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Digital transformation and economic development in Europe: Classical and machine-oriented approaches

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Abstract. The article analyses the influence of digital transformation on the economic development of European countries using a combination of classical econometric approaches and machine learning algorithms. The study uses 85 indicators of digital economy and society for 27 countries during 2017–2022, covering various aspects of digitalisation: human capital, digital infrastructure, broadband coverage, ICT specialisation, business innovation activity, etc. After preliminary

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data processing, multicollinearity diagnostics, and hierarchical clustering, factor analysis identified four latent components: digital competence and business innovation, digital infrastructure and connectivity, broadband coverage and penetration, ICT human resources and specialisation. To evaluate the relationships between digital factors and GDP per capita, pooled OLS, ridge, lasso regressions, random forest, XGBoost, and support vector regression models were applied. The highest forecasting accuracy was demonstrated by the SVR model, which provided minimal error values and effectively captured nonlinear dependencies in panel data. Feature-importance analysis revealed the leading role of digital competence and business innovation, as well as the considerable cross-country heterogeneity of digital drivers of economic development. The results confirm the need for developing differentiated digital-policy strategies and provide the basis for further advancement of causal and spatial modelling of the digital economy.

Keywords: digital transformation, digital indicators, economic development, machine learning, regression modelling.

JEL Classification: C63, F63, O33.

1. INTRODUCTION

Digital transformation is a complex and multifaceted process, which involves deep integration of modern digital technologies into all functioning aspects of the economy, state regulation, and society as a whole. It is not only an implementation of novel IT solutions but also a fundamental redefinition of the approaches to managing business, providing state services, and ensuring an effective interaction between citizens and the state. With the help of digital transformation, it becomes possible to considerably increase efficiency, productivity, and competitiveness in different sectors of the economy, thus contributing to sustainable economic development of a country as a whole.

In 2025, the global leaders in digital economy development are Switzerland, the USA, Singapore, Hong Kong, and Denmark (IMD, 2025). Switzerland specialises in fintech and its security, using its stable financial ecosystem for blockchain technology development (PwC, 2025). The U.S. strategy focuses on building digital solidarity, based on implementing digital and cyber potential in the long term, while providing international rights for partners (U.S. Department of State, 2024). Singapore implements the new National AI Strategy 2.0, which involves using AI in advanced manufacturing, financial services, healthcare, education, and public services and secures national and international interests (International Trade Administration, 2024). Hong Kong's government, along with expanding the data processing centres and investing in AI and robotics, introduced several initiatives on attracting talent and deepening regional cooperation for smart city creation (Innovation, Technology and Industry Bureau, 2025). Denmark outperforms other European countries in science and research and innovation spheres, with considerable efforts being made in the development of semiconductor and quantum ecosystems, as well as smart electricity networks (European Commission, 2025).

Introducing artificial intelligence, the internet of things, blockchains, and big data allows companies to optimise production processes, automatise routine operations, lower production costs, and better understand the clients' needs. Digital transformation opens new opportunities for innovation, contributing to the creation of new business models and to the development of startup ecosystems, as well as to the growth in the number of jobs in information technology and knowledge-intensive industries. E-government and online platforms for state services help raise the transparency of governance processes, which, in turn, contributes to reducing corruption. Introducing telemedicine allows patients to remotely receive doctors' consultations, which is of particular importance to the residents of distant regions. In the education sector, digitalisation contributes to the development of online courses and platforms for distant learning, making education affordable for all categories of citizens and providing new opportunities for self-development and professional development. In other words, today, digital transformation becomes a strategic direction, which influences all spheres of life, while stimulating economic growth and improving social welfare.

On the other hand, digital transformation is accompanied by several risks and challenges. One of the main obstacles is the low level of digital skills among the population, which narrows its abilities to adapt to new conditions in the labour market and can lead to social isolation and loss of competitiveness. Insufficient development of infrastructure in certain regions results in a country's digital isolation, reducing the growth possibilities of e-commerce, distance learning, and healthcare. Apart from technical issues, many countries face a shortage of specialists in the field of information technology, which complicates the implementation and maintenance of digital systems. Digitalisation also leads to the growth of cyber threats, including attacks on critical infrastructure, confidential data leaks, and financial fraud. As companies and state institutions use cloud solutions and the internet of things more often, there is a growing risk of cyberattacks, which may result in significant financial losses and undermining consumer trust. The rapid development of technologies such as artificial intelligence, blockchain, and big data creates challenges for regulatory bodies that are not always capable of adjusting legal frameworks and ethical recommendations.

Despite the obvious potential of digital transformation as a driver of innovation, productivity, and structural changes, its actual contribution to economic development remains uneven and dependent on the interconnection of infrastructural, professional, and technological components, which significantly differ among EU countries. This is why a deeper and structurally grounded understanding of the mechanisms of digitalisation's influence on economic development is needed, with particular attention to the heterogeneity of digital indicators, their dynamic interactions, and the peculiarities of national development. In this context, particular importance is given to the integration of classical econometric methods with machine learning algorithms, used to detect latent interconnections, model nonlinear effects, and provide the accuracy of forecasts. Given the outlined issues, the main objective of this paper is to perform a quantitative evaluation of the digital transformations' influence on the economic development of the EU's countries with the help of a comprehensive methodological approach, which combines classical and machine-oriented approaches.

2. LITERATURE REVIEW

2.1. Digital transformation, sustainability and public governance

The first cluster of scientific research can be identified as the combination of digital transformation and the sustainability of economic systems in the context of addressing issues of sustainable development and public governance. In this direction, there is a growing interest in the impact of digitalisation on the national security of countries (Zámek & Zakharkina, 2024; Korjonen-Kuusipuro & Wojciechowski, 2025). Economic development, cybersecurity, education and business are also associated with technology (Kozhushko, 2023). In addition, globalisation and digitalisation are key conditions for achieving state sustainability (Paraschiv et al., 2023). Developed countries have been learning about the critical role of technology and capital for several decades, while developing countries are adopting their approaches into their own economic strategies (Kusairi et al., 2023). As a result, digital inequality is formed, particularly in the structure and determinants of digital readiness among EU countries, which is due to different investment approaches and state support (Valaskova et al., 2025a; Valaskova et al., 2025b).

Continuing this line of research, it is worth noting that innovative and technological factors have proven effective in curbing corruption, which was proven by the example of EU countries (Yefimenko et al., 2025). They also contribute to increasing transparency, optimising government processes and facilitating public access to information, which is confirmed by the cases of North African countries (Guemmou, 2024). A similar effect is observed in Ukraine, where digitalisation has contributed to a significant reduction in shadow operations in the economy (Bozhenko et al., 2024).

Turning to the economic and governance aspects of digital change, it should be emphasised that digital technologies stimulate the rethinking of traditional business models, increase production productivity and support innovations in the fintech sector, e-commerce and public administration. At the same time, challenges such as the digital skills gap, regulatory constraints, uneven infrastructure and differences in political readiness remain and affect the ability of European countries to fully exploit the potential of digital transformation (Jarzębowski et al., 2024). That is why it is important to implement successful behavioural strategies in the European digital governance system (Crăciun et al., 2025). It is also necessary to consider economic, environmental and social determinants, best practices of countries seeking to improve natural resource management through digital solutions (Kuanaliyev et al., 2024). In conclusion, Temerbulatova et al. (2025) emphasise the need for adaptive and targeted policy strategies for technological transformation, considering the national context.

2.2. Organisational and managerial dimensions of digital transformation

The second cluster is research on digital transformation from the perspective of management and organisational development of companies (leadership, culture, knowledge, strategy). In this context, it appears not only as an advanced means of exchanging management practices, but also as a factor significantly affecting leadership in terms of new styles, skills, competencies and other capabilities necessary for organisations to successfully navigate a new stage of technological upheaval (Benchea & Ilie, 2023). At the same time, strategic management factors can be perceived as a driving force for the digital transformation of enterprises (Červinka, 2023). Additionally, digital management plays a key role in the development of antifragility in public sector organisations (Bartuseviciene & Butkus, 2024). In the same vein, Saifi & Saifi (2025) analyse the impact of digitalisation through customer experience, internal operations, business models and employee productivity.

In terms of technological success factors, Al-Smadi (2025a) demonstrates that change effectiveness (readiness for resources, IT and cognitive capabilities) and contextual conditions (cultural, strategic and partner readiness) have a positive impact on digital transformation. At the same time, Hamitouche et al. (2024) highlight information technology as a key determinant of knowledge management in the company. Significantly, organisations successfully developing digital services can stand out among competitors, attract and retain the best talents, promote a culture of innovation and continuous improvement (Nafei et al., 2025).

Moving to the micro level, digital transformation helps optimise the structure of human capital, accelerates the implementation of “green” technological innovations and improves the quality of governance, which ultimately improves the ESG indicators of enterprises (Yu, 2025). In addition, a significant positive relationship has been found between organisational, environmental, and technological factors and digital transformation, confirming their importance in the digital transition process in various countries (Al-Smadi, 2025b). At the same time, Hernik et al. (2025) recognise that the technology implementation is not only a rational process, but also one that is deeply rooted in human values and social context. Therefore, understanding this interaction helps organisations develop human-centred digital transformation strategies. In addition, there is the issue of digital inclusion and the ethics of digital transformation, which requires a mandatory solution and alignment with the strategic priorities of companies (Ali & Haikal, 2025).

2.3. Technological innovations and cross-sectoral effects of digitalisation

The third research cluster is technological innovations and their impact on various industries – finance, medicine, ecology, manufacturing, HR, etc. In this context, Sahnouni & Kadri (2025) emphasise the key role of ICT investments in increasing the flexibility and competitiveness of organisations in a dynamic market environment. In addition, the integration of digital technologies with sustainable development strategies enhances the financial benefits and the impact of strategic social responsibility on the current and future success of companies (Wang et al., 2024). As El Massaoudi et al. (2025) showed, automation provides the most transformative changes in the management system, followed by business analytics and big data, cybersecurity and cloud mobile technologies. In the same vein, big data, blockchain and artificial intelligence are the most promising tools at the state and corporate levels (Skrynnyk & Lyeonov, 2022).

