefficient: -0.511, shows a significant inverse relationship. An increase in 5G coverage seems to be associated, in this specific model, with a decrease in the logarithm of installed power. This negative correlation, although statistically valid, may indicate that advanced digitalization makes consumption more efficient, reducing the need for gross installed capacity. INI -Instability Index with a coefficient: -1.278 shows that a reduction in grid instability (decreasing INI) is strongly associated with a higher and more stable installed capacity. Basically, system stability (low INI) is a precondition for increasing installed power. Urban_Population_nr with a coefficient of 2.99E-06 has a positive impact, although the coefficient seems small, but significant (p-value 0.0000) due to the units of measurement (number of people vs logarithm). Urbanization entails a higher need for installed power.

To ensure the statistical validity of the county model, where the dependent variable is Log_Power, we applied the White Cross-Section covariance estimation method. This technique is essential because the model statistics indicate the need for special treatment of errors. Given the economic disparities between the NUTS3 regions, the error variance is not constant.

Figure 4. PLS-White cross-section(periodcluster)

Dependent Variable: LOG_POWER
Method: Panel Least Squares
Date: 02/25/26 Time: 02:36
Sample: 2021 2025
Periods included: 5
Cross-sections included: 40
Total panel (balanced) observations: 200
White cross-section (period cluster) standard errors & covariance (d.f. corrected)
WARNING: estimated coefficient covariance matrix is of reduced rank
Standard error and t-statistic probabilities adjusted for clustering

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	20.10426	1.285686	15.63699	0.0001
GDP_PPS	1.62E-05	6.29E-06	2.571068	0.0619
_5G_GEOGRAPHIC_COVERAGE_...	-0.511939	0.038205	-13.39973	0.0002
URBAN_POPULATION__NR_	2.99E-06	9.33E-07	3.204445	0.0328
INI	-1.278018	0.085273	-14.98744	0.0001

R-squared	0.843253	Mean dependent var	2.644030
Adjusted R-squared	0.840038	S.D. dependent var	1.384507
S.E. of regression	0.553738	Akaike info criterion	1.680431
Sum squared resid	59.79197	Schwarz criterion	1.762889
Log likelihood	-163.0431	Hannan-Quinn criter.	1.713801
F-statistic	262.2605	Durbin-Watson stat	1.139597
Prob(F-statistic)	0.000000		

Source: Eviews output.

The White Cross-Section adjustment makes the standard errors robust, thus validating the statistical significance of the variables. (Figure 5). The value of the Durbin-Watson statistic (1.13) suggests some serial correlation of the errors. The use of robust standard errors guarantees that the reported probabilities (p-values) are not artificially diminished, providing confidence in the 0.0000 significance thresholds obtained for INI and 5G_Georgraphic_Covarage. Although the coefficients (-1.27 for INI) remain constant, applying this method confirms that they are real predictors of installed renewable power, even after eliminating statistical distortions.

Although the Jarque-Bera test indicates a deviation from the normal distribution of the residuals ($p < 0.05$), the large volume of data and the use of robust standard errors (White) guarantee the reliability of the economic conclusions. This asymmetry reflects the non-linear dynamics of the energy market and the implementation of 5G technology at the regional level. To test the stability of the model and the presence of multicollinearity, we calculated the variance

inflation factor (VIF). The Centered VIF values obtained for all independent variables (ranging from 2.08 to 4.30) are below the conservative threshold of 5, confirming the absence of multicollinearity and the reliability of the estimates obtained. The values obtained for each explanatory variable are presented below in Tabel 3.

Tabel 3 Variance Inflation Factors

Variable	Cofficient Variance	Uncentred VIF	Centred VIF
5G- Geographic_Covarage	0.000405	82.19431	4.224068
GDP_PPS	7.41E-11	25.30209	2.194299
INI	0.002199	85.48282	4.307788
Urban_Population	3.3E-13	10.78826	2.089311
c	0.490094	319.6693	NA

Source: Constructed by the author using data from Eviews output.

