ISSN 1611-1699/eISSN 2029-4433

VILNIUS TECH
Vilnius Gediminas Technical University

JOURNAL of BUSINESS ECONOMICS & MANAGEMENT

2025
Volume 26
Issue 4
Pages 1007–1026
https://doi.org/10.3846/jbem.2025.24839

AN INTEGRATED SYSTEM FOR EVALUATING THE IMPACT OF FIRM-BASED INNOVATIONS ON GDP

Aurelija BURINSKIENĖ ✉, Olga LINGAITIENĖ, Olga IURASOVA

Business Management Faculty, Vilnius Gediminas Technical University, Vilnius, Lithuania

Article History:
- received 08 May 2025
- accepted 18 August 2025

Abstract. The study analyses the impact of innovation on the economy in the EU and related countries (Norway and Switzerland), highlighting the large differences between these countries. An integrated measurement framework is proposed to assess the long-term impact of firm-based innovations on GDP comprehensively. The literature analysis sheds light on the link between firm-based innovations and economic growth, and the study follows a three-step methodology: firstly, data on innovation and GDP are collected from Eurostat and OECD, followed by an econometric analysis to identify the links between firm-based innovation performance and economic growth, and finally, a cluster analysis is performed. This cluster analysis grouped countries according to their level of innovation and economic performance. The empirical results showed that Germany, Denmark, Finland, the Netherlands, Sweden, and Ireland have high innovation and GDP growth rates, and their innovation ecosystem contribute significantly to economic prosperity. The study confirms that innovation drives GDP growth, but its impact varies across countries depending on R&D investment, workforce skills, and policy environment. Therefore, policymakers should develop innovation strategies that consider each country's specificities following the results of cluster analysis to maximise the economic impact.

Keywords: firm-based innovation, integrated framework, cluster analysis, GDP, economic growth, indicators.

JEL Classification: M41, C83, L20.

✉Corresponding author. E-mail: ***aurelija.burinskiene@vilniustech.lt***

1. Introduction

Innovation is considered to be one of the most important drivers of growth in modern economies, especially in the context of the knowledge economy. However, the impact of innovation on Gross Domestic Product (GDP) is not the same in all countries, due to different structural, institutional, and sectoral characteristics. This raises the need for a comprehensive and integrated model for measuring the impact of innovation on the economy. In a context of increasing global competition, the impact of innovation on GDP is becoming relevant to the academic debate and essential for policymakers and businesses. The results of this study provide insights into how innovation strategies and their practical implementation can boost long-term economic growth in different countries.

The literature review provides a comprehensive assessment of the country's innovation performance, summarizes the latest research findings, and analyzes various types of innovation (product, process, and organizational), as well as various innovation indicators, such as expenditure on research and development, patents, and human capital, to understand their impact on economic performance.

The proposed three-step methodology (data collection, econometric analysis, cluster analysis) allows for a systematic assessment of the impact of firm-based innovation on GDP, and an integrated assessment model is developed. *Principal Component Analysis* identifies the most important determinants of countries' innovativeness, even with limited data. *Empirical studies* provide strong evidence that innovation significantly impacts GDP, but this impact depends on the maturity of a country's innovation ecosystem, R&D investment, the skills of its workforce, and policy environment. The study proposes concrete *policy actions* personalised innovation strategies based on identified clusters to increase innovation efficiency and foster sustainable economic growth.

This study hypothesizes that countries with a high level of innovation ecosystem development achieve higher GDP growth than countries with weaker innovation systems.

The theoretical framework linking innovation to economic growth is supported by documents such as Schumpeter's (1934) concept of creative destruction, according to which innovation stimulates economic development by replacing obsolete technologies and processes with new ones. The works of Aghion and Howitt (1992) and Romer (1990) provide a theoretical basis for how innovation contributes to economic growth. However, empirical research often focuses on innovation and GDP indicators without addressing the specific mechanisms and ways innovation influences economic activity results. The share of EU countries' GDP spent on R&D is directly proportional to a country's commitment to innovation (Hall et al., 2010).

This paper proposes a model for an integrated framework for assessing the impact of firm-based innovation on GDP and provides a clustering analysis of such innovations' impact on the GDP of the EU and other countries. The study's objective shall be to conduct new research by identifying mechanisms through which firm-based innovations stimulate the impact of growth-enhancing and growth-enhancing policies based on innovation in the EU and related countries.