In terms of practical applications, the combination of robotic automated processes with artificial intelligence and machine learning increases operational efficiency, reduces costs and improves productivity (Orlandić et al., 2024). AI technologies also improve environmental and operational indicators in the field of waste management, reducing costs and environmental burdens (Kajda & Karwot, 2025). Additionally, new methods of monitoring and analysing working conditions allow for the automatic detection of hazards (Zaryczańska & Karwot, 2025). Digital solutions for analysing customer feedback, determining sentiment, and promptly responding to problems effectively affect the level of customer satisfaction (Kildei et al., 2025), and also contribute to the development of digital marketing strategies and audiences (Sang, 2024).

Expanding the spectrum of technology's impact, a study by Tossekbayev et al. (2025) showed that the life expectancy of citizens of different countries is closely related to the level of medicine digitalisation. It creates a need to implement digital health information standards, attract relevant specialists, and create appropriate infrastructure, services, and programs. Similar trends are also characteristic of the banking sector, where the integration of artificial intelligence strengthens the competitiveness of the industry in a changing financial environment (Alassuli, 2025).

Labour market transformations that are closely correlated with digital changes deserve special attention. On the one hand, migration processes and the emergence of digital nomads can positively affect the economic development of cities, increasing tax revenues and providing an additional inflow of financial resources (Bilan et al., 2025; Andrade et al., 2023). On the other hand, the development of AI transforms professional areas, potentially creating a shortage or surplus of certain categories of workers. However, such trends do not cause concern among young people - future market participants (Yarovenko et al., 2024). In this regard, there is a growing need to increase funding for IT specialities and develop technical education to meet market needs and avoid tension in society due to rising unemployment (Kangalakova et al., 2025).

2.4. Methodological approaches to assessing digital transformation and economic development

To study the impact of digital transformations on economic development, it is crucial to choose the appropriate mathematical tools. The basic and most common approach remains the construction of simple regression models. In particular, Anton (2024) used this method to prove the key role of digital transformation in the development of public policy aimed at stimulating entrepreneurial activity. In a similar vein, Dobrovolska & Kolomiiets (2024) assessed the impact of digital determinants on the development of public health, showing that technologies can increase the efficiency and accessibility of services.

At the same time, most scientists turn to panel regressions to investigate the various effects of digital changes. For example, Nicolescu et al. (2024) found a strong threshold effect between the digital inclusion of the population and the creation of new businesses and confirmed the importance of the skills, knowledge, experience of entrepreneurs and their education. Alshourah et al. (2023) assessed the positive impact of digital strategic orientation and environmental uncertainty on firm performance. In turn, Kuzior et al. (2024) demonstrated the interdependencies between digitalisation (Internet access, use of online resources, digital literacy) and public health indicators (life expectancy, mortality, self-rated health). Kiseľáková et al. (2024) confirmed the economic and social links of improving digitalisation as strategic management consequences for public policy. Panel analysis also made it possible to assess the effects of integrating local government structures with digital innovation models (Jumaiyah et al., 2025). At the same time, Yarovenko et al. (2025) showed that individual aspects of digital development function independently of each other and can provide economic effects only with strong institutional support.

Along with this, a wider range of methods is used in digital transformation studies. For example, based on fuzzy sets, Kolupaieva & Tiesheva (2023) identified directions for reducing the digital divide in EU countries by changing the priorities of innovation spending, increasing productivity and diversifying digital technologies. Bilozubenko et al. (2025) clustered EU countries using the k-means method and found significant differences in digital development and ICT accessibility. Ciucu (Durnoi) et al. (2023) proved the existence of a relationship between digitalisation and sustainable development in EU countries using ARIMA modelling. Mussayeva et al. (2025) extended Porter's five forces model to analyse the competitive environment of the global digital economy, taking into account the threat of new entrants, the bargaining power of suppliers and buyers, substitutes, innovations and the intensity of competition. Additionally, structural modelling confirmed a mediated direct relationship between green human resource management and green innovation in digital services (Ingsih et al., 2025).

Thus, despite the widespread use of classical regression models, they remain the dominant tool in most studies of digital transformation. However, modern machine-oriented methods demonstrate greater flexibility and the ability to work effectively with high-dimensional indicators, uneven samples and complex nonlinear dependencies without the need for strict assumptions about the data structure or their prior transformation. They cope better with multidimensionality, multicollinearity and structural heterogeneity, which are characteristic of digital economy indicators. That is why the article focuses on machine learning models, which turned out to be more effective for the data used and made it possible to more accurately assess the relationship between digital transformation and the economic development of European countries.

3. METHODOLOGY

To fulfil the study objective, a methodology was developed, which was then implemented with the help of the Python programming language.

At *the first stage* of the research, a set of data for the analysis was formed, including statistical indicators of 27 European countries for 2017-2022. As a dependent variable and a key indicator for evaluating economic development, welfare, and living standards, GDP per capita was used (World Bank Group, 2024). The primary array of independent variables consisted of 85 indices comprising the Digital Economy and Society Index (DESI) framework, which provides a comprehensive evaluation of digital development levels in EU countries (European Commission, 2024). The usage of these indicators is justified by the fact that utilising primary, or "raw", data results in higher modelling accuracy, allows for more flexible handling with various aspects of digital transformation, and provides the possibility to remove indicators with missing information without losing the characteristics of the index or processes under consideration. These indicators were chosen as they are the markers of a country's readiness to implement digital technologies and characterise ease and accessibility of users' interaction with public authorities.

At *the second stage*, the input data were preprocessed and checked for missing and abnormal values. The indices of digital economy and society were coded into variables Var1-Var85 for easier modelling, with each of the variables corresponding to a specific aspect of digital transformation (e.g., the access to high-speed internet, the level of digital skills, the integration of digital technologies into business, etc.) (Appendix A). For variables with missing data, the procedures of extrapolation, averaging, or replacement with zero value were applied to minimise the potential influence of incomplete data on the modelling results. The variables with the excessive amount of missing data that could not be recovered were removed from further analysis. The dependent variable was log-transformed to reduce right-sided asymmetry and raise the stability of data distribution.

At *the third stage*, the data were checked for the presence of multicollinearity between the variables. The need for this is due to the significant amount of "raw" indicators in the set and the risk of obtaining biased estimates of model parameters. In the future, this may lead to issues with result interpretation, instability of regression coefficients, and lower forecasting accuracy. To check for multicollinearity, variance inflation factor (VIF) was applied. At this stage, the data were also standardised to remove the effect of different scaling of the variables and to potentially reduce the multicollinearity level.

As the traditional methods, particularly standardisation and removing multicollinear variables, in this case could lead to the loss of a considerable amount of information, we grouped the most correlated indicators for our research. For this, Ward's hierarchical clustering method was applied, followed by iterative removal of separate perfectly correlated variables, with a VIF check at each step. This approach allowed for forming grouped, combined, and mutually uncorrelated variables, preserving at the same time key informational content of the initial array of data.

At *the fourth stage* of the methodological framework, we analysed the latent influence of individual variables with the help of factor analysis of variables clustered using the hierarchical method. The need for this stage is justified by the fact that even after removing the multicollinearity by grouping the most correlated indicators, the data can still contain the complex inner structure, which is not limited to formal correlational connections. Factor analysis allows for revealing latent constructs, which lie at the basis of a country's digital characteristics, and for generalising the information in the form of conceptually meaningful factors. As opposed to the clustered variables, which only reflect grouping by similarity, factors reflect common variation of indicators and fit further analysis better, as they minimise the risk of information duplication and ensure structural interpretability.

Before factor analysis, we assessed sampling adequacy using Kaiser-Meyer-Olkin (KMO) tests and Bartlett's sphericity test, which allow for confirming the presence of a correlational pattern suitable for the identification of latent factors. It is these factors, obtained at this stage, that were used for further research, as they not only ensure data reduction, remove the issue of residual multicollinearity, increase the stability of parameter estimates, and allow for building more generalised and interpreted models but also consider variability and latency.

At *the fifth stage*, pooled ordinary least squares regression (pooled OLS) was built in two specifications: with the inclusion of the independent factors only and with the expansion of the model with the years and countries' dummy variables. The implementation of this step is caused by the need to evaluate the basic connection between the latent factors and the dependent variable without taking into account individual peculiarities of the objects, as well as to check the stability of this connection after control over time trends and countries' fixed effects.

The presence of systematic differences in panel data between countries and changes in time may cause shifts in estimates; therefore, comparing two specifications of pooled OLS allows for assessing the sensitivity of the model to data's structural characteristics and whether ignoring these effects distorts the assessment of the main factors' influence.

At *the sixth stage*, ridge and lasso regressions, random forest, eXtreme gradient boosting (XGBoost), and support vector regression (SVR) models were built. Although our study is based on panel data, the preference was given to the methods above over classical fixed effects (FE) or random effects (RE). The reason for this is a relatively small time panel compared to cross-sectional units, which complicates a reliable evaluation of the dynamics for individual countries. Under such circumstances, FE/RE models may be unstable, and coefficient estimates can be sensitive to a small number of time observations. The use of regularised linear models and modern non-linear machine-learning algorithms may provide more stable assessments and better forecasting ability with the reduced risk of "overfitting" associated with fixed effects, which are difficult to assess with a short panel.

Ridge and lasso regressions are based on the same principles as classical linear regression but add penalty terms to the loss function to reduce model complexity and avoid overfitting. Ridge reduces the value of the coefficients, leaving all model features, whereas Lasso selects features, zeroing some of them. Random forest allows for creating reliable forecasting models even in challenging situations, where other methods may give weaker results. The model is built on the ensemble of decision trees with averaging their forecasts for the final result, which allows for reducing the forecast variance and increasing the stability and accuracy of the model. XGBoost has the ability to find complex dependencies in data and secure high accuracy of forecasts by building the sequence of trees and correcting previous mistakes. SVR's aim is to find such a function that minimises errors while at the same time keeping the significant number of data points within the given tolerance. The points that are within its borders are not considered in the optimisation process, which allows the model to focus on significant deviations.