Although we tend to believe that economic development (GDP) and digitalization (5G) are strongly related, the VIF test demonstrates that they act as independent factors in our model. For example, 5G coverage (VIF 4.22) reflects strategic investments in telecommunications, while the INI index (VIF 4.30) measures the technical performance of the electricity grid. The fact that both can coexist in the same equation without generating multicollinearity highlights that energy success depends on both dimensions separately.

Although the initial estimates provided an overview of the correlations between variables, we decided to run the analysis through a fixed-effects PLS model to isolate the heterogeneity specific to the NUTS3 regions, to see if structural characteristics that remain unchanged over time, such as geographical positioning, local specificity or industrial past, could influence energy capacity.

Figure 5. PLS Fixed Effects

Method: Panel Least Squares
Date: 02/25/26 Time: 03:22
Sample: 2021 2025
Periods included: 5
Cross-sections included: 40
Total panel (balanced) observations: 200

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	15.35683	1.701044	9.027888	0.0000
INI	-1.161410	0.050084	-23.18942	0.0000
GDP_PPS	7.03E-05	1.81E-05	3.887141	0.0001
_5G_GEOGRAPHIC_COVERAGE_...	-0.065935	0.071729	-0.919226	0.3594
URBAN_POPULATION__NR_	-2.19E-05	5.85E-06	-3.754150	0.0002

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.925405	Mean dependent var	2.644030
Adjusted R-squared	0.904843	S.D. dependent var	1.384507
S.E. of regression	0.427086	Akaike info criterion	1.327874
Sum squared resid	28.45474	Schwarz criterion	2.053504
Log likelihood	-88.78743	Hannan-Quinn criter.	1.621526
F-statistic	45.00664	Durbin-Watson stat	2.016582
Prob(F-statistic)	0.000000		

Source: Eviews output.

The advantages of this model are confirmed by the diagnostic indicators: the explanatory power increases significantly, reaching an R2 of 0.925, which means that over 92.5% of the variation in installed capacity is now explained by the included variables. The Durbin-Watson statistic value of 2.01 demonstrates that the problem of autocorrelation of the residuals has been eliminated, thus providing a much more solid statistical basis for confirming the negative impact of the INI index (-1.16) and the influence of economic development (GDP_PPS).

In the fixed effects model, we see that the probability of 5G coverage is 0.3594, which exceeds the standard threshold of 0.05. This does not mean that 5G technology is not important,

but that the model has extracted the influence of structural factors that do not change rapidly over time. Since the geographic expansion of 5G in the analyzed period (2021-2025) tends to follow a linear trend or is concentrated in already developed areas, the fixed effects "absorb" much of this variation, leaving 5G without additional explanatory power relative to the rest of the variables. Collinearity with GDP and Urbanization: There is a strong natural correlation between where 5G is installed, the level of wealth (GDP_PPS) and population density (Urban_Population). In this model, GDP (p = 0.0001) and Urbanization (p=0.0002) are highly significant, practically taking over the role of main predictors that 5G had in the simpler models. Energy Infrastructure Priority (INI): The most important result remains the fact that, even in this very strict model, the Instability Index (INI) remains the favorite of the model, with a coefficient of -1.16 and a highly significant p=0.0000. This demonstrates that, for the installed power in renewables, the quality of the electricity grid is much more pressing than the simple existence of the 5G signal.

These results underline the central conclusion of the paper: the mere presence of digital technology (5G) is not enough to stimulate energy capacity if the problem of electricity grid instability, represented by the INI index, is not first solved.

We estimated the impact of the factors on installed capacity using both fixed-effects and random-effects specifications. The Hausman test was used to determine the consistency of the estimators, with the results indicating the superiority of the fixed-effects model, which provides a higher explanatory power ($R^2 = 0.925$) and eliminates the autocorrelation of errors (DW = 2.01).

