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DIGITAL TRANSFORMATION, ECONOMIC PERFORMANCE, AND SUSTAINABILITY WITHIN THE EU

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Abstract

By using triple time segmentation and dual model specifications, this paper investigates the relationship between digital transformation, economic performance, and sustainability within the European Union. By employing a multi-stage methodology (PCA, cluster analysis, and fixed effects (FE) panel regression modeling) across 27 EU countries, the study confirms the complex interdependence among these three dimensions. Findings identify four heterogeneous clusters, highlighting a contradiction between digital - economic leaders and sustainability leaders, indicating a significant challenge in decoupling growth from sustainability impacts. The panel regression results confirm digitalization as a robust and statistically significant driver of economic growth. Most importantly, the positive impact of renewable energy sources on economic performance confirms their endogenous benefits.

Keywords: digital transformation, economic growth, sustainability, cluster analysis, principal component analysis, panel regression

1. INTRODUCTION

Digital transformation is a pivotal goal for the EU as it plays a role in economic development, and social well-being. The adoption of digital technologies has transformed industries by increasing efficiency (Omol, 2024) and enabling companies to withstand economic shocks through agility (Hokmabadi et al., 2024). While recent research in this field has focused on the digital transformation of specific sectors like airports (Spremić, 2025) or healthcare (Pira & Pira, 2025), such systems inherently rely, among other factors, on a stable energy supply (Katal et al., 2023; Tiep et al., 2020; Colak & Irmak, 2023). This study extends discourse by arguing that sustainable energy sources (that represents sustainability) might be the vital catalyst that powers digital infrastructure, simultaneously enhancing endogenous growth potential for the economy. During the COVID-19 pandemic, digital infrastructure became essential for remote work, emissions reduction and energy optimization (Kylili et al., 2025). In this period, large language models provided health instructions, psychological support, and enabled online medical examinations, thereby preserving the continuity of healthcare (Lai et al., 2023). Weaker digital infrastructure hindered the provision of health services during the pandemic (Mbunge et al., 2022). Digitalization increases the availability of public services (Ponti et al., 2022), while the Internet of Things (IoT) and big data analysis help optimization of energy consumption (Liu et al., 2024). Ultimately, the relationship between digital transformation, economic growth, and sustainability remains complex and reciprocal (Guo et al., 2023).

Alongside this benefit, digital transformation enables achieving sustainable goals and optimizing energy consumption, thereby integrating economic and environmental objectives. That emphasizes how digitalization can align with sustainable goals to generate more resilient economic growth. Conversely, the COVID-19 crisis demonstrated the role of digitalization in society (e.g., remote work, emissions reduction while working from home, and maintaining healthcare).

While initial investments in digitalization might be expensive, they might bring long-term productivity and endogenous benefits. Previous studies, including Bocean and Varzaru (2023), offered key insights into digitalization, sustainability, and economic performance in Europe but noted limitations such as static cross-sectional analysis and challenges in generalizing results. They called for longitudinal, multidimensional research. The work also failed to provide a direct comparison between the Digital Economy and Society Index (DESI) and a major sustainable indicator, such as renewable energy share (Tiep et al., 2020). This aligns with the broader application of advanced econometrics in analyzing EU-wide determinants (e.g., Škrabić Perić et al., 2025), which underscores the importance of using robust panel data approaches to capture structural relationships across member states. This study addresses these gaps using fixed effects panel regression to provide a comprehensive, longitudinal view of these relationships. However, despite the emphasized benefits of digitalization, regional disparities in digital infrastructure remain a significant challenge for the equitable distribution of these benefits. This challenge often manifests as inconsistent economic returns despite high digital maturity - a phenomenon recognized in the literature as the *digitalization paradox* (Gebauer et al., 2020; Sengupta et al., 2021). The empirical findings of this study resolve the *digitalization paradox* in the EU context, confirming that digitalization (measured by Internet use and the DESI Index) is a robust and statistically significant driver of economic growth. Furthermore, the analysis reveals that the share of renewable energy sources positively contributes to economic performance, directly supporting the role of strategic sustainable digitalization.

The theoretical background is based on endogenous growth, innovation diffusion, and sustainable development theories, which emphasize technology as a key driver of modern economies. Most studies confirm positive links between digital maturity (often measured by indices such as DESI) and macroeconomic indicators (Gu & Liu, 2024), as well as sustainable benefits (Sengupta et al., 2021). However, despite general agreement on digitalization's advantages, evidence of its consistent, direct impact on national economic growth (GDP per capita) varies across EU states.

The urgency of this research is underscored by the debate on degrowth (Kemp-Benedict, 2025), which posits that continuous economic expansion within an unsustainable environment requires a transition to controlled economic contraction. This study might provide an indirect answer, if strategic sustainable digitalization might be a viable solution to neutralize the negative effects of degrowth.

The paper is structured into seven key sections. Section 2 establishes the conceptual framework consisting of theoretical background, literature review, and the development of hypotheses. Section 3 presents the data and methodology used in the study. The paper ends with sections of results, discussion, limitations, and conclusion.

2. CONCEPTUAL FRAMEWORK

The conceptual framework establishes the theoretical foundation through three intersecting theories. This is followed by a literature review that identifies research gaps and helps to formulate the study's hypotheses.