The comparison of the modelling results was carried out with the help of R^2, MSE, MAE, MAPE, and MAD. As a result, the model with the best characteristics was chosen, and feature selection was implemented based on a permutation technique, which allowed for assessing the importance of digital transformation components for Europe and individual countries.

4. EMPIRICAL RESULTS

At *the first and second stages* of the proposed methodology, the dataset was formed, which was then preliminarily processed and transformed. As a result, 66 independent variables were obtained, which were used for the realisation of the next stages of the research (Appendix A).

An analysis of the multicollinearity *at the third stage* was carried out using VIF, the results of calculations of which were visualised as a histogram (Fig. 1). The values indicate a significant multicollinearity of the variables under analysis, as they exceed the critical threshold (VIF > 10). Only three indicators show no significant correlation; that is, their interconnection is not strong enough to influence the accuracy of the assessment of the other variables in the model.

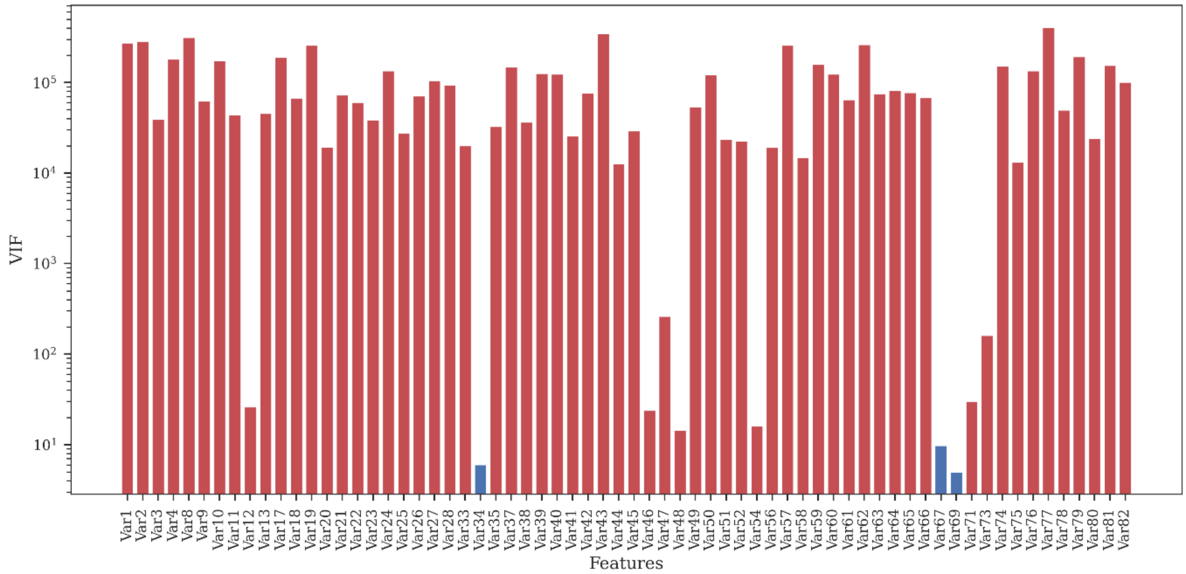

Figure 1. Graphical representation of results of VIF

Source: Authors' calculations.

To identify the indicators that can be grouped with the sequential elimination of the most correlated, Ward's hierarchical clustering was carried out. The results of this procedure are shown in the dendrogram (Fig. 2), which demonstrates hierarchical grouping of the indicators into clusters at different levels of similarity. 12 clusters are clearly singled out, marked with different colours, which serves as the basis for variable grouping with minimisation of the multicollinearity effect.

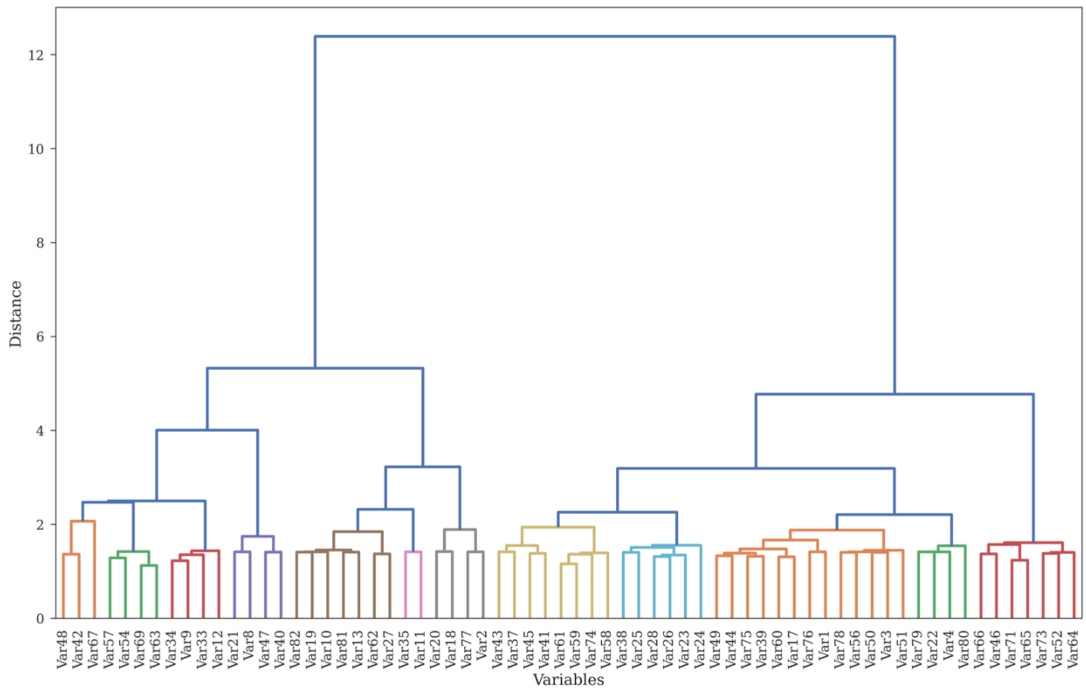

Figure 2. Dendrogram of hierarchical clustering results for the studied variables

Source: Authors' calculations.

The results of calculated VIF values for grouped variables are presented in Fig. 3. As can be seen from calculations, the obtained results have quite acceptable values ($VIF > 10$), which denotes the absence of significant correlation between independent variables or the presence of insignificant correlation, acceptable for interconnection analysis. Thus, the influence of the correlation of factors on further stages of research is minimised.

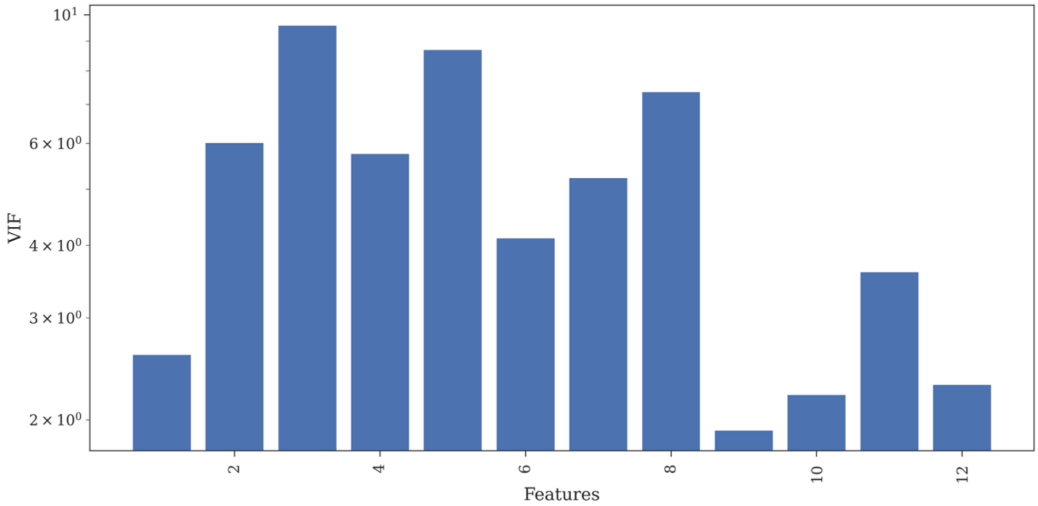

Figure 3. Graphical representation of VIF cluster results

Source: Authors' calculations.

The justification for factor analysis *at the fourth stage* was carried out based on the results of the Kaiser-Meyer-Olkin (KMO) test and Bartlett's sphericity test. The KMO test's value is 0.7959, signifying very good sample adequacy, as the result is close to 0.8. Bartlett's test indicates that $X^2 = 1720.9165$ and $p = 0.0000$, rejecting the null hypothesis. The data are suitable for factor analysis.

To define the optimal number of factors, a scree plot was built – a graph of eigenvalues (Fig. 4).

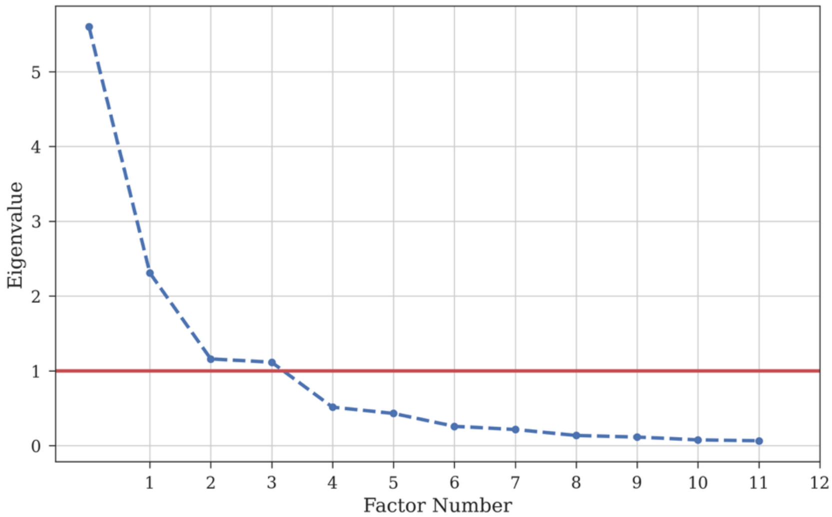

Figure 4. Graphical representation of the selection of the optimal number of factors for factor analysis

Source: Authors' calculations.