The analysis adopts a multidimensional approach, reflecting the cooperation on innovation activities, service innovations, and value-chain creation innovations factors, and proposes an integrated framework for measuring the impact of these innovations on GDP and clustering countries following the above-stated impact significance.

The paper is organized into 5 sections. The Section 2 presents literature analysis, Section 3 – research methodology, the Section 4 – research results, and the last two – discussions and conclusions.

2. Literature review

It is widely recognised that innovation is an important factor in economic growth and competitiveness of business, with a direct impact on productivity by increasing the efficiency of production processes and enabling the development of new services. However, it is important to establish the relationship between innovation and business efficiency and the indicators that influence it.

Depending on the degree, innovation can be attributed to an enterprise, industry, region, country, business block, or global aspect, and there is a close relationship between all these levels. First, the quality of a particular product or service determines the enterprise's competitiveness. On the other hand, the economic results of an enterprise are related to the results of a particular industry, region, or country at the international level. As a result of globalization and liberalisation, the boundaries between national and international markets have disappeared, eliminating the gap between national and international effects to consider the basis of theoretical content: economic theory of development, new business theory, and all its consequences for the development of innovations.

We have therefore carried out a literature review on the importance of innovation for firm performance and the impact of different types of innovation on economic performance. In examining the literature from this period, we found that most studies find a link between innovation and GDP (Sawng et al., 2021; Sojoodi & Baghbanpour, 2024), but few studies delve into the specific mechanisms by which different types of innovation affect economic performance. Based on our observations, in this Section we describe the link between innovation and economic growth, the indicators influencing innovation, the challenges of innovation-led growth, and the policies that support innovation.

This literature review examines the relationship between the level of innovation and GDP in European region countries. The European Innovation Scoreboard, treated as an innovation indicators, provides a comprehensive assessment of a country's innovation performance, covering a range of indicators. According to their overall innovation performance, EU countries are ranked, focusing on pioneers such as Sweden, Denmark, and Finland (European Commission, 2021).

The changing environment and new perspectives call for an update of the mechanisms and instruments provided by innovation policies. Most of the issues are new, and a learning process is required to build new, strong innovation policy targets and measures. The summary of issues and suggestions for possible instruments is provided in Table 1.

Table 1. Main policy issues and instruments (source: according to Organisation for Economic Co-operation and Development [OECD], 2018)

Policy issue	Policy instruments
Data is the main source of innovation	Data access policies Markets for knowledge
Transformation of firm to provide innovative and invaluable services	Building the ability to launch innovations in services
Foster acceleration in innovation	Improving the reactivity and versatility of instruments
Improve ecosystems	Support for cooperation Public policies, knowledge transfer
Entrepreneurship	Entrepreneurship policies Data access Fostering competition
Absorption of new markets	Smart specialisation

Many aspects are important in building contemporary innovation policy. Geronikolaou and Papachristou (2008) indicate firm-oriented European venture capital innovations that could ensure the broadest access to data and knowledge.

Antonucci and Pianta (2002) highlight the effects of employment on product and process innovation in Europe. Innovations oriented to service require a deep understanding of digital technologies, which are not yet widespread, especially among small and medium-sized enterprises from traditional markets. Such innovations foster trade and knowledge sharing (Simmie et al., 2002).

Roper et al. (2008) focus on the transfer of innovations through value chain. Prajogo et al. (2008) investigate the impact of value chain on innovation. Ambos et al. (2021) research the nature of innovations in global value chains. Esko et al. (2013) analysed the readiness of businesses for value chain-related innovations.

The authors of this paper have noticed that an integrated framework for assessing the impact of firm-based innovation on GDP has not been proposed or explored by other authors in the academic literature and have therefore decided to fill this research gap by proposing a multidimensional approach that reflects the interaction of cooperation on innovation activities, service innovations, and value-chain creation innovations factors.

An integrated framework for measuring the impact of firm-based innovation on GDP is reflected in Figure 1.