2.1. Theoretical framework

Given the interdisciplinary nature of this study, the theoretical foundation is established through three intersecting theories: the theory of endogenous growth, the theory of innovation diffusion, and the theory of sustainable development.

The endogenous growth theory posits that economic growth is primarily the result of internal processes and factors within an economy (Romer, 1994), rather than exogenous forces.

In the context of digital transformation, this theory suggests that investments in digital infrastructure and the development of digital capabilities can become self-sustaining drivers of economic growth (Mai et al., 2024). Thus, this theory emphasizes that the DESI index, which represents an economy's innovativeness and digital transformation, should serve as an internal driver of economic growth. However, for digital transformation to act as an internal driver of growth, the underlying technologies must be diffused throughout the economic system, which underscores the relevance of the innovation diffusion theory.

The innovation diffusion theory (Rogers et al., 2014) explains how new ideas and technologies spread through communication channels and social systems over time (Lin & Burt, 1975). High internet usage serves as a signal of efficient communication, accelerating the adoption of digital technologies across the economy. Internet penetration is a key indicator of digitalization, particularly in periods preceding the DESI index (Gu & Liu, 2024). In the Industry 4.0 era, widespread internet use promotes the adoption of advanced technologies such as the IoT and big data, enhancing productivity and competitiveness, in line with endogenous growth theory (Romer, 1994). While these digital advancements drive efficiency, the long-term viability of such growth must be evaluated through the lens of environmental and social impacts, as defined by sustainable development theory.

Sustainable development theory emphasizes balancing economic growth with environmental protection and social equity to meet present needs without compromising future generations (Bossel, 1999). Countries excelling in digitalization, sustainability, and economic performance tend to have more resilient economies (Bocean & Vărzaru, 2023). A critical question remains whether digital-driven economic growth could harm environmental sustainability and long-term equity. Integrating sustainable practices, such as the use of IoT to enhance energy optimization, helps reduce environmental impact, cut costs, and improve efficiency, thereby strengthening economic resilience against shocks (Bocean & Vărzaru, 2023; Bayrakçeken, 2024). Finally, these three theories converge to form a multidimensional framework where digital transformation and sustainability are not isolated processes but interconnected pillars of modern economic performance.

2.2. Literature review

Digital transformation represents the comprehensive integration of digital technologies to reshape how organizations operate and deliver value (Sewpersadh, 2023). Its primary objective is to boost productivity, innovation, and efficiency, thereby driving economic growth and social progress. Technologies like cloud computing, big data, and the IoT enable more efficient operations, reducing operational costs and environmental impact (Criveanu, 2023). The European Commission (2020) identifies digital transformation as vital for sustainable economic growth and for enhancing member states' competitiveness (Jarzębowski, 2024). Furthermore, Bocean and Vărzaru (2023) emphasize its role in GDP growth through efficiency and market expansion. Higher digital adoption correlates with stronger economic performance (Gu & Liu, 2024), and Škare et al. (2024) highlight digital innovation as a key driver for sustainable long-term growth and value creation. However, the realization of these economic benefits remains deeply intertwined with the broader socio-economic infrastructure and the adaptability of the workforce.

Digital technologies yield mixed benefits. While e-commerce reduces the need for physical stores, it cuts costs and expands customer reach (Hosen, 2024). Cloud computing lowers physical infrastructure costs but simultaneously increases energy demand (Katal et al., 2023). Furthermore, automation shifts labor demand towards specialized digital skills, challenging workforce adaptability (Marku, 2024). Consequently, bridging the digital divide via broadband access, digital literacy, and support for small businesses is vital (Criveanu, 2023; Bocean & Vărzaru, 2023). Digital infrastructure development boosts access to essential e-services (Webber et al., 2022). During lockdowns, remote work (primarily enabled by digital infrastructure) improved efficiency and reduced travel, but raised issues of autonomy and blurred work-life boundaries (Wang et al., 2021; Hossain et al., 2023). Digitalization enables remote businesses with lower costs, supporting sustainability and payroll continuity in lower-income firms, fostering economic growth, well-being, and reduced emissions through the elimination of traveling to the workplace (Emanuel & Harrington, 2024; Metselaar & Vermeeren, 2023). Despite these advancements in infrastructure and flexibility, the transition from digital adoption to measurable economic prosperity is not always linear, often manifesting as a complex disparity across regions.

Digital transformation brings notable benefits but also reveals disparities. The Digital Economy and Society Index (DESI) shows uneven progress, with some countries digitally advanced and others lagging (Tokmergenova, 2023). Despite high digitalization, economic growth measured by GDP per capita does not always follow, a phenomenon known as the *digitalization paradox* (Gebauer et al., 2020). This suggests that social factors play a crucial role in converting digitalization into economic gains (Sengupta et al., 2021). Environmentally, digital growth increases energy demand and e-waste (Katal et al., 2023; Ádám et al., 2021), potentially causing rebound effects that may hinder sustainability goals. Unchecked digital growth risking environmental degradation contradicts sustainable development principles (Bossel, 1999). Thus, digital investment must accompany organizational and social adaptations to unlock sustainable, long-term economic benefits. The identified inconsistencies in how digitalization, sustainability, and economic performance interact toward a significant gap in the current literature.