As can be seen from Fig. 4, the principal factors explaining the variability in the dataset are 0, 1, 2, and 3, as their eigenvalues are greater than one. Therefore, for further analysis, it was decided to use these four factors, since they provide the most informative representation of the data structure and allow for the identification of key latent dimensions relevant to digital transformation.

Factor analysis was conducted using the VARIMAX method, which allowed for obtaining a clearer factor structure, making connections between variables and latent components more obvious (Fig. 5). Observing the structure of factor loads reveals distinct patterns in relationships. Zero factor exhibits high loadings on several variables (Var 1-5 and Var 11), which indicates its dominant role in explaining data variance. The first factor clearly correlates with the other block of variables (Var 6-9), forming a separate dimension. The second and third factors display specific connections (Var 10 and Var 12), which confirms the presence of structured multidimensional organisation within the studied phenomena. The obtained loading pattern indicates the adequacy of the chosen factor model and its ability to consistently reproduce the basic interconnections in the initial data set.

The extracted factors can be identified in the following way. The zero group, "Digital competence and business innovation", includes indicators corresponding to human capital, digital skills, digital technology integration, e-government, and the application of digital solutions in business. The first group, "Digital infrastructure and connectivity", includes the indicators related to internet connectivity, broadband access, connection price index, and open government data. The second group, "Broadband coverage and penetration", includes coverage characteristics and usage of fixed broadband internet, including high-speed and ultra-high-speed technologies. The last one, the third group, "Human resources and specialisation in the field of information and communication technologies (ICT)", includes indicators related to graduates in ICT fields, their number, and role in e-commerce.

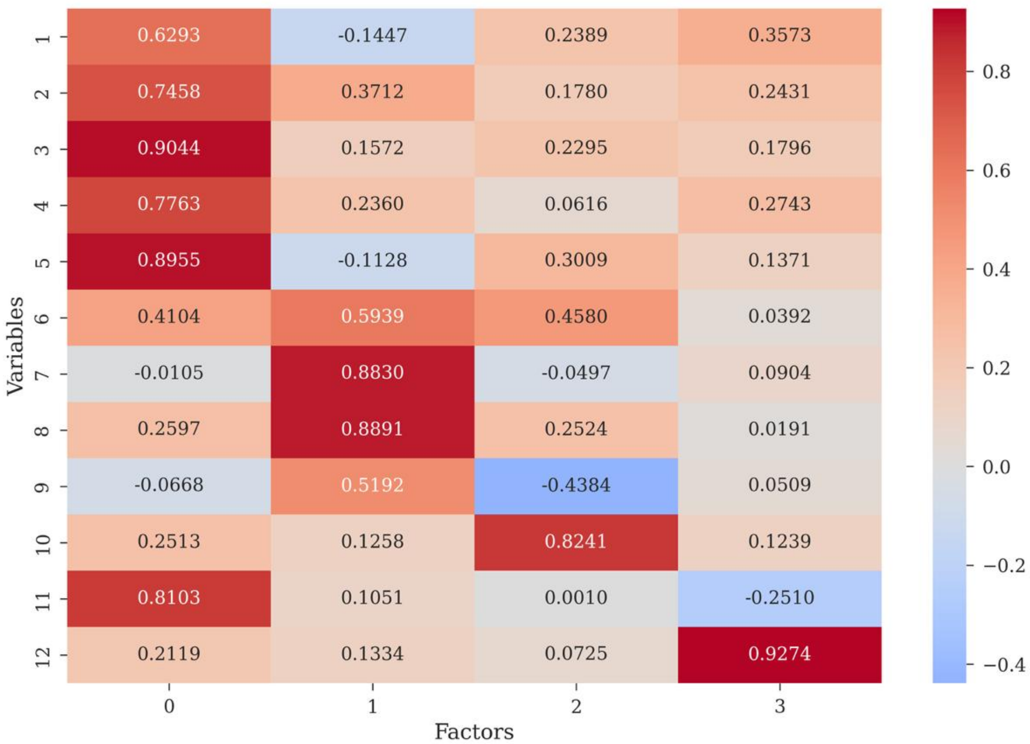

Figure 5. Results of factor analysis

Source: Authors' calculations.

The combination of hierarchical clustering and factor analysis (the "bottom-up" approach) allowed us not to impose an a priori structure on the data, but to reveal its natural configuration, enabling the data to "speak" for itself about its own organisation. The resulting four distinct factors serve as a powerful confirmation and validation of the theoretical four-dimensional DESI structure. However, this empirical approach revealed a more detailed hierarchy, differentiating general digital competencies from ICT specialisation and isolating broadband penetration as a separate factor. The factors form a structure for assessing strengths and weaknesses in the digital transformation sphere, such as human capital competence, digital infrastructure quality, the level of broadband Internet penetration and the degree of specialisation in the ICT sector. In turn, it creates a basis for effective strategies and policies aimed at improving a country's digital ecosystem, optimising resources, and raising its competitiveness in a global digital economy.

At *the fifth stage* of the study, firstly, pooled OLS regression with the inclusion of the independent factors was estimated (Table 1). To minimise potential heteroscedasticity issues and obtain effective assessments, robust standard errors were immediately applied, as indicated in Covariance Type (HC3).

Table 1

Results of pooled OLS regression

Dep. Variable:	Log of GDP per capita	**R-squared:**	0.641
Model:	Pooled OLS	**Adj. R-squared:**	0.631
Method:	Least Squares	**F-statistic:**	108.4
No. Observations:	162	**Prob (F-statistic):**	3.94e-44
Df Residuals:	157	**Log-Likelihood:**	-60.905
Df Model:	4	**AIC:**	131.8
Covariance Type:	HC3	**BIC:**	147.2

	coef	**std err**	z	**P>|z|**	**[0.025**	**0.975]**
const	10.3284	0.029	362.234	0.000*	10.273	10.384
Factor1	0.4226	0.025	17.139	0.000*	0.374	0.471
Factor2	-0.0664	0.029	-2.321	0.020*	-0.123	-0.010
Factor3	0.1927	0.034	5.643	0.000*	0.126	0.260
Factor4	0.0925	0.028	3.310	0.001*	0.038	0.147

Omnibus:	29.361	**Durbin-Watson:**	2.051
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	44.181
Skew:	0.965	**Prob(JB):**	2.55e-10
Kurtosis:	4.679	**Cond. No.**	1.13

Source: Authors' calculations. * means statistical significance at p = 0.05.

According to the results of regression analysis, the dependent variable, GDP per capita (log-transformed), is explained by four statistically significant factors. The *R*-squared value is 0.641, which signifies the model's sufficient explanatory power. This is a totally expectable level of determination that confirms that, apart from digitalisation, GDP per capita is influenced by other fundamental determinants; still, the influence of digital components remains substantial. The p-value for F-statistics indicates the model's overall statistical significance, and the Durbin-Watson value (2.051) indicates the absence of significant autocorrelation of residuals, which is a positive feature of the model's specification. However, the normality tests (Omnibus, Jarque-Bera) suggest that the residuals are not normally distributed ($p < 0.05$), which can indicate some limitations of the model. This may result from the panel structure of the data, and it can only be assumed that certain countries have either their own development trajectory or that it is better to apply nonlinear dependencies for more effective modelling.

Factor 1, "Digital competence and business innovation", has the most prominent positive influence on GDP per capita, meaning that its increase by one point is associated with an approximate increase in GDP per capita of 52.5924% ($(e^{0.4226}-1)\times 100\%$). Factor 3, "Broadband coverage and penetration", also has a significant positive effect, leading to an increase of the dependent feature of 21.2519%. Factor 4, "Human resources and specialisation in the field of ICT", demonstrates moderate positive influence (9.6913%). Only Factor 2, "Digital infrastructure and connectivity", shows a negative statistically significant effect (-6.8654%), which can be the consequence of the differences in the quality of countries' infrastructure or asynchrony between the development of a country's infrastructure and its actual economic use.

The obtained results highlight the key role of the digital transformations in the strengthening of the economic development of the EU countries. The obtained positive interconnection between digital factors and economic development corresponds to a common European trend of transition to the knowledge economy, which is based on high-tech sectors and services (mainly in the tertiary and quaternary sectors of the economy). This means that digital transformations today stimulate not only productivity but also structural changes in the economy, particularly the expansion of the sectors of information services, innovative technologies, and digital commerce.

The results of the second specification of pooled OLS regression with the expansion of the model with the years and countries' dummy variables are presented in Table 2.