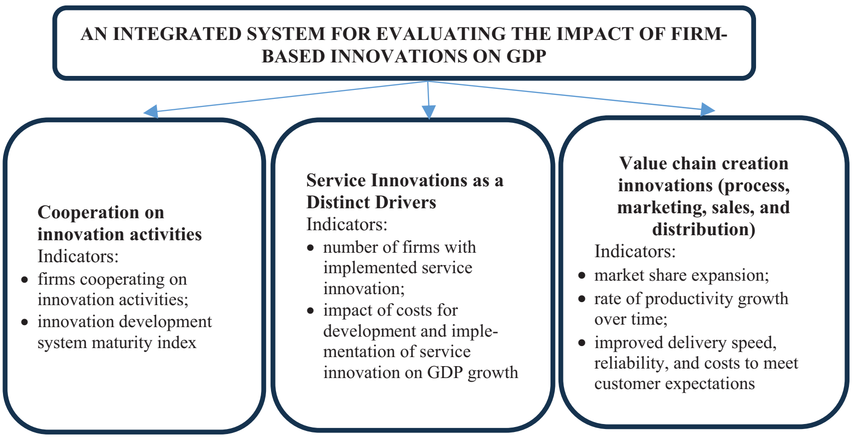

Figure 1. Model of integrated firm-based innovations impact on GDP assessment system (source: authors' suggestion)

In the EU, innovation is a key driver of economic growth and a driver of countries competitiveness. Understanding the link between firm-based innovation aspects provides valuable information on their impact on GDP and the emergence of countries' clusters.

2.1. Firm-based innovation and economic growth

Researchers have yielded ambiguous results on the link between innovation and economic performance. Hajighasemi et al. (2022) study highlighted the importance of policy frameworks that support innovation. Similarly, Harrison et al. (2014) used company-level data to show that innovation improves economic performance and contributes to employment and economic growth. On the other hand, regional studies such as Pijnenburg and Kholodilin (2014) show that the impact of innovation can vary significantly between the countries, suggesting that local factors and policies play a very important role.

Fernández-Cerezo and Montero (2021) are conducting a sectoral analysis of the Spanish economy and identifying future challenges and opportunities for innovation-based growth.

Their results show that the impact of innovation varies greatly across sectors and that the impact of growth is more pronounced in high-tech sectors.

Fagerberg and Verspagen (2002) examine the concept of technological gaps and show how differences in countries' ability to innovate lead to different economic outcomes. Countries that deploy and disseminate advanced technologies can fill these gaps and accelerate economic growth. This mechanism is particularly important for the less developed EU countries.

Maradana et al. (2017) provide empirical evidence in a study of the positive link between innovation and economic growth in European countries. The authors showed that increased innovations associated with R&D costs and patent applications is associated with GDP growth. This mechanism is reinforced by the role of a catalyst for policies that foster innovations.

Bottazzi and Peri's (2003) study examines the importance of the impact of innovation by using patent data as a substitute for innovation. Griliches (1990) points out that patent accounting can be used to measure a country's technological development and innovative capacity. This study underlines the importance of regional networks and cross-border cooperation in enhancing the economic impact of innovation. Griliches (1990) examines the use of patent statistics as economic indicators and links them to innovation and economic growth. Patents are the innovation benchmark and help increase productivity and economic performance. This mechanism underlines the importance of bringing intellectual property rights and innovations to the market.

Other authors have noted the link between innovation and firm size, for example, Damanpour (1992) carried out a meta-analytical review of the relationship between organisation size and innovation and found a positive relationship between organisation size and innovation. Symeonidis (1996) also examined Schumpeter's hypothesis and found a proportional relationship between firm size and R&D expenditures, although the relationship between R&D intensity and market concentration remains inconclusive.

The impact of innovation on macroeconomic indicators of GDP growth in the EU countries is significant and varied. This impact depends on various factors: the country's economic structure, the development of the innovation ecosystem level, investment into research and technology, and government policies and strategies.

To assess the macroeconomic situation of countries, researchers often look at three indicators of macroeconomy and their interaction with innovation: per capita GDP, a measure of a country's economic output, and employment, which reflects entrepreneurial activity (Wei, 2022; Pijnenburg & Kholodilin, 2014).

The innovation role and impact in each country depends on the unique combination of socio-political factors and infrastructure available. Analysing the research on the impact of innovation on GDP in different countries, it is possible to identify one of the most characteristic aspects identified by researchers.

Table 2 highlights the most common areas of innovation's impact on GDP that have been explored in research by other authors.

Many authors (Destefanis & Rehman, 2023; Grafström et al., 2023) have highlighted the impact of R&D on innovation (Boeing et al., 2022) but have indicated that the application of R&D depends on regional characteristics, where regions have a medium or high level of innovation, R&D is more likely to stimulate employment (Paula & da Silva, 2021; Kučera & Fiľa, 2022; Ersin et al., 2022).