Sustainability is defined as maintaining economic activity while protecting environmental and social dimensions (Bossel, 1999). The link between digitalization, economic performance, and sustainability can be explored through principal component analysis (PCA) to reveal their underlying interconnections (Hansmann et al., 2012). Existing policies often fail to leverage the synergy between digitalization and sustainability because they overlook sociotechnical factors (Brenner & Hartl, 2021).

Comparable studies have used cluster analysis to examine economic performance and digital transformation, but often omitted key variables such as the share of renewable energy, a crucial sustainability indicator given that digitalization and digital infrastructure require significant electrical energy (Tiep et al., 2020; Colak & Irmak, 2023). Previous research also tends to exclude the DESI index, relying solely on the SDG index, thereby lacking a direct comparison between comprehensive digitalization and sustainability metrics (Bocean & Vărzaru, 2023).

This study addresses these gaps by investigating the *digitalization paradox*, the phenomenon where high digitalization does not always lead to expected economic growth, and by determining whether digitalization, combined with sustainability, significantly influences economic performance in the European Union. By employing a robust, multidimensional panel approach, this paper aims to provide insights into these interconnected relationships. Based on the literature review and the identified gaps, the following hypotheses are formulated:

- **H1:** EU member states exhibit significant heterogeneity in their levels of digitalization, economic performance, and sustainability, forming distinct clusters that reflect the digitalization paradox.
- **H2:** Digital transformation (measured by the DESI index and internet users) has a significant positive impact on economic performance (GDP per capita) across the EU.
- **H3:** Sustainability, specifically the renewable energy sources and the achievement of SDG targets, significantly enhances economic performance.

3. DATA AND METHODOLOGY

This section outlines the empirical framework used to examine the complex relationship between digitalization, economic performance, and sustainability in the EU. It begins with a description of the data and selected variables, followed by a multistage methodology. Principal component analysis reduces the multidimensional dataset to identify underlying factors. Next, these factor scores are used in a grouping technique to classify countries, revealing inherent heterogeneity across EU member states. The analysis is further refined through fixed - effects panel regression models, applied with triple time-period divisions and dual model specifications, to provide detailed, longitudinal insights into the drivers that shape the economic perspective of the EU.

3.1. Data

The empirical analysis utilizes an unbalanced panel dataset covering 27 European Union (EU) member states from 2000 to 2023. While 2023 serves as the final observation point for assessing the contemporary state of these relationships, the study specifically requires longitudinal insights, necessitating the observation of trends over this extended preceding period. However, the requirement for a robust longitudinal perspective presents challenges regarding data consistency and the availability of sophisticated indices across the entire time series. To address this, a strategy of variable substitution was employed, ensuring the overall integrity of the panel regression models used to investigate the impact of sustainability and digitalization on economic performance.

The research framework consists of three dimensions, with key variables summarized in Table 1. Economic performance is measured by GDP per capita[1] (Rollnik and Bartkutė Norkūnienė, 2024) and the unemployment rate (% of active job seekers) (Mamo and Ayele, 2024). The unemployment rate can be perceived as a control variable within the models to capture the consistency of Okun's law across models. Okun's law posits a robust inverse relationship between GDP growth and unemployment rate, in which rising economic output typically corresponds to decreasing unemployment, thereby reinforcing the reliability of the model's economic performance.

The sustainability dimension includes per capita GHG emissions (Zeraibi et al., 2024), the share of renewable energy, and the aggregate SDG index. Digital transformation is captured by internet users (%) and the DESI index, focusing specifically on its "Internet use" component (Asoy, 2024; Figueiredo, 2024). This focus is justified as internet use underpins broad access to digital services across the economy, moving beyond narrow corporate technology adoption (Olczyk & Kuc-Czarnecka, 2022).

To address data inconsistencies from 2000 to 2023, the model specifications are dynamically adjusted. Early periods rely on macroeconomic and sustainability data, while the DESI index, available since 2017 onward, enables more refined analysis. Model 2 tests robustness by incorporating the share of renewable energy. This variable is included because it represents decarbonization efforts and the supply-side transition in the energy sector, offering a direct measure of a country's commitment to sustainable growth beyond regulatory emissions controls. It is a critical component for testing the benefits of strategic sustainable digitalization. Consequently, model 3 substitutes GHG emissions and the renewable energy share with the aggregate SDG index (which inherently incorporates these two variables), allowing direct comparison with the DESI index within fixed effects panel regressions. This approach ensures a comprehensive assessment of the interplay among sustainability, digitalization, and economic performance.

[1] GDP per capita for the period 2000 – 2023, was independently calculated using chain volume GDP and population data from Eurostat to maintain temporal consistency across the entire study period.

Table 1 Observed variables

Variable	Data Explanation	Dimension	Reference
GDP per capita (chain link volumes)	Gross domestic product in chain-linked volumes (with 2020 as the reference year) and divided by population to get GDP per capita	Economic performance	Eurostat*
Unemployment rate (%)	How many unemployed people do countries have?	Economic performance	World Bank
GHG per capita (tCO2/person)	Consolidating various greenhouse gases into a single comparable unit based on their global warming potential measured in megatons per capita. (tons of CO_2 equivalents per person)	Sustainability	World Bank
Share of renewable energy sources (%)	Share of renewable energy a country has in its energy mix.	Sustainability	Eurostat
Internet users (%)	How many Internet users does each country have? (Internet users are individuals who have used the Internet (from any device and location) in the last 3 months.)	Digital transformation	World Bank
DESI index	Digital Economy and Society Index measures digital competitiveness and progress in digital transformation. (Individuals who use the internet at least once a week.)	Digital transformation	European Commission
SDG Index Score	Index that measures sustainability.	Sustainability	European Commission

*GDP in chain-linked volumes and population have been obtained from Eurostat.