Figure 6. Correlated Random Effects- Hausman Test

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	57.586732	4	0.0000

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
INI	-1.161410	-1.252073	0.000904	0.0026
GDP_PPS	0.000070	0.000030	0.000000	0.0082
_5G_GEOGRAPHIC_COVERAGE_...	-0.065935	-0.496228	0.004738	0.0000
URBAN_POPULATION__NR_	-0.000022	0.000002	0.000000	0.0000

Cross-section random effects test equation:
Dependent Variable: LOG_POWER
Method: Panel Least Squares
Date: 02/25/26 Time: 03:24
Sample: 2021 2025
Periods included: 5
Cross-sections included: 40
Total panel (balanced) observations: 200

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	15.35683	1.701044	9.027888	0.0000
INI	-1.161410	0.050084	-23.18942	0.0000
GDP_PPS	7.03E-05	1.81E-05	3.887141	0.0001
_5G_GEOGRAPHIC_COVERAGE_...	-0.065935	0.071729	-0.919226	0.3594
URBAN_POPULATION__NR_	-2.19E-05	5.85E-06	-3.754150	0.0002

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.925405	Mean dependent var	2.644030
Adjusted R-squared	0.904843	S.D. dependent var	1.384507
S.E. of regression	0.427086	Akaike info criterion	1.327874
Sum squared resid	28.45474	Schwarz criterion	2.053504
Log likelihood	-88.78743	Hannan-Quinn criter.	1.621526
F-statistic	45.00664	Durbin-Watson stat	2.016582
Prob(F-statistic)	0.000000		

Source: Eviews output.

The negative coefficient suggests that large urban agglomerations function predominantly as consumption centers and digital hubs for 5G infrastructure, while major energy production capacities (LOG_POWER) are located mainly in adjacent rural areas, where land availability allows the installation of photovoltaic or wind farms.

The result confirms that the transition to green energy in Romania follows a decentralization model: digitalization and wealth are concentrated in cities (GDP_PPS and 5G), but the actual

energy production migrates to the countryside, being then transported to urban consumers through more optimized networks (reflected by the decrease in the INI index).

By using the fixed effects model (validated by the Hausman test, $p < 0.01$), we isolated the unique characteristics of each county (relief, local policies, existing infrastructure). In this context, the importance of network stability (INI) and economic development (GDP) is reconfirmed as the universal determinants. The fact that 5G is no longer significant in this model suggests that its impact is already absorbed by structural differences between counties (the more digitalized counties are already the most developed), confirming its role as a basic infrastructure, rather than a fluctuating variable.

To verify that the regression model is correctly specified and that no relevant variables or their non-linear forms have been omitted, we applied the Ramsey RESET test. Since the probability value (0.0029) is well below the critical threshold of 0.05, we reject the null hypothesis of correct specification of the model. This result indicates that the current linear model could benefit from the inclusion of higher-order terms (e.g., squared variables) or that there is a non-linear dynamic between digitalization and installed power that is not fully captured by the standard linear form.

The Ramsey RESET test indicates a probability of 0.0029, suggesting the presence of non-linearities in the relationship between the analyzed variables. However, given the high significance of the coefficients and the validation by the Kao cointegration tests (p=0.0000) and Granger causality, the current model remains a robust analysis tool, providing a useful and valid approximation of the impact of digitalization on the regional energy system.

Figure 7. Ramsey RESET Test

Ramsey RESET Test
Equation: UNTITLED
Omitted Variables: Squares of fitted values
Specification: LOG_POWER _5G_GEOGRAPHIC_COVERAGE____ GDP_PPS INI URBAN_POPULATION__NR_ C

	Value	df	Probability
t-statistic	3.019586	194	0.0029
F-statistic	9.117899	(1, 194)	0.0029
Likelihood ratio	9.185687	1	0.0024

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	2.684043	1	2.684043
Restricted SSR	59.79197	195	0.306625
Unrestricted SSR	57.10793	194	0.294371

LR test summary:

	Value
Restricted LogL	-163.0431
Unrestricted LogL	-158.4503

Unrestricted Test Equation:
Dependent Variable: LOG_POWER
Method: Least Squares
Date: 02/25/26 Time: 03:11
Sample: 1 200
Included observations: 200