Table 2. Key research areas used for studying the innovation and economic growth link

Impact area	Description	References
Firm-based innovation role in economic growth	Innovation increases the productivity of labor and capital, enables more efficient use of resources, lowers production costs, and increases output. Innovation increases the competitiveness of firms and country in international markets and stimulates export growth and foreign investment.	Sojoodi and Baghbanpour (2024), Liu et al. (2022), Raghutla and Kolati (2023), Bresciani et al. (2021), Mewes and Broekel (2022), Dokas et al. (2023).
Relationship between R&D investment and the impact of innovation on the economy	Countries that devote a higher share of GDP to R&D tend to see a higher economic impact from innovation.	Boeing et al. (2022), Sawng et al. (2021), Kučera and Fiľa (2022), Ersin et al. (2022).
Government initiatives, policy incentives, as innovation support	The government encourages innovation through policy instruments (innovation support programs, regulations, etc.).	Boeing et al. (2022), Paula and da Silva (2021), Häggmark and Elofsson (2022).
Disparities in innovation development in the country relative to GDP	Regional policies and Structural Funds could be used to reduce disparities between regions.	Bresciani et al. (2021), Dempere et al. (2023), Hardi et al. (2024), Zhao et al. (2023), Destefanis and Rehman (2023).

Guzman et al. (2024) in the study found that innovation policy interventions are not targeted at specific research projects but are aimed at transforming the interactions between researchers and other stakeholders in a given geographic area.

3. Research methodology

Various methods are used to examine the impact of various innovations on GDP in countries, including econometric analysis, regression models, panel data analysis, comparative analysis, case studies, qualitative analysis, enterprise-level data analysis, input-output data analysis, and spatial econometric models. To understand the effect of innovation on economic growth, the research utilizes the three-step methodology: 1) data collection; 2) econometric analysis (PCA (Principal Component Analysis)) method application; 3) clustering analysis (clustering algorithm (i.e., K-Means) application.

To begin with, we utilized statistical indicators on the adoption of innovations in companies across the EU and related countries from 2023. The objective is to derive quantitative assessments of the number of innovations in each country's economy and their impact on its GDP overall.

A set of statistical indicators characterizes each country. To model the impact of innovation numbers on production volume, each indicator is represented as X_n. All indicators can be represented as vectors (1):

$$X = \left(X_1, X_2, \ldots, X_n\right), \tag{1}$$

where $X_i = \left(x_{i(1)}, x_{i(2)}, \ldots, x_{i(p)}\right)^T$ $X_i = \left(x_{i(1)}, x_{i(2)}, \ldots, x_{i(p)}\right)^T$ is a vector of values for the analyzed characteristics $\left(x_{i(1)}, x_{i(2)}, \ldots, x_{i(p)} x_{i(1)}, x_{i(2)}, \ldots, x_{i(p)}\right)$ associated with the i-th entity, and i is an integer from 1 to n characteristics.

To ensure uniform scaling across all indicators, we applied min-max normalization within the range 0–1. For dimensionality reduction, we defined various linear orthogonal normalized combinations of the initial indicators as permissible transformations, following the approach outlined in (Liu et al., 2024). Specifically (2):

$$\theta_i = \frac{\theta^2\left(X_i\right)}{\sum_{j=1}^{p} \theta^2\left(X_j\right)}, \tag{2}$$

where θ^2 (X_i) represents the variance of the corresponding random variable. Based on Kaiser's criterion, this method maximizes the variance of factor loadings for each factor and involves a rotation of factor axes (Varimax rotation) toward the center of the cluster of depicted points in the factor space, simplifying factor interpretation.

We obtained a set of linear orthogonal transformations known as principal components (PCs). PCA aims to reduce the dimensionality of high-dimensional data while preserving as much informational content as possible. PCA is an unsupervised learning method that helps in dimensionality reduction and analyzes only the original dataset without explicit target parameters.

The research is based on the PCA method, setting a target matrix. The rotation aims to find the factor mapping closest to some given matrix. To simplify the description of the columns of the factor matrix, the Varimax method is used, in which the dispersion of the squares of the loadings of the factor is considered instead of the variance of the squares of the variable. The factor structure is the simplest when all variables have a factor complexity equal to one.