Source: Author's compilation

Furthermore, to ensure the robustness of the findings and to investigate the potential impact of extreme outliers on the estimated coefficients, the three regression models (model 1, model 2, and model 3) were estimated across two distinct sample configurations. Table 2 provides a comprehensive overview of the variable composition, period of analysis, and sample configuration for each estimated model. Specifically, model A utilizes the full panel dataset comprising all (N=27) European Union member states. Model B, conversely, excludes two specific countries (N=25): Luxembourg and Ireland. This methodological decision is directly informed by the preceding cluster analysis (RQ1), which identified these two nations as *Digital-economic leaders* due to their exceptionally high GDP per capita and DESI scores. Given that the dependent variable, the logarithm of GDP per capita, is highly sensitive to such extreme values, model B serves as a critical robustness test, deliberately decreasing the range of GDP per capita and mitigating the potential for these outliers to disproportionately influence the regression estimates. The comparison between the results of model A and model B allows for a more confident interpretation of the coefficients, especially given the documented heterogeneity among EU member states (Bańkowski et al., 2022).

Table 2 Variables within the models

Variable	Dimension	Model 1		Model 2		Model 3		Reference
		1.A	1.B	2.A	2.B	3.A	3.B	
Period		2000-2023		2004-2023		2017-2023		
GHG	Sustainability	●	●	●	●			World Bank
internet	Digital transformation	●	●	●	●			World Bank
renew	Sustainability			●	●			Eurostat
SDG	Sustainability					●	●	European Commission
DESI	Digital transformation					●	●	European Commission
GDP	Economic performance	●	●	●	●	●	●	Eurostat
unemploy	Economic performance	●	●	●	●	●	●	World Bank

Source: Author's compilation

3.2. Methodology

In the first stage, Principal Component Analysis (PCA) was carried out to reduce dimensionality and to compute factor scores. These scores were then utilized in a cluster analysis to identify homogeneous groups of countries. Finally, the panel regression with fixed effects was employed to examine dynamic interdependencies.

3.2.1. Principal component and cluster analysis

The first stage of the methodology addresses the heterogeneity among EU member states through a combination of principal component and cluster analysis.

Principal component analysis is a statistical technique used to reduce the given dimensionality of the dataset while retaining as much of the original variability as possible (Jolliffe & Cadima, 2016). The method transforms a set of correlated variables into a smaller set of uncorrelated linear combinations called principal components (Johnson & Wichern, 1992, p. 357). Ideally, the variances of the principal components should be as large as possible, but the components themselves remain uncorrelated with each other. The first principal component: linear combination $l_1'X$ that maximizes $Var(l_1'X)$ subject to $l_1'l_1 = 1$, and the second principal component: linear combination $l_2'X$ that maximizes $Var(l_2'X)$ subject to $l_2'l_2 = 1$, including the condition that indicates the uncorrelation between the principal components expressed as $Cov(l_1'X, l_2'X) = 0$ (Johnson & Wichern, 1992, p. 357).

Calculating principal components enables tracking correlations between each component and each variable (Wang et al., 2023). Examining the factor loadings (coefficients for the original variables) helps understand each variable's influence on the principal components. The approach outlined by Oyewole and Thopil (2023), employing a two-stage cluster analysis combined with Principal Component Analysis (PCA), is highly suitable given the diverse nature of the variables in the dataset (Almais et al., 2023). Reduced dimensions can be beneficial for identifying representative variables for use in subsequent multivariate analyses such as cluster analysis (Hair et al., 2010, pp. 91-95). Following this approach, factor analysis is used together with other multivariate techniques, such as cluster analysis (Hair et al., 2010, pp. 91-95). Based on the results of factor analysis, factor scores are obtained for each individual country, which are then used in the second cluster analysis. In this way, countries are grouped into clusters according to similarities in relation to the main components identified by factor analysis, providing a more integrated and meaningful basis for grouping countries. To test the adequacy of the data for factor analysis, it is necessary to perform specific statistical tests. The fulfillment of assumptions must be verified by Bartlett's test of sphericity, where the significance is <0.05 and the MSA (Kaiser-Meyer-Olkin) test, which must be >0.5 (Hair et al., 2010; Shrestha, 2021). Finally, the Varimax orthogonal factor rotation method was used to minimize the number of variables with high loadings on each factor.

Considered a technique for this research, cluster analysis is a multivariate statistical technique used to group objects or subjects into clusters based on their similarities across measured variables (Cornish, 2007). The optimal number of centroids (clusters) can be given by conducting the Elbow method and identifying the minimum (Bayesian Information Criterion) BIC (Shi et al., 2021). Proximity between observations is measured using the Euclidean distance, calculated as:

$$d_{ij} = \sqrt{(x_{i1} - x_{j1})^2 + (x_{i2} - x_{j2})^2 + \cdots + (x_{ip} - x_{jp})^2} \tag{1}$$

where d_{ij} is the distance between two objects *i* and *j* across *p* variables.