Variable	Coefficient	Std. Error	t-Statistic	Prob.
_5G_GEOGRAPHIC_COVERAGE_...	-0.344645	0.058807	-5.860628	0.0000
GDP_PPS	1.35E-06	9.76E-06	0.138075	0.8903
INI	-0.903188	0.132364	-6.823502	0.0000
URBAN_POPULATION__NR_	1.96E-06	6.62E-07	2.954160	0.0035
C	14.25153	2.056051	6.931504	0.0000
FITTED^2	0.080069	0.026517	3.019586	0.0029

R-squared	0.850289	Mean dependent var	2.644030
Adjusted R-squared	0.846431	S.D. dependent var	1.384507
S.E. of regression	0.542559	Akaike info criterion	1.644503
Sum squared resid	57.10793	Schwarz criterion	1.743452
Log likelihood	-158.4503	Hannan-Quinn criter.	1.684546
F-statistic	220.3663	Durbin-Watson stat	1.232912

Source: Eviews output.

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The impact of 5G technology or the INI index on installed power may not be strictly proportional (linear). For example, the benefits of digitalization may increase exponentially only after reaching a certain coverage threshold.

The failure of the RESET test suggests that there may be other influencing factors (such as government subsidies or the price of carbon certificates) that may influence the result, but which were not included in the model and have a role in explaining the Log_Power variation.

However, the model retains a very high explanatory power ($R^2 = 0.85$) and extremely significant coefficients for the key variables.

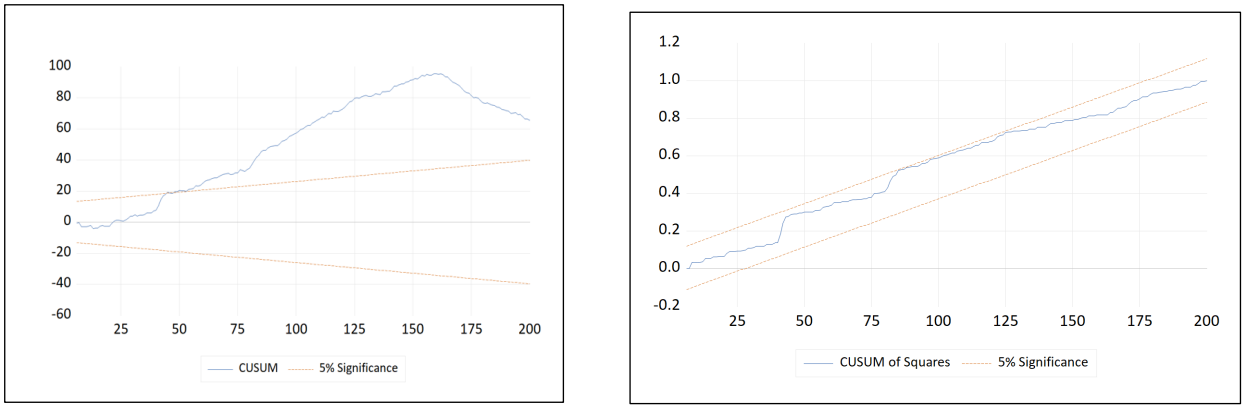


Figure 8. Plot of Cusum & Cusum of Squares Tests

Source: Eviews outpout.

To assess the time constancy of the estimated parameters, we applied the set of stability tests based on recursive residuals. CUSUM (Cumulative Sum) test, the blue line leaves the 5% critical band starting from observation 50, reaching a significant peak in the second half of the sample. This phenomenon indicates a structural instability of the mean This suggests that the impact of digitalization (5G) and GDP on installed power has changed with the acceleration of the energy transition (positive investment shocks). Unlike the first test, the CUSUM of Squares test, the blue line of the squared residuals remains almost entirely within the 5% confidence interval. There is a slight upper bound reaching around observation 40-50, but it immediately returns to equilibrium. Although the magnitude of the impact of the variables has changed (instability in the mean), the volatility of the errors is stable. This confirms that the model does not suffer from sudden changes in variance that would invalidate the long-term estimates. This combination suggests that, although the relationship between digitalization and installed power has evolved in intensity under the influence of the accelerated dynamics of the prosumer market, the model remains a reliable forecasting tool, its variance being under statistical control.