The first principal component, $PC1(X)$, of the examined system of indicators is defined as the normalized-centered linear combination of these indicators, which has the greatest variance among all other normalized-centered linear combinations. Similarly, the k-th PC (k = *2, ..., p; k = 2, ..., p*) is the normalized-centered linear combination uncorrelated with the first $k-1$ PC and has the greatest variance among all other normalized-centered and uncorrelated linear combinations.

PC can be used for several key data analysis tasks:

1. Dimensionality reduction to simplify statistical models and classification tasks to facilitate computation and interpretation of statistical conclusions.
2. Visualization to represent high-dimensional data by projecting it onto the first, first two, or first three PCs.
3. Elimination of multicollinearity, which is useful in regression modelling.

Data compression: Reducing the storage volume of statistical information.

Interpreting PCA involves transitioning to a new coordinate system where the axes are the PC of the distribution. The geometric interpretation involves shifting the origin to the center of data dispersion, where the PCs form the semi-axes of a hyperellipsoid. Each PC represents a new generalized property of all objects in the study sample, being a function of the specific characteristics of each examined object.

The Eq. (3) for the final model (f_r) that consist of *n* number (n = 1, ..., *p*) of principal components (y) with component weight (a) assigned to each principal component corrected for θ variance is:

$$f_r = \frac{1}{\theta}\left(a_{1r}y_1 + a_{2r}y_2 + \ldots + a_{np}y_n\right). \quad (3)$$

This approach allows for ranking and classifying objects based on calculated rating estimates.

For classifying countries, we applied the k-means clustering algorithm. K-Means clustering algorithm is an unsupervised learning algorithm that partitions a dataset into *k* distinct clusters based on the similarity of data points to their centroids. This method is particularly effective for grouping unlabeled data into meaningful categories.

This algorithm minimizes the sum of squared deviations of cluster points from their respective centroids by dividing the dataset into a predefined number of clusters. At each iteration, centroids are created based on the first *q* rows method and recalculated in subsequent iterations. Data points are reassigned to clusters based on the closest centroid according to a chosen distance metric. The algorithm terminates when no further changes occur in the intra-cluster distance. The K-Means algorithm groups countries into clusters based on their innovation levels.

4. Data analysis and research results

4.1. Data analysis

The study examined various indicators characterizing the main components of innovative development in the EU and related countries (Eurostat, 2024; OECD, n.d.). The main criterion for selecting indicators was data availability for companies in the EU and related countries for 2015–2023. 12 indicators were selected that characterize not only the total volume of innovations in companies, but also the industry and focus of these innovations (Table 3).

Table 3. List of indicators and abbreviations for further use

Index	X	Mean	min	max	st dv	skewness
Innovation-active firms	X1	51.406	7.548	100	14.849	–0.827
Firms with innovation of goods	X2	20.930	0.037	75.641	7.547	–0.060
Firms with innovation of services	X3	18.066	0.241	66.667	7.423	0.382
Firms with new-to-market innovations	X4	14.912	0.000	58.335	5.609	–0.359
Business process innovative firms	X5	42.203	1.028	97.059	14.101	–0.522
Firms with innovations in the production	X6	21.899	0.298	70.338	8.491	0.271
Firms with innovations in distribution and logistics	X7	13.969	0.073	69.048	7.474	1.485
Firms with innovations in marketing and sales	X8	16.748	0.508	71.759	7.839	0.709
Firms with innovations in digital sales systems	X9	24.187	0.268	80.952	11.327	1.429
Firms cooperating on innovation activities	X10	10.941	2.391	64.368	4.998	0.810
Share of employees in innovative firms	X11	69.321	1.185	100	13.421	–1.851
Turnover in innovation active firms	X12	71.982	0.008	100	14.331	–1.339

Romania has many missing values in the chosen indicators, which were removed from the analysis.

4.2. PCA results

The first step in creating a PC is to determine the number of PCs. Based on the cumulative variance (Table 4), 8 PC explain 99%. This indicates that the PCA effectively captures the underlying variability in our dataset, and the extracted PCs are enough to interpret most statistical variability.

Table 4. Variation explained by components

	Eingenvalues	Explained variation	Cumulative variance
RC1	8.32	0.69	0.69
RC2	1.23	0.11	0.8
RC3	0.89	0.07	0.87
RC4	