3.2.2. Panel regression with fixed effects

The final stage of the methodology is focused on estimating the impact of digitalization and sustainability on GDP per capita (RQ2). Given the inherent dynamics and persistence of economic growth, advanced models designed to explicitly account for the lagged dependent variable and control for potential endogeneity were initially considered (Arellano & Bond, 1991; Blundell & Bond, 1998; Roodman, 2009). However, these GMM models failed to satisfy basic diagnostic assumptions across multiple specifications and time periods, often yielding invalid results based on the *AR(2)* serial correlation test or the Hansen test of instrument validity.

However, the fixed effects (FE) panel regression model was ultimately chosen over the random effects (RE) model based on strong theoretical and empirical priors. The prior cluster analysis, which confirmed significant, unobserved heterogeneity among the EU member states, represents the consequential results of the entire preceding period's development. These structural differences from the cluster analysis based on factor scores, necessarily indicate a high probability that the unobserved heterogeneity (μ_i) is correlated with the explanatory variables (X_{it}), thereby violating the core assumption of the RE model that is given as $Corr(\mu_i, X_{it}) = 0$ (Hausman, 1978; Baltagi, 2008).

Therefore, the fixed effects estimator was selected as the most robust and conservative static approach. The FE model ensures that the analysis yields consistent and unbiased estimates by effectively controlling the confirmed unobserved heterogeneity (μ_i) (and their high probability of correlation with the explanatory variables X_{it}), allowing the research to focus exclusively on the longitudinal insight (Chrysikou & Kapetanios, 2024; Mugnier, 2025) within country variation that is fundamental to understanding the interrelationship.

Given the data inconsistencies detailed in Section 3.1, particularly the varying longitudinal availability of sophisticated indices such as DESI and SDG, the regression analysis was segmented into three separate models: model 1, model 2, and model 3. This strategic segmentation allows for a multifaceted approach: (1) it enables a more nuanced insight by testing different dimensions; (2) it serves as a robustness test due to the systematic substitution of variables and (3) it ensures a comprehensive temporal scope, leveraging the availability of macroeconomic and core sustainability data to gain the broadest possible insight over the two decades (2000-2023). The final specifications for the three core models are formally represented by the fixed effects panel regression equations (2), (3), (4), and (5). Specifically, panel regression (5) incorporates the SDG, DESI, and unemployment variables, as the renewable energy and gas emissions variables are both components of the SDG index (Magazzino & Zoundi, 2025), while the internet users variable is a core component of the DESI index (Bruno et al., 2023; Gu & Liu, 2024). The rationale for this approach is that including renewable sources of energy, gas emissions, and internet users alongside these composite indices might increase multicollinearity within the model, thus it is better to retain confronting the main indices SDG and DESI, alongside the control variable unemployment rate (Olczyk & Kuc-Czarnecka, 2022; Paraschiv et al., 2024).

$$BDP_{i,t} = \beta_0 + \beta_1 X_{1,it} + \cdots + \beta_k X_{k,it} + \mu_i + \varepsilon_{it} \tag{2}$$

$$LGDP_{it} = \beta_1 GHG_{it} + \beta_2 internet_{it} + \beta_3 unemploy_{it} + \mu_i + \varepsilon_{it} \tag{3}$$

$$LGDP_{it} = \beta_1 GHG_{it} + \beta_2 renew_{it} + \beta_3 internet_{it} + \beta_4 unemploy_{it} + \mu_i + \varepsilon_{it} \tag{4}$$

$$LGDP_{it} = \beta_1 SDG_{it} + \beta_2 DESI_{it} + \beta_3 unemploy_{it} + \mu_i + \varepsilon_{it} \tag{5}$$

4. RESULTS

This section presents the findings of the multi-stage analysis, beginning with the descriptive statistics (Table 3). Prior to PCA, an inspection of the correlation matrix was conducted (Figure 1). The matrix revealed a high degree of intercorrelation among several key variables. This confirmed the presence of multicollinearity within the dataset in 2023, providing methodological justification for the subsequent use of principal component analysis.

Figure 1 Correlation matrix

Variable	DESI	SDG	GDP	unemploy	renew	internet	GHG
DESI	—	0.323	0.662	0.048	-0.170	-0.021	0.440
SDG	0.323	—	0.096	0.132	0.012	0.066	0.220
GDP	0.662	0.096	—	-0.047	-0.221	-0.112	0.556
unemploy	0.048	0.132	-0.047	—	0.250	-0.210	0.032
renew	-0.170	0.012	-0.221	0.250	—	-0.031	-0.380
internet	-0.021	0.066	-0.112	-0.210	-0.031	—	0.089
GHG	0.440	0.220	0.556	0.032	-0.380	0.089	—

Source: Author's calculation

Table 3 Descriptive statistics of EU Countries, N=27

Variable	*Description*	*N (Valid)*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
GDP	*GDP per capita (chained-link volumes)*	*27*	*34,18*	*22,08*	*10,95*	*103,3*
DESI	*Digitalization index*	*27*	*90.43*	*4.860*	*79.83*	*98.92*
GHG	*Greenhouse Gas Emissions (tCO2 per capita)*	*27*	*7.459*	*2.350*	*3.745*	*14.14*
SDG	*Sustainable Development Goals Index*	*27*	*80.24*	*3.063*	*72.92*	*86.35*
unemploy	*Unemployment rate (%)*	*27*	*5.750*	*2.274*	*2.579*	*12.18*
renew	*Share of renewable energy Sources (%)*	*27*	*27.27*	*12.99*	*14.31*	*66.39*
internet	*Internet users (%)*	*27*	*90.92*	*4.904*	*80.39*	*99.35*

Source: Author's calculations

To conduct PCA and to uncover structural relationships between dimensional variables, the necessary assumptions and prerequisite tests have been conducted and presented in Table 4, thereby confirming that the data set from 2023 is adequate for the principal component analysis.