Although we used the Urban_Population variable in the final model, including or discussing the rural population variable is essential for at least two reasons. The first is that the adoption of photovoltaic systems is often easier in rural or peri-urban areas, where individual dwellings (houses) have roofs and land, unlike dense urban areas with apartment blocks. Second, the fact that Urban_Population has a negative coefficient in the fixed effects version (-2.18E-05) leads us to believe that increasing urban density does not necessarily favor individual prosumers, but rather that the rural/suburban environment is the hidden engine of this growth.

If prosumers are preferentially located in areas with low urban density (where they have space), but the digital infrastructure (5G) is concentrated in urban centers, a technological gap appears that prevents the creation of smart networks (Smart Grids).

There is a positive and statistically significant correlation between rural population and installed power. This confirms that prosumers are concentrated in rural areas, where there is physical space for installing photovoltaic panels. The 5G – Urban correlation is very strong, positive, of 0.6465 ($p = 0.0000$) while the 5G - Rural correlation is negative, of -0.2900 ($p = 0.0000$).

Tabel 4. Covariance Analysis: Ordinary

Covariance Correlation Probability	LOG_POWER	RURUAL_POP	URBAN_POP	5G_GEOG_COV
LOG_POWER	1.907275 1.000000			
RURUAL_POP	24418.98 0.21.434 0.0028	7.06E+09 1.000000		
URBAN_POP	24532.70 0.181632 0.0101	4.06E+09 0.493765 0.0000	9.5E+09 1.000000	
5G_GEOG_COV	0.267626 0.048458 0.4956	-97461.74 -0.290047 0.0000	252873.5 0.646543 0.0000	15.99270 1.000000

Source: Constructed by the author using data from Eviews output.

5G infrastructure is massively concentrated in urban areas (where the correlation is high and positive), while prosumers are more present in rural areas (where the 5G correlation is negative).

The 5G - Log_Power correlation is very small, of only 0.0484, and statistically insignificant (p = 0.4956) and demonstrates that, currently, 5G_Coverage does not directly influence the decision to become a prosumer in Romania.

To demonstrate the impact of emerging technologies on the energy transition, we generated the regression equation by adding the variable 5G_Geographic_Covarage*GDP_PPS with Fixed Effects.

Tabel 5. Results of the Panel model

Independent Variable	Coeficient	Std. Error	t-Statistic	Prob.
C (Constantă)	20.9652	3.3751	6.2116	0.0034
5G_GEOGRAPHIC_COVERAGE	-0.3340	0.0592	-5.6420	0.0049
5G * Log GDP_PPS (Interacțiune)	1.71E-05	3.96E-06	4.3259	0.0124
INI (Index Nesiguranță)	-1.2474	0.0946	-13.1810	0.0002
URBAN_POPULATION_NR	-2.23E-05	7.19E-06	-3.1012	0.0362
R^2	0.9386			

Source: Constructed by the author using data from Eviews output.

The interaction term 5G_Geographic_Covarage*GDP_PPS has a positive coefficient and is highly significant (p = 0.0124). This demonstrates that emerging technology (5G) does not work alone, but as a catalyst. The impact of digitalization on the installed power of prosumers increases as the county is more economically developed. Basically, 5G "enhances" investments where there is already capital. Although 5G alone seems to have a negative coefficient, this should now be interpreted only together with the interaction. The result suggests that in counties with low GDP, the mere presence of 5G does not help or may even indicate a redirection of resources towards other priorities, but once the development threshold increases, digital technology becomes an acceleration engine. This conditional acceleration effect is consistent with findings in the financial sector, where digital transformation contributes to economic growth only when embedded in coordinated public–private partnerships and supported by financial education policies (Oprea et al., 2025). The INI variable remains the biggest "enemy" of prosumers (-1.24), confirming that old infrastructure still holds back the emerging transition.