Table 2

Results of pooled OLS regression

Dep. Variable:	GDP per capita	**R-squared:**	0.992
Model:	Pooled OLS	**Adj. R-squared:**	0.990
Method:	Least Squares	**F-statistic:**	789.7
No. Observations:	162	**Prob (F-statistic):**	2.59e-133
Df Residuals:	130	**Log-Likelihood:**	250.21
Df Model:	31	**AIC:**	-436.4
Covariance Type:	HAC	**BIC:**	-337.6

	coef	**std err**	z	**P>|z|**	**[0.025**	**0.975]**
const	-119.4825	25.719	-4.646	0.000*	-169.891	-69.074
Factor1	-0.1002	0.035	-2.900	0.004*	-0.168	-0.032
Factor2	-0.0051	0.024	-0.213	0.832	-0.052	0.042
Factor3	-0.0575	0.019	-3.106	0.002*	-0.094	-0.021
Factor4	0.0020	0.016	0.124	0.901	-0.030	0.034
Year	0.0645	0.013	5.069	0.000*	0.040	0.089
Country_BE	0.0458	0.035	1.289	0.197	-0.024	0.115
Country_BG	-1.7715	0.073	-24.404	0.000*	-1.914	-1.629
Country_CY	-0.5093	0.042	-12.113	0.000*	-0.592	-0.427
Country_CZ	-0.7737	0.037	-21.073	0.000*	-0.846	-0.702
Country_DE	-0.0655	0.035	-1.866	0.062	-0.134	0.003
Country_DK	0.3293	0.064	5.148	0.000*	0.204	0.455
Country_EE	-0.7819	0.054	-14.552	0.000*	-0.887	-0.677
Country_EL	-1.0681	0.056	-19.222	0.000*	-1.177	-0.959
Country_ES	-0.5137	0.054	-9.579	0.000*	-0.619	-0.409
Country_FI	0.1017	0.068	1.489	0.136	-0.032	0.236
Country_FR	-0.2659	0.037	-7.134	0.000*	-0.339	-0.193
Country_HR	-1.2101	0.037	-32.531	0.000*	-1.283	-1.137
Country_HU	-1.1966	0.050	-24.049	0.000*	-1.294	-1.099
Country_IE	0.5974	0.070	8.506	0.000*	0.460	0.735

Country_IT	-0.4376	0.046	-9.420	0.000*	-0.529	-0.347
Country_LT	-0.9679	0.051	-18.928	0.000*	-1.068	-0.868
Country_LU	0.9354	0.053	17.507	0.000*	0.831	1.040
Country_LV	-1.1029	0.060	-18.414	0.000*	-1.220	-0.986
Country_MT	-0.3749	0.053	-7.093	0.000*	-0.478	-0.271
Country_NL	0.2695	0.063	4.291	0.000*	0.146	0.393
Country_PL	-1.2810	0.057	-22.403	0.000*	-1.393	-1.169
Country_PT	-0.7877	0.047	-16.685	0.000*	-0.880	-0.695
Country_RO	-1.5937	0.088	-18.013	0.000*	-1.767	-1.420
Country_SE	0.1961	0.071	2.748	0.006*	0.056	0.336
Country_SI	-0.6490	0.037	-17.539	0.000*	-0.721	-0.576
Country_SK	-1.0194	0.038	-26.651	0.000*	-1.094	-0.944

Omnibus:	2.316	**Durbin-Watson:**	1.509
Prob(Omnibus):	0.314	**Jarque-Bera (JB):**	1.748
Skew:	0.062	**Prob(JB):**	0.417
Kurtosis:	2.506	**Cond. No.**	1.19e+07

Source: Authors' calculations. * means statistical significance at p=0.05. BE – Belgium, BG – Bulgaria, CY – Cyprus, CZ – Czechia, DE – Germany, DK – Denmark, EE – Estonia, EL – Greece, ES – Spain, FI – Finland, FR – France, HR – Croatia, HU – Hungary, IE – Ireland, IT – Italy, LT – Lithuania, LU – Luxembourg, LV – Latvia, MT – Malta, NL – Netherlands, PL – Poland, PT – Portugal, RO – Romania, SE – Sweden, SI – Slovenia, SK – Slovakia.

The built pooled OLS model demonstrates high quality of data approximation (R-squared = 0.992 and Adj. R-squared = 0.990), as well as the adequacy of the general specification of the model (p(F) < 0.001). Such a result is quite expected due to the inclusion of a large number of the variables. Normality tests of residuals (Omnibus and Jarque–Bera) did not reveal any violations, which confirms the correctness of error distribution. The moderate value of Durbin–Watson (1.509) suggests the autocorrelation of the residuals, which is typical for panel structures and does not lead to biased estimates, as HAC estimates were used.

Only latent Factor 1 and Factor 3 appeared to be statistically significant but with an unexpectedly negative sign. This result may be due to the present structural differences between the countries, which outweighed the direct influence of digital components in this specification. Time variable has also appeared to be statistically significant, which reflects a general upward trend in economic development regardless of country.

Country effects demonstrate significant cross-country differences in the influence of digital transformations on economic development. For most of the countries of Central and Eastern Europe (in particular for Bulgaria, Romania, Croatia, Hungary, Poland, Latvia, Lithuania, Slovenia, and Slovakia), the estimates are negative, which indicates the lower basic level of GDP per capita compared to the reference group. At the same time, the countries with more developed economies (Luxembourg, Ireland, the Netherlands, Denmark, and Sweden) have positive and statistically significant coefficients, which is consistent with their higher economic potentials. For Belgium, Germany, and Finland, country effects of the digitalisation influence on GDP per capita appeared to be statistically insignificant.

Overall, the results of pooled OLS with an extended specification signify the ambiguity of the impact of digital factors and confirm the importance of a dominant influence of stable and structural differences. This stresses the need to apply more flexible linear or nonlinear methods able to account for the complex interconnection of digital and macroeconomic indicators in dynamics.

At *the sixth stage* of the suggested methodology, ridge and lasso regression models, as well as random forest, XGBoost, and SVR models, were built. The forecast values of the logarithm of GDP per capita, taking into account digital development influence and panel structure, for ridge and lasso regressions are presented in Figures 6 and 7.

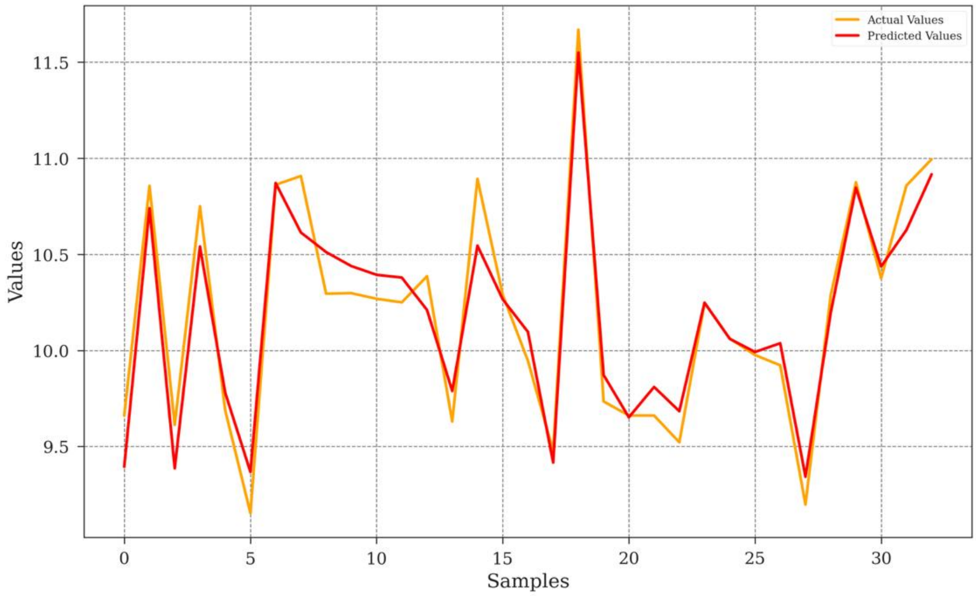

Figure 6. Forecast values of the logarithm of GDP per capita, considering the influence of digital development and the panel structure (ridge regression)

Source: Authors' calculations.

Ridge regression (Fig. 6) demonstrates a high ability to reproduce the observed values of the logarithm of GDP per capita. The forecast values, in general, reflect the dynamics of real data well, which confirms the adequacy of the chosen model specification and its stability. Minor deviations between real and forecast values in individual observations indicate the absence of the systematic overfitting and the good generalising ability of the model. The obtained results generally confirm that the inclusion of the digital predictors improves the generalising ability of the models regarding the economic development of the countries.

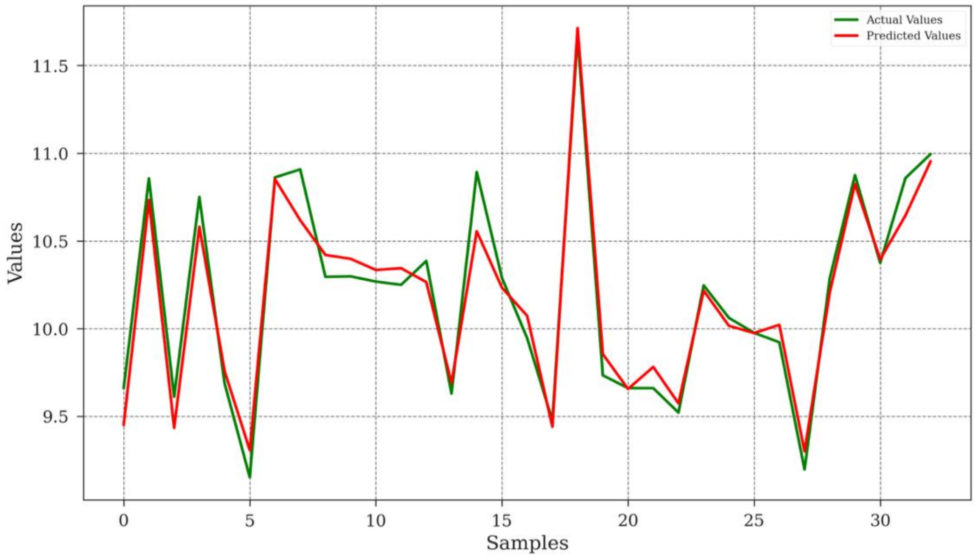

Figure 7. Forecast values of the logarithm of GDP per capita, considering the influence of digital development and the panel structure (lasso regression)

Source: Authors' calculations.

Lasso regression (Fig. 7) provides an even more precise approximation of the logarithm of GDP per capita for individual observations compared to ridge regression. Thus, one can assume an effective adaptation of the model to the features of the panel structure and identification of basic patterns by automatically selecting relevant features. Local differences between observed and forecast values confirm that the model is stable without signs of overfitting. Therefore, applying ridge and lasso regressions is well grounded for evaluating the digitalisation influence on the economic development.