Table 4 Kaiser-Meyer-Olkin and Bartlett's test

Kaiser-Meyer-Olkin Test		
Overall Measure of Sample Adequacy		0,640
Bartlett's Test		
X^2	df	p
92.338	21.000	< .001

Source: Author's calculations

Table 5 PCA after Varimax rotation

Component	**1**	**2**	**3**
Variable	**Economic and digital development**	**Sustainability**	**Economic vulnerability**
GDP per capita	**0,886**	-0,094	**-0,123**
Unemployment rate (%)	-0,038	0,144	**0,935**
*GHG emissions per capita in t**	**0,614**	0,228	-0,359
Share of renewable energy sources (%)	0,075	**0,864**	0,286
SDG index	0,137	**0,899**	-0,086
Internet users (%)	**0,937**	**0,119**	0,072
DESI index	**0,899**	0,212	0,061

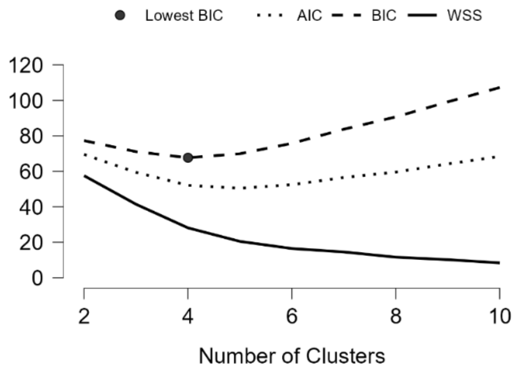
*t indicates the unit of measurement of one ton

Source: Author's calculations

The results of the rotated component matrix are presented in Table 5, clearly illustrating the differentiation between the components. The three extracted components capture different underlying dimensions within the dataset. Component 1 represents economic and digital development, with high positive loadings on GDP per capita, the DESI index, and internet users. It is notable that higher greenhouse gas emissions per capita are also associated with this component. In contrast, component 2 denotes sustainability, strongly defined by the SDG index and the share of renewable energy sources. On the other hand, component 2 shows moderate economic performance. Finally, component 3 reflects economic vulnerability, primarily weighted by the unemployment rate, negatively correlated with GDP per capita.

The Bayesian Information Criterion (BIC), as shown in Figure 2, indicated four clusters as the most appropriate solution, consistent with the lowest BIC value. Furthermore, ANOVA (Table 6) confirmed that the four-cluster solution yielded the most significant differentiation among groups across all three variables. The mean values of the variables within each cluster are presented in Table 7, providing a profile for each identified cluster.

Figure 2 Elbow method to determine number of clusters



Source: Author's calculation

Table 6 ANOVA of the cluster analysis

Principal components	**Cluster**		**Error**		**F**	**Sig.**
	Mean Square	df	Mean Square	df		
REGR factor score 1	5,808	3	0,373	23	15,574	<,001
REGR factor score 2	5,735	3	0,382	23	14,999	<,001
REGR factor score 3	5,031	3	0,474	23	10,607	<,001

Source: Author's calculations

Table 7 The final centers of the cluster analysis

Principal components	**Digital-economic leaders**	**Vulnerable followers**	**Stable followers**	**Sustainability leaders**
REGR factor score 1	1,59317	-0,47005	-0,66818	0,53388
REGR factor score 2	-0,93071	-0,42662	-0,1152	1,41401
REGR factor score 3	-0,47629	0,89415	-0,91835	0,20076

Source: Author's calculations

Cluster 1, the *digital-economic leaders*, is defined by a highly positive score on the *economic and digital development* component (+1.593) but simultaneously a very low score on the *sustainability* component (-0.931). This group represents digital and economic powerhouses whose success is currently achieved at the expense of environmental sustainability, as the GHG relation indicates. Conversely, cluster 4, the *sustainability leaders*, demonstrates exceptionally high performance in s*ustainability* (+1.414), coupled with an above-average score in *economic and digital development* (+0.534), positioning them as pioneers who have successfully integrated sustainable transition with economic growth. Cluster 2, the *vulnerable followers*, is characterized by high *economic vulnerability* (+0.894), reflecting higher unemployment rates and instability, alongside below-average performance in the first two components. Finally, cluster 3, the *stable followers,* exhibits lower levels of *economic and digital development* (-0.668), but is distinguished by the lowest *economic vulnerability* (-0.918), suggesting stable but less dynamic economies. These findings provide strong empirical support for H1, as the identification of four distinct groups confirms the significant heterogeneity across the EU and illustrates the nuanced nature of the digitalization paradox, particularly in its interplay with sustainability within the European context. The visualization of EU member states by clusters is provided on a map of Europe (Figure 3).