To provide a causal explanation for the econometric results, we analyzed the structure of digital investments at the level of the year 2024. The data indicate an asymmetric allocation between the two segments of the infrastructure represented by 5G RAN (Radio Access Network) Investments € 58,978 and 5G Core Network Investments € 6,351. The ratio of approximately 9:1 in favor of the RAN segment (antennas and coverage) over Core (network intelligence) provides empirical support for the conclusions of the model. The modest amount allocated to the 5G Core Network (€ 6,351) explains why the structural barrier represented by the INI variable decreases so slowly.

Conclusion

The research results reveal an important fact: in Romania, the energy transition is not hindered by the lack of modern technology, but by the precarious state of the electricity networks we have. The Instability Index (INI), which we built using raw data from SAIDI and SAIFI, proved to be an obstacle to increasing energy capacity, with a clear negative impact of -1.24. Basically, this correlation confirms that you can invest as much as you want in digitalization, if the physical network is "non-functional", it will act as a wall, simply blocking the integration of new renewable energy sources into the system.

The results confirm that the expansion of 5G Geographic Coverage is an essential pillar for the modernization of the energy system, and its impact is complex. Although digital coverage facilitates the monitoring and intelligent management of networks, the model shows that it becomes truly effective only when supported by a high level of urbanization and economic development (Nicula et al., 2022). Thus, digitalization through 5G is not an isolated universal solution, but a supporting tool that enhances the other structural variables of NUTS3 regions.

An important result of this work is the identification of the synergy effect between technology and regional wealth. The interaction term (5G * Log GDP_PPS) presents a positive and significant coefficient (p=0.0124), indicating that the economic benefits of digital infrastructure are amplified in counties with a higher standard of living. This finding suggests the risk of a "digital and energy gap" between regions, where already developed counties take advantage of the advantages of 5G technology more quickly to secure their energy independence. Similar structural asymmetries have been identified in the financial sector, where digitalization tends to amplify pre-existing regional disparities (Oprea & Nicula, 2026).

From a methodological perspective, the success of the fixed-effects model, which achieved a coefficient of determination of over 92%, highlights that the development of installed renewable power is the result of a mix of local factors. The fact that urbanization and economic development remain constant predictors suggests that public policies should not be limited to subsidizing photovoltaic panels, but should also aim at modernizing the grid and increasing technological literacy in local communities.

The paper provides solid statistical arguments for a paradigm shift in energy poverty strategies in Romania. Reducing the INI index from historically high values to the projected targets for 2025 must remain priority zero for the authorities. Synchronizing investments in digital infrastructure (5G) with those in the stability of electricity networks and regional economic stimulation can ensure a fair energy transition, capable of transforming Romanian counties from simple consumers into active hubs of sustainable renewable energy production.

The main original contribution consists in quantifying the technical barriers of the network by transforming the continuity indicators SAIDI and SAIFI into a unitary risk index. This provides a precise measure of how legacy infrastructure hinders modern investments.

The paper uses a panel model with 200 observations, capturing the disparities specific to the NUTS 3 regions of Romania.

The model introduces and validates the interaction term between digital infrastructure and living standards (5G - GDP), demonstrating that 5G technology does not generate uniform benefits, but depends on the local economic context.

Using the fixed-effects model, we were able to demonstrate that urbanization and network quality are much more important predictors of energy capacity than the mere presence of a digital signal.

One of the important limitations of this research is the use of forecasted data for the period 2024-2025 (extrapolated from ANRE trends), which, while providing a necessary perspective on the near future, may be influenced by external shocks or unforeseen regulatory changes.

Although the fixed-effects model corrects for a large part of the disparities between counties, there are qualitative factors (such as the specific policies of local distribution operators) that are not captured in the available numerical variables.

The INI index focuses on technical reliability (outages), but cannot fully measure the absorption capacity of the network (congestions), which is another important dimension of renewables integration. Although geographic coverage is an indicator of accessibility (Avadanei et al., 2019; Nicula et al., 2019), the model could not include data on connection quality or the actual degree of use of 5G networks by prosumers, due to the lack of public reporting at the county level.

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References

Abdulkarim, A., Faruk, N., Alozie, E., Olagunju, H., Aliyu, R. Y., Imoize, A. L., ... & Usman, D. J. (2024). Advances in the design of renewable energy power supply for rural health clinics, case studies, and future directions. Clean Technologies, 6(3), 921-953.