Fig. 8 presents the results of forecasting the logarithm of GDP per capita with the application of the random forest model. This model successfully reproduces the overall trend of changing of the dependent variable under the influence of digital transformations. Although some observations have certain deviations, they do not have a clear link to the countries with minimal or maximal GDP levels. This may indicate that the model has a good ability to approximate data, taking into account the interconnection between time series and cross-country differences without the tendency of overfitting.

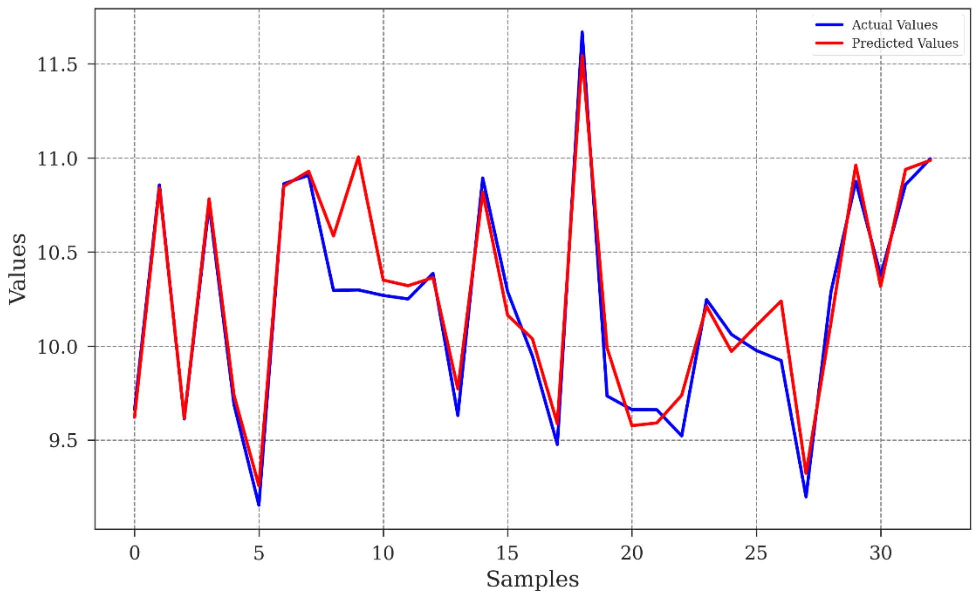

Figure 8. Forecast values of GDP per capita logarithm, considering the effects of digital development and panel structure (random forest)

Source: Authors' calculations.

The XGBoost model (Fig. 9), like the previous ones, shows high qualitative results, providing accurate prediction of the modelled values compared to the observed ones. Although deviations are present for individual observations, the overall forecasts are closer to the observed values than in random forest. This indicates that XGBoost adapts better to the dynamic changes and variability between the objects of the study, which is a key characteristic of panel data. In addition, consecutive refinement of errors in the process of boosting allows XGBoost to identify complex nonlinear dependencies more accurately and enhance its forecast reliability.

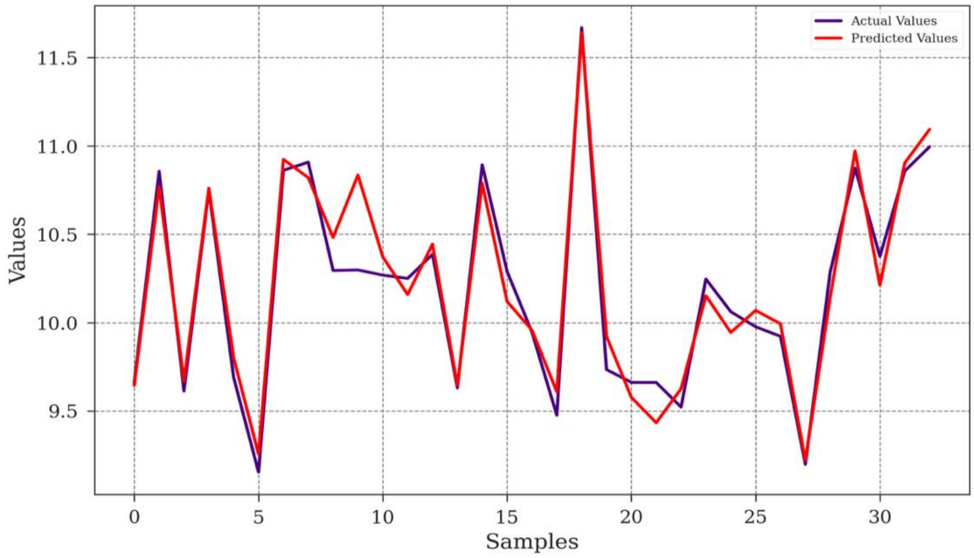

Figure 9. Forecast values of the logarithm of GDP per capita, considering the influence of digital development and the panel structure (XGBoost)

Source: Authors' calculations.

The visualisation of the SVR model forecasts (Fig. 10) demonstrates the highest accuracy among all applied algorithms. The curve of the modelled values almost perfectly reproduces the behaviour of the observed values, including characteristic trends and local extremes. This indicates that SVR can effectively capture complex nonlinear interconnections between digital transformations and economic development, as well as to adapt itself to cross-country differences and time variations. Minimal and rare deviations of data are observed across the entire dataset, which confirms the high stability of the machine learning algorithm. Such a result confirms that SVR is one of the most effective instruments for panel data in the context of the analysis and forecasting of the influence of digital factors on economic development.

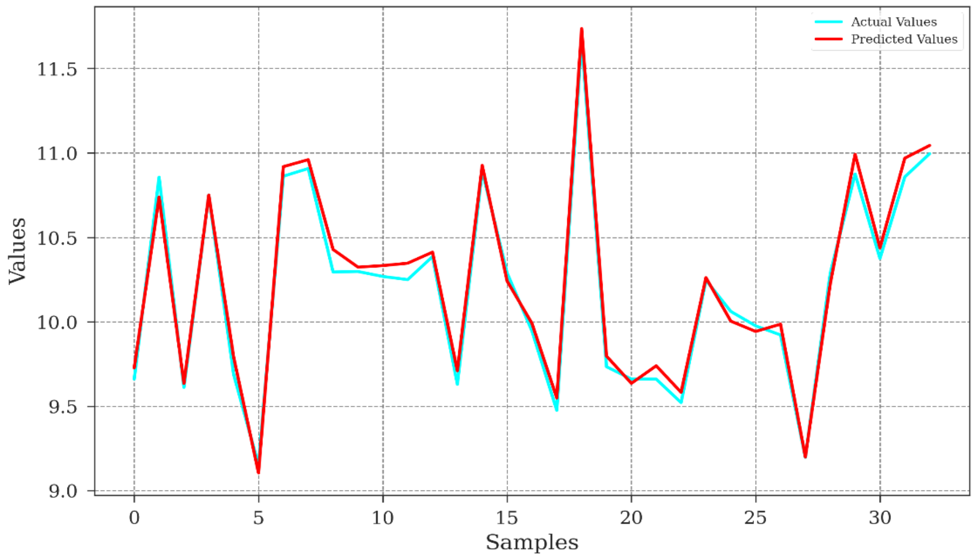

Figure 10. Forecast values of the logarithm of GDP per capita, considering the influence of digital development and the panel structure (support vector regression)

Source: Authors' calculations.

Table 3 presents the results of the forecast quality assessments for five models. Each model yielded extremely high coefficients of determination (R^2), particularly ridge and lasso regressions (0.9924), which is partially due to the inclusion of both main factors and variables reflecting the year of observation and countries' dummy variables. As a result, there is observed a significant "fitting" of the model to data, as R^2 in this case reflects not only the ability of the model to explain the actual dependencies but also the effect of considering structural constant components of data. In this context, the obtained values of R^2 will not be used as the main metrics for model comparison, as they may overestimate the real forecasting ability of the model.

Table 3

Forecast quality assessments for the built models

Quality criterion	Ridge Regression	Lasso Regression	Random Forest	XGBoost	SVR
R² Score	0.9924*	0.9924*	0.9110	0.9414	0.9865
MSE	0.0246	0.0163	0.0303	0.0200	0.0046*
MAE	0.1304	0.1015	0.1164	0.1065	0.0595*
MAPE	1.2827%	0.9939%	1.1557%	1.0501%	0.5822%*
MAD	0.1291	0.0945	0.1164	0.1065	0.0595*

Source: Authors' calculations. * indicates the best score value.

More informative are the MSE, MAE, MAPE, and MAD errors, which allow for evaluating the forecast accuracy independently of structural variables. Analysis of the results of these metrics showed that SVR provides the lowest error values (MSE = 0.0046, MAE = 0.0595, MAPE = 0.5822%, MAD = 0.0595), indicating its high forecasting accuracy compared to other models. The gradient boosting model (XGBoost) also showed high efficiency, providing low error values and quite high R^2 (0.9414), whereas random forest proved to be less accurate on most metrics. Ridge regression has a high R^2; however, it still demonstrates a lower ability to reduce errors compared to nonlinear models, which indicates the latter's advantage in modelling complex dependencies in data. Yet, lasso regression can be a good competitor to the SVR model, as its results are not much worse.

To model the influence of digital transformation on GDP per capita, the SVR model was chosen, as it not only demonstrates the best ability to reflect the dependencies and make a forecast, which is confirmed by visualisation and corresponding quality metrics, but also considers nonlinear dependencies. The SVR model allowed for assessing the importance of the features and structure of components, which form economic development through the lens of digital transformations in Europe and in individual countries (Fig. 11).