Figure 3 Grouping EU countries due to factor scores within cluster analysis

Source: Author's illustration

After applying a logarithmic transformation to variable GDP per capita, fixed effects panel regressions (Table 8) were employed to examine the relationship among the three dimensions. All six models showed good fit, as indicated by R^2 values ranging from 0.5450 to 0.8200, along with highly significant F-statistics confirming the relevance of the included variables.

Table 8 The results of fixed effects panel regression

	Model (1A)	Model (1B)	Model (2A)	Model (2B)	Model (3A)	Model (3B)
Sample:	Full (N=27)	Cleaned (N=25)	Full (N=27)	Cleaned (N=25)	Full (N=27)	Cleaned (N=25)
Number of Groups	27	25	27	25	27	25
Number of Obs (N)	648	600	540	500	189	175
Period	2000-2023	2000-2023	2004-2023	2004-2023	2017-2023	2017-2023
Coefficients						
GHG	0.0108862***	0.0186979***	0.0093009***	0.0172970***		
internet	0.0057095***	0.0057101***	0.0051994***	0.0048447***		
renew			0.0030181**	0.0045602***		
SDG					−0.004885	−0.0052382
DESI					0.0087158***	0.0081449***
unemploy	−0.0238504***	−0.0231586***	−0.0224602***	−0.0214694***	−0.0076230**	−0.0075828**
Constant	9.778691***	9.623966***	9.760936***	9.592596***	9.910592***	9.897221***
Model Statistics						
R2 (Within)	0.7978	0.8200	0.7392	0.7596	0.5497	0.5450
F-statistic	812.56***	868.33***	360.66***	372.13***	64.71***	58.70***

*** Significant at level 1% (p < 0,01),
** Significant at level 5% (p<0,05),
* Significant at level 10 % (p<0,10)

Source: Authors' calculations and compilation

The results provide crucial evidence for the role of digitalization and sustainability in economic performance (GDP per capita). Across all specifications (models 1A to 3B), the rate of unemployment (*unemploy*) showed a robust, highly significant negative impact on economic performance, confirming that the models accurately reflect the economic system.

Crucially, the coefficients for the digitalization indicators - Internet users (internet) in models 1 and 2, and the DESI index in model 3 were consistently positive and highly significant, and this finding effectively resolves the noted "paradox of digitalization" within the EU context, confirming that digital advancement is a clear and robust driver of economic growth. This finding effectively resolves the noted *digitalization paradox* within the EU context and provides an empirical grounding for the full acceptance of H2, confirming that digital advancement is a clear and robust driver of economic growth across the EU. However, the analysis of sustainability indicators yielded nuanced important findings. Consistent across models 1 and 2, GHG emissions exhibited a statistically significant positive coefficient. This result reinforces the PCA findings, suggesting that, historically, economic growth (and the success of the d*igital-economic* *leaders*) has been intrinsically coupled with higher emissions. However, the models, including the share of renewable energy sources (*renew*), within models 2A and 2B, provided a statistically significant positive impact on GDP per capita.

This indicates that the shift toward sustainable energy sources acts as a contributor to growth rather than a constraint, providing partial confirmation for H3. While renewable energy aligns with economic performance, the lack of statistical significance in the aggregate SDG index suggests that the broader sustainability transition involves complex trade-offs not yet fully captured in GDP fluctuations.

5. DISCUSSION

The study's results can be meaningfully interpreted within the conceptual lens of the paper's theoretical framework. The consistently significant positive coefficient for Internet users across models 1 and 2 indicates that widespread adoption of digital technologies meaningfully contributes to GDP growth. This supports innovation diffusion theory, where broad internet access efficiently disseminates new ideas and capabilities, generating positive macroeconomic effects.

Supporting endogenous growth theory, the DESI index shows a highly significant positive impact on economic performance (model 3), and the share of renewable energy also exhibits a significant positive effect. Together, these findings suggest that investments in digitalization and sustainable (renewable) sources of energy foster endogenous advantages that enhance economic efficiency and productivity.

The sustainability analysis reveals that while positive coefficients for GHG emissions reflect pollution-intensive traditional growth, the positive impact of renewable energy points to decoupling possibilities. This finding addresses the core hypothesis: traditional growth still remains *polluted*, but sustainable digitalization, by combining digitalization with renewable energy, offers a robust pathway to boost economic performance and counteract degrowth risks in the EU.

Importantly, the SDG index might not remain significant, possibly because it is a comprehensive measure encompassing social and environmental dimensions beyond the economic focus. This underscores the importance of analyzing specific sustainability components alongside composite indices.

Cluster analysis shows only a minority of EU states with fully integrated sustainability into their economic systems, highlighting heterogeneity and the persistent challenge. Leading countries should share best practices and policies to accelerate the integration of sustainability and digitalization across the EU.

6. LIMITATION AND FURTHER RESEARCH

A very interesting and insightful finding is that the aggregate SDG index failed to show a statistically significant influence on economic performance, which contrasts with the theoretical expectation of a significant positive contribution from sustainability on economic performance. Given the simultaneous positive impact of the share of renewable energy sources, this suggests that the aggregate nature of the SDG index may mask complex relationships. The partial confirmation of H3, in which only specific sustainable indicators such as renewable energy show a significant impact, serves as a strong indication that the SDG index needs to be disaggregated in future studies. It remains interesting and useful to investigate the influences of individual SDG components on economic performance to determine the actual *sacrifice ratio* - the economic cost of achieving a wide range of sustainable development goals.

Furthermore, consistent with the initial *digitalization paradox*, it remains crucial to examine the specific channel through which digital transformation positively influences economic growth. For instance, does the influence mainly operate through the channel of increased consumption (e.g., demand for ICT goods and services), or does it reflect deeper technological improvements enhancing efficiency and productivity across the economy? More nuanced insights could be gained by disaggregating the DESI index or utilizing micro-level data. Furthermore, while this paper applied a unified FE model across the entire EU, future research should leverage cluster analysis to assess heterogeneity within the EU, specifically by testing how the impact of key variables differs across the cluster groups.

In addition, *the rebound effect* represents a persistent threat to the environmental benefits of digital advancements. While technologies optimize resource use at the micro-level, the efficiency gains can lead to lower effective costs for energy and services. This reduction in costs can stimulate higher energy demand, potentially offsetting or even surpassing the initial energy capacities, and consequently, increasing aggregate energy demand and emissions if energy does not come from renewable sources. Future research must, therefore, quantify this effect in the context of the energy demand generated by digital technologies to ensure net sustainability gains (Polzin, 2017).

Finally, the clusters identified in this paper serve as a foundation for further policy research. Future work should focus on establishing the successful factors that could enable the transition of other EU member states towards the model established by the *sustainability leaders*.

7. CONCLUSION

This paper employed a robust multi-stage methodology by combining PCA, cluster analysis, and fixed - effects panel regression to examine the complex interplay between digitalization, economic performance, and sustainability across the EU. The findings confirm the interrelationship among these three dimensions and offer two principal conclusions.

Firstly, the study resolves the potential *digitalization paradox* within the EU, showing that digitalization could be a significant and robust driver of economic growth. Furthermore, the results support the endogenous growth theory, indicating that investments in both digitalization and renewable energy sources create vital endogenous advantages. Crucially, the positive coefficient for the share of renewable energy sources suggests that this form of sustainable development could be a significant contributor to growth.

Secondly, the cluster analysis confirmed significant heterogeneity, identifying four distinct groups. Overall, the evidence suggests that while traditional growth drivers remain pollution-intensive, strategic sustainable digitalization, where digital capacity is powered by renewable sources, offers a proven, robust mechanism to drive economic performance while achieving the EU's Green Deal goals. Policymakers should prioritize cross-border knowledge sharing to facilitate the transition of lagging member states toward the model of the *sustainability leaders*.

To encourage the exchange of knowledge and improve the processes of digitalization and sustainability within the EU, it is necessary to develop target-oriented policies that take into account the different development needs and potentials of the member states. The recommendations presented in Table 9 can serve to shape a coherent EU policy that enables a sustainable and inclusive digital transition.

Table 9 Policy recommendations for each cluster of EU countries

Cluster	Profile	Recommendations
Cluster 1: "Digital-economic leaders"	High GDP and digitalization, but also high GHG emissions and low share of renewable energy sources.	Green digital transformation, importing sustainability innovations, or R&D for sustainable innovation, while initially costly, offer significant long-term benefits.
Cluster 2: "Vulnerable followers"	Higher unemployment rates, challenges in economic stability.	Prioritizing job creation, skills development, digital inclusion, and economic diversification through sustainable investments offers a feasible solution to unemployment and environmental issues. Moderate initial government costs are offset by long-term environmental gains and increased tax revenues (from the income tax).
Cluster 3: "Stable followers"	Very low unemployment rate and high resilience to shocks; attention needed on sustainability.	Integrating sustainability into all economic policies, supported by tax subsidies for green initiatives, entails initial costs but yields long-term benefits through a healthier environment and reduced remedial expenses.
Cluster 4: "Sustainability leaders"	High level of environmental sustainability.	Foster sustainable innovation for export by leveraging the country's environmental base as a research field. This approach, supported by moderate initial investment in incubators and strong IP protection, can yield high long-term economic benefits within the EU's supportive policy framework (requires diplomatic efforts).

Source: Author's compilation

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DIGITALNA TRANSFORMACIJA, EKONOMSKA USPJEŠNOST I ODRŽIVOST UNUTAR EU-A

Sažetak

Trostrukom vremenskom segmentacijom i dvostrukim specifikacijama modela ovaj rad istražuje odnos između digitalne transformacije, ekonomske uspješnosti i održivosti unutar Europske unije. Korištenjem višestupanjskom metodologijom (PCA, klaster analiza i model panel regresije s fiksnim učincima) za 27 zemalja EU-a, studija potvrđuje složenu međuovisnost ovih triju dimenzija. Nalazi identificiraju četiri heterogena klastera, ističući kontradikciju između digitalno-ekonomskih lidera i lidera održivosti, što ukazuje na značajan izazov u odvajanju rasta od utjecaja na održivost. Rezultati panel regresije potvrđuju digitalizaciju kao robustan i statistički značajan pokretač gospodarskog rasta. Najvažnije je da pozitivan utjecaj udjela obnovljivih izvora energije na ekonomske uspješnosti potvrđuje endogene koristi obnovljivih izvora energije.

Ključne riječi: digitalna transformacija, ekonomski rast, održivost, klaster analiza, analiza glavnih komponenti, panel regresija.

JEL klasifikacija: O33, O47, Q42, Q56, C32.