Ani, V. A. (2021). Powering primary healthcare centres with clean energy sources. Renewable Energy and Environmental Sustainability, 6, 7.

Autoritatea Națională de Reglementare în Domeniul Energiei. (2021). Raport anual de activitate 2021. https://anre.ro/despre/rapoarte/

Autoritatea Națională de Reglementare în Domeniul Energiei. (2021). Raport de monitorizare a activității prosumatorilor 2021. Disponibil pe https://anre.ro (secțiunea Rapoarte).

Autoritatea Națională de Reglementare în Domeniul Energiei. (2022). Raport anual de activitate 2022. https://anre.ro/despre/rapoarte/

Autoritatea Națională de Reglementare în Domeniul Energiei. (2022). Raport de monitorizare a activității prosumatorilor 2022. Disponibil pe https://anre.ro (secțiunea Rapoarte).

Autoritatea Națională de Reglementare în Domeniul Energiei. (2023). Raport de monitorizare a activității prosumatorilor 2023. Disponibil pe https://anre.ro (secțiunea Rapoarte).

Autoritatea Națională de Reglementare în Domeniul Energiei. (2023). Raport anual de activitate 3 2023. https://anre.ro/despre/rapoarte/

Autoritatea Națională de Reglementare în Domeniul Energiei. (2024). Raport anual de activitate 2024. https://anre.ro/despre/rapoarte/

Autoritatea Națională de Reglementare în Domeniul Energiei. (2025). Raport anual de activitate 2025. https://anre.ro/despre/rapoarte/

Avadanei, V., Surdu, I., Medveschi, I., Cocis, E.-A., Pacurar, B.-N., & Nicula, A.-S. (2019). Analysis of discording geodemographic structures and space polarization in regional context using GIS technology: Case study: Apuseni Mountains Romania. In L. Chivu, V. Ioan-Franc, G. Georgescu, & J. V. Andrei (Eds.), Romanian economy. A century of transformation (1918–2018): Proceedings of ESPERA 2018 (pp. 1011–1022).

Bîrsanuc, E.-M., Cocis, E.-A., Gligor, V., Man, T.-C., Nicula, A.-S., & Stoica, M.-S. (2020). Performing democracy: An analysis of church-based electoral capital in Romania. Transylvanian Review, 29(Suppl. 2), 291–309.

Happy, A. T., Hossain, M. I., Islam, R., Shohel, M. S. H., Jasem, M. M. H., Faysal, S. A., ... & Sunny, A. R. (2024). Enhancing pharmacological access and health outcomes in rural communities through renewable energy integration: Implications for chronic inflammatory disease management. Journal of Angiotherapy, 8(12), 1-12.

Hausman, J.A. (1978), Specification Tests in Econometrics, Econometrica. Vol46(6), pag1251-1271, https://doi.org/10.2307/1913827

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, 115(1), 53-74.

Izuka, U., Ojo, G. G., Ayodeji, S. A., Ndiwe, T. C., & Ehiaguina, V. E. (2023). Powering rural healthcare with sustainable energy: a global review of solar solutions. Engineering Science & Technology Journal, 4(4), P-No.

Levin, A., Lin, C. F., & Chu, C. S. J. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of Econometrics*, 108(1), 1-24.

Magda Moner-Girona, Georgia Kakoulaki, Giacomo Falchetta, Daniel J. Weiss, Nigel Taylor. (2021) Achieving universal electrification of rural healthcare facilities in sub-Saharan Africa with decentralized renewable energy technologies,Joule,Volume 5, Issue 10,2021, Pages 2687-2714, ISSN 2542-4351, https://doi.org/10.1016/j.joule.2021.09.010.

Maja, P. W., Meyer, J., & Von Solms, S. (2020). Development of smart rural village indicators in line with industry 4.0. IEEE access, 8, 152017-152033.

Ngoh, S. K., Bakehe, J. F., & Fils, P. E. (2022). Green electricity and medical electrolytic oxygen from solar energy-A sustainable solution for rural hospitals. Scientific African, 17, e01389.