Factor 1, "Digital competence and business innovations", demonstrates the highest forecasting importance among the latent factors, indicating the key role of human capital development, digital skills, and innovative environment in stimulating economic development. Compared to it, Factor 3, "Broadband coverage and penetration", and Factor 2, "Digital infrastructure and connectivity", have significantly lower importance, indicating declining marginal returns from investments into digital infrastructure and technologies providing broadband coverage and penetration. This finding is in line with empirical research stating that the main increase in network technology effects happens at the earlier stages of their development. Factor 4, "Human resources and specialisation in the field of ICT", demonstrates the lowest importance among the factors. This may indicate the necessity of engaging and teaching highly qualified ICT specialists, though this factor is not a sufficient condition for the acceleration of general economic development. In addition, its importance can be offset by its integration into the innovative business processes and business activity.

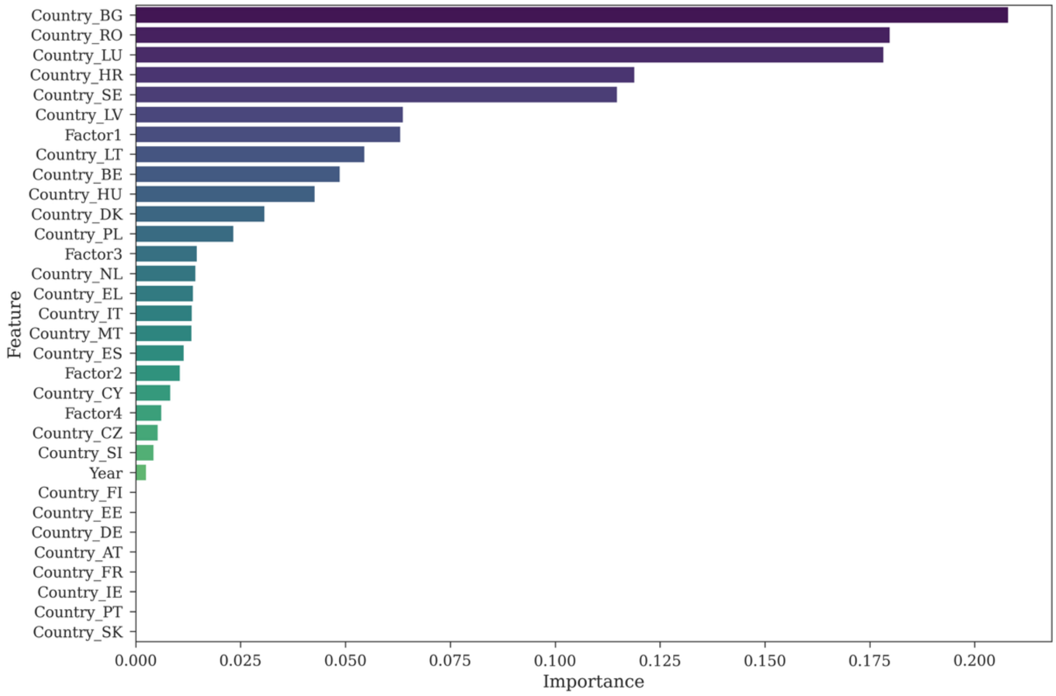

Figure 11. Feature importance for model variables (support vector regression)

Source: Authors' calculations. BG – Bulgaria, RO – Romania, LU – Luxembourg, HR – Croatia, SE – Sweden, LV – Latvia, LT – Lithuania, BE – Belgium, HU – Hungary, DK – Denmark, PL – Poland, NL – Netherlands, EL – Greece, IT – Italy, MT – Malta, ES – Spain, CY – Cyprus, CZ – Czechia, SI – Slovenia, FI – Finland, EE – Estonia, DE – Germany, AT – Austria, FR – France, IE – Ireland, PT – Portugal, SK – Slovakia.

The time variable has a relatively low importance, indicating stability of the discovered interconnections in the time frame. Such a peculiarity can also be a consequence of a limited number of chosen periods. The deepening of the time scope would contribute to the clarification of the importance of time effects for the dependent variable dynamics.

According to Fig. 11, country effects form approximately four clusters. Bulgaria, Romania, Luxembourg, Croatia, and Sweden demonstrate the highest importance (≈12%-20%). Latvia, Lithuania, Belgium, and Hungary are characterised by an average level of importance (≈5%-7%). Denmark, Poland, the Netherlands, Greece, Italy, Malta, Spain, Cyprus, the Czech Republic, and Slovenia have a low level of importance (≈0.1%-5%). Effects are almost absent for Finland, Estonia, Germany, Austria, France, Ireland, Portugal, and Slovakia. The received results confirm that there were formed various national institutional peculiarities of digital transformations in EU countries. The corresponding structural characteristics of their economies and historical development paths form unique national contexts, which determine the effectiveness of digital solutions. Additionally, the results may be partially influenced by the applied permutation methodology, which, in the case of fewer time observations, sometimes fails to detect minor effects.

An analysis of the importance of the characteristics for the countries, chosen with the permutation method, is presented in Fig. 12. For each country, one can observe three types of factor contributions: high positive value – the variable is very important for forecast accuracy; the value close to zero – the variable barely influences a forecast; negative value – the country's model doesn't use these factors for forecast improvement. In general, the results demonstrate a strong heterogeneity of digital driver influence on economic dynamics, indicating the impossibility of forming a unified approach to digital policy in different EU countries.

Figure 12. Feature importance for selected countries (support vector regression)

Source: Authors' results. BE – Belgium, BG – Bulgaria, CY – Cyprus, ES – Spain, HR – Croatia, LT – Lithuania, LV – Latvia, MT – Malta, RO – Romania, SE – Sweden.

For Belgium, Factors 1-3 play a leading role, although Factor 3, "Broadband coverage and penetration", is critically important compared to the others. This may be due to the country's high concentration of services, which are oriented at data, and internet-dependent business models, which demand stability and capabilities of the network to handle high traffic volumes. For Bulgaria, only one factor appeared to be important – "Digital competency and business innovations". Such a result is due to building human capital in Bulgaria's digital economy, which needs the development of competencies and innovations. Cyprus demonstrates the high importance of Factors 1, 2, and 4, with "Digital infrastructure and connectivity" as dominating. Cyprus, as an island country, is considerably dependent on the quality of digital channels of connection and infrastructure, providing integration of its economy in global markets and the service sector.

For Spain, Lithuania, and Malta, all factors, including time dynamics, have considerable influence on economic development. However, for Spain, "Digital competence and business innovation" and "Human resources and specialisation in ICT" are dominating, which may be due to the increase of state investments into digital skills and supporting technological sectors after the 2008 crisis. For Malta, Factor 4, "Human resources and specialisation in ICT", is revealed to be the key, which identifies the country as an ICT hub, where specialised personnel form the core of competitiveness. Nevertheless, for Lithuania, time dynamics are decisive in GDP per capita, which indicates the transitional nature of its development. The country is actively catching up with EU leaders and demonstrating steady growth in GDP per capita.

Croatia has a strong and moderate influence of Factors 1, 3, and 4, with a significant advantage in "Human resources and specialisation in ICT" and, at the same time, a very weak influence of time. This result reflects the strengthening of the role of IT services in Croatia's economy with a steady trend of its development. For Latvia, all factors, except Factor 4, appeared to be decisive, with Factor 1 having an advantage. This is completely in line with the country's policy towards the innovation sector, startup ecosystems, and the development of digital skills. For Romania, the time parameter is of critical importance, indicating a catch-up of the economic growth. However, Factors 2-4 also have a moderate impact, caused by the gradual development of internet infrastructure and the technology sector. Sweden, as one of the most technologically developed countries, demonstrates a high importance of the time component. This indicates that its economic development has a stable inertial nature and is strengthened by an already well-established digital ecosystem; therefore, most of the structural digital factors hardly vary over time.

The obtained results underline that the efficiency of the digital policy depends on structural peculiarities of the economy of each country, the level of maturity and development of a country's digital infrastructure, and historically formed specialisations, which necessitate a differentiated regional approach to stimulating digital transformation.

5. DISCUSSION

The primary objective of this article is to identify the impact of transformation processes on the economic development of European countries, which was carried out through the detection of four latent factors and an investigation of their relationship with GDP per capita based on a comparison of the productivity of classical regression and machine-oriented models. The obtained empirical results should be considered in the context of the literature review, which allows us to outline the agreement or disagreement with the conclusions of representatives of various international scientific schools.

Firstly, the models constructed in the article, especially the SVR, confirmed the dominance of the factor "Digital competence and business innovation". This result correlates with the conclusions of various studies that emphasise the critical role of human capital and the innovation environment. Thus, Nicolescu et al. (2024) revealed the existence of a threshold effect of digital inclusion in the creation of a new business. Our results also confirm that the key determinants of economic growth are the development of digital skills, innovative business activity and entrepreneurial experience. This is also consistent with the relevant findings of Nafei et al. (2025) and Yu (2025), who emphasised that digital services and green technological innovations perform better through optimising human capital, attracting talent, and changing management practices.

Second, the extended pooled OLS model shows a negative coefficient for "Digital infrastructure and connectivity", which, after controlling for other factors, demonstrates a negative effect on economic development. Such an effect of the infrastructure factor in linear specifications is partially confirmed by the findings of Jarzębowski et al. (2024) on the asynchrony between infrastructure construction and its economic capitalisation in different countries, which may confirm the existence of a digital break. This is also consistent with the idea of Valaskova et al. (2025a; 2025b) on digital inequality, i.e. countries with a lack of business environment and public investment in infrastructure may have low returns or a delayed effect. In other words, the functioning of infrastructure without appropriate human skills and an innovation ecosystem does not guarantee a direct increase in welfare, which is confirmed by our results.

Third, machine learning algorithms such as SVR, XGBoost, and random forest demonstrate high predictive performance compared to classical panel data models. Other authors have confirmed the advantages of such trends in their studies. For example, Bilozubenko et al. (2025), Kolupaieva & Tiesheva (2023), and Ingsih et al. (2025) indicated that k-means, fuzzy sets or structural modelling are effective for certain tasks, although modern ML algorithms better capture nonlinearities and multivariate interactions of indicators, and are also aimed at identifying differences in national development. Our conclusions are methodologically consistent with the thesis about the feasibility of a combined approach: classical models are useful only for explanatory interpretation (Anton, 2024; Dobrovolska & Kolomiiets, 2024), while ML methods (especially SVR in our case) provide higher forecast accuracy and better reveal latent relationships.

Fourth, the heterogeneous impact of factors across countries identified in the study reinforces the findings of Kusairi et al. (2023) and Valaskova et al. (2025a; 2025b) regarding different national trajectories of digital development. For example, in countries with a high degree of innovation integration (Sweden, Luxembourg, Ireland), competence and innovation factors prevail, while in island countries (Cyprus), the infrastructure factor has the greatest weight. This is consistent with the cases described in Jumaiyah et al. (2025) and Bilozubenko et al. (2025). Such differentiation confirms the findings of Temerbulatova et al. (2025) and Kuanaliyev et al. (2024) regarding policy adaptability and national orientation.

Fifth, the positive relationship between digital competence factors and GDP per capita, as well as the aforementioned impact on transparency, confirms the role of digitalisation in reducing shadow transactions and increasing transparency. This result is consistent with the findings of Yefimenko et al. (2025), Guemmou (2024) and Bozhenko et al. (2024), and strengthens the argument that digital tools have not only productive but also institutional effects.

Finally, a comparison with articles that pointed to the specifics of individual industries (Sahnouni & Kadri, 2025; El Massaoudi et al., 2025; Tossekbayev et al., 2025) shows that national factors correlate with sectoral effects. For example, "Digital competence and business innovation" translates into greater financial benefits in the fintech and healthcare sectors, provided that technology and human resources are appropriately integrated. Thus, the empirical results confirm many of the conclusions of other scholars but also introduce certain clarifications.

To conclude, infrastructure investments do not always produce the expected effect without the parallel development of digital competences and innovations (Mishchuk et al., 2025). Also, machine learning methods can detect subtle, nonlinear dependencies and threshold phenomena that classical models do not notice. Therefore, this strengthens the argument for differentiated, context-specific policies and combined methodologies for researching digital transformations in EU countries.

6. CONCLUSION

The study conducted allowed for assessing the influence of digital transformation on the economic development of 27 European countries based on the approaches of classical econometrics and machine learning. In the study, a methodical framework was formed, which includes the procedures of pre-processing a dataset of digital indicators, diagnosing multicollinearity, implementing clustering, factor analysis, and constructing pooled OLS, ridge, and lasso regressions, random forest, XGBoost, and SVR. The assessment of the models' accuracy allowed for justified determining of Support Vector Regression as the most effective tool for an analysis of complex, nonlinear, and heterogeneous connections between digital characteristics and GDP per capita. In addition, an analysis of the factor importance at European and national levels allowed for revealing considerable differences in the structure of economic development drivers.

The combination of hierarchical clustering and factor analysis (the "bottom-up" approach) allowed us to identify a natural, objectively existing data structure, and obtaining four clear factors became a powerful statistical confirmation of the theoretical four-dimensional architecture of the DESI index. This result demonstrates an example of convergent validity, where two independent methods led to the same output, indicating a stable underlying pattern in the data rather than a random occurrence.

The obtained results of factor analysis confirmed the key role of digital transformation as a systemic factor of socio-economic development of European countries and demonstrated the multidimensional structure of digital development, based on four latent factors: digital competence and business innovation, digital infrastructure and connectivity, broadband coverage and penetration, and human resources and specialisation in the ICT sector. At the same time, the digital competence and business innovation appeared to be the dominant factor, while other components had lower marginal returns.

The results of the assessment with pooled OLS models revealed the presence of the statistically significant connection between key latent factors of digital transformation and the level of economic development. The nature of this connection appeared to be heterogeneous: factors reflecting broadband coverage and penetration and business innovation activity demonstrated more significant positive influence on the logarithm of GDP per capita, while infrastructure components had unexpectedly negative effects. This can indicate an asynchrony between infrastructure development and its economic capitalisation in individual countries. The expanded pooled OLS model allowed for the identification of cross-country effects, which confirm the dependence of economic returns on digital technologies and on the historically formed structure of national economies.

Unlike linear approaches, the support vector regression model demonstrated the most accurate recreation of empirical patterns with minimal forecasting errors, confirming the advantage of machine-orientated algorithms when dealing with high heterogeneity of the panel. The model allowed for identification of complex, nonlinear connections between digital characteristics and economic development, taking into account the time and cross-country components. The study of the importance of characteristics within SVR has demonstrated the dominance of the factor of digital competence and business innovation, while the role of infrastructural and ICT-personnel components appeared to be relatively lower, although still significant. An analysis has revealed major country differentiation, indicating a considerable dependence of digitalisation effects on national economic context, the level of technological maturity, and formed institutional trajectories.

Thus, digitalisation is not a uniform driver of economic growth, as countries demonstrate different sensitivity to one or another digital component. The efficiency of a national digital strategy significantly depends on the level of human capital, the innovation ecosystem, the quality of the combination of infrastructure and competence components, and the characteristics of national development. This is why ensuring high rates of economic development based on digital transformation requires differentiated approaches orientated at specific national needs and structural features of digital ecosystems. This conclusion confirms the necessity to reorient digital policy from universal solutions to targeted strategies, which could reduce the digital gap, account for the heterogeneity and dynamics of digital processes, and, as a result, provide continuous economic effect in the long term. Therefore, the results of this research can become a base for forming complex, causally grounded, and structurally sensitive models of digital development, able to provide deeper understanding of the mechanisms of the digital economy and raise the effectiveness of strategy planning both at the level of individual countries and the EU as a whole.

Further research of the given issue requires deeper analysis by extending the time frame, allowing us to identify more accurately temporal effects and separate short- and long-term connections, as well as check the stability of the results in the periods of crisis shocks (the COVID-19 pandemic, military conflicts, geopolitical transformations, etc.). The improvement of the methodological framework can be achieved by applying causal methods (e.g., synthetic control or difference-in-differences approaches) to identify the causal effects of digital reforms.

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APPENDIX A

Table A.1

List of independent variables selected for analysis and modelling: initial set and after preprocessing

Variable ID	Variable value	Variable ID	Variable value
Var1*	Human capital	Var44*	Internet user skills (above basic digital skills)
Var2*	Connectivity	Var45*	Internet user skills (at least basic digital content creation skills)
Var3*	Integration of Digital Technology	Var46*	Enterprises providing ICT training (all enterprises, 10 employees or more)
Var4*	Digital Public Services	Var47*	Female ICT specialists (total)
Var5	5G spectrum, 5G pioneer bands	Var48*	ICT graduates (total)
Var6	Overall 5G coverage	Var49*	ICT specialists (total)
Var7	Broadband price index	Var50*	Digital intensity
Var8*	Broadband price index	Var51*	Digital technologies for businesses
Var9*	Fixed broadband coverage	Var52*	e-Commerce
Var10*	Very high-capacity network coverage	Var53	Artificial intelligence
Var11*	Fibre to the premises coverage	Var54*	Big data
Var12*	Fixed broadband take-up	Var55	Cloud
Var13*	Ultrafast broadband take-up	Var56*	SMEs with at least a basic level of digital intensity
Var14	Gigabit broadband subscription	Var57*	Digital technologies for businesses (Electronic information sharing)
Var15	5G coverage	Var58*	Digital technologies for businesses (Social media)
Var16	5G connectivity	Var59*	Digital technologies for businesses (Big data)
Var17*	Mobile Broadband Take-up	Var60*	Digital technologies for businesses (Cloud)
Var18*	Fixed broadband take-up	Var61*	Digital technologies for businesses (AI)
Var19*	Fixed broadband coverage	Var62*	Digital technologies for businesses (ICT for environmental sustainability)
Var20*	Mobile broadband	Var63*	Digital technologies for businesses (e-Invoices)
Var21*	Broadband price index	Var64*	e-Commerce (SMEs selling online)
Var22*	Digital public services, eGovernment	Var65*	e-Commerce (turnover)
Var23*	eGovernment users	Var66*	e-Commerce (Selling online cross-border)
Var24*	Pre-filled forms	Var67*	e-Commerce turnover (SMEs, 10-249 employees)
Var25*	Public services citizen interaction technologies	Var68	e-Invoices (all enterprises, 10 employees or more)
Var26*	Public services business interaction technologies	Var69*	Electronic information sharing (all enterprises, 10 employees or more)
Var27*	Open data from government	Var70	ICT for environmental sustainability (all enterprises, 10 employees or more)
Var28*	eGovernment users (last 12 months)	Var71*	Selling online cross-border (SMEs, 10-249 employees)
Var29	Open data	Var72	SMEs with at least a basic level of digital intensity (10-249 employees)
Var30	Pre-filled forms (all life events)	Var73*	SMEs selling online (10-249 employees)
Var31	Public services business interaction technologies (all life events)	Var74*	Social media (SMEs, 10-249 employees)
Var32	Public services citizen interaction technologies (all life events)	Var75*	Mobile broadband take-up (all individuals)
Var33*	Fast broadband (NGA) coverage (total)	Var76*	DESI (human capital)
Var34*	Overall fixed broadband take-up (all households)	Var77*	DESI (connectivity)

Variable ID	Variable value	Variable ID	Variable value
Var35*	Fibre to the premises coverage (total)	Var78*	DESI (integration of digital technology)
Var36	At least 1 Gbps broadband take-up (all households)	Var79*	DESI (digital public services)
Var37*	Internet User Skills	Var80*	DESI
Var38*	Advanced Skills and Development	Var81*	At least 100 Mbps fixed broadband take-up (all households)
Var39*	ICT specialists	Var82*	Fixed very high-capacity network (VHCN) coverage (total)
Var40*	Female ICT specialists	Var83	Above basic digital skills
Var41*	Enterprises providing ICT training	Var84	At least basic digital content creation skills
Var42*	ICT graduates	Var85	At least basic digital skills
Var43*	Internet user skills (at least basic digital skills)	X	X

Source: Constructed based on European Commission (n.d.). * indicates variables that were included in the data frame after preprocessing.