Nicula, A.-S., Botan, C. N., Gligor, V., & Cocis, E.-A. (2022). Celebrating the Great Union through smart digital solutions: Lessons from Alba Iulia, Romania. Journal of Urban History, 48(2), 425–443. https://doi.org/10.1177/0096144220940713.

Nicula, A.-S., Medveschi, I., Avadanei, V., Surdu, I., & Cocis, E.-A. (2019). Accessibility and ecclesiastic polarization of monastic settlements in the Romanian Carpathians: Case study: Monastic settlements on the Occidental Carpathians. In L. Chivu, V. Ioan-Franc, G. Georgescu, & J. V. Andrei (Eds.), Romanian economy. A century of transformation (1918–2018): Proceedings of ESPERA 2018 (pp. 1097–1108).

Nicula, E.-A., Cretan, R., & Nicula, A.-S. (2024). Personal protective equipment (PPE) during the COVID-19 crisis: A review of current knowledge and future directions. Environmental Engineering and Management Journal, 23(6). https://doi.org/10.30638/eemj.2024.103.

Nneoma, U. C., Chukwudi, O. F., Nnenna, U. J., & Paul-Chima, U. O. (2025). Hybrid biofactories: integrating microalgae and engineered microbiomes for enhanced biofuel production in circular carbon systems. Frontiers in Energy Research, 13, 1654079.

Olatomiwa, L., Sadiq, A. A., Longe, O. M., Ambafi, J. G., Jack, K. E., Adekunle, T. A., & Adeniyi, S. (2022). An overview of energy access solutions for rural healthcare facilities. Energies, 15(24), 9554. https://doi.org/10.3390/en15249554

Opoku, R., Adjei, E. A., Obeng, G. Y., Severi, L., & Bawa, A. R. (2020). Electricity access, community healthcare service delivery, and rural development nexus: Analysis of 3 solar electrified CHPS in off-grid communities in Ghana. Journal of Energy, 2020(1), 9702505.

Oprea, I. M., & Draghici, L. G. (2024). Bank Digitalization, Financial Literacy, and Inclusion In Romania. Manager (University of Bucharest, Faculty of Business & Administration), 39(1).

Oprea, I. M., Panait, C., Draghici, L. G., & Georgescu, M. R. (2025). Digital Banking, Capital Market, Financial Education and Public-Private Partnerships in Romania's Economic Development. In Proceedings of the International Conference on Business Excellence (Vol. 19, No. 1, pp. 2951-2966). Sciendo. DOI: 10.2478/picbe-2025-0226

Oprea, I-M., Nicula, E-A. (2026). Banking digitalization and financial inclusion: bibliometric analysis and perspectives in emerging economies. Access to science, business, innovation in digital economy, ACCESS Press, 7(1), 21-42, https://doi.org/10.46656/access.2026.7.1(2)

Pacurar B.-N., Nicula S.-A., Strinu O., Surd V. (2016), Indexing the Innovative Capability of Romanian NUTS 3 (Counties) Subdivisions. Journal of Settlements and Spatial Planning, 7(1), 45-49. DOI: 10.19188/05JSSP012016.

Ramsey, J.B. (1969), Tests for Specification Errors in Classical Linear Least Squares Regression Analysis, Journal of the Royal Statistical Society: Series B, 31, 350-371

Simionescu, M., & Nicula, A. S. (2024). Sentiment analysis as innovation in the inflation forecasting in Romania. Marketing and Management of Innovations, 15(2), 13–25. https://doi.org/10.21272/mmi.2024.2-02.

Simionescu, M., & Nicula, A.-S. (2025). The role of sentiment analysis and central bank interest rate decisions in forecasting inflation: A Bayesian non-parametric approach for Czech Republic and Romania. Romanian Statistical Review, (1), 3–24.

Soto, E. A., Hernandez-Guzman, A., Vizcarrondo-Ortega, A., McNealey, A., & Bosman, L. B. (2022). Solar energy implementation for health-care facilities in developing and underdeveloped countries: Overview, opportunities, and challenges. Energies, 15(22), 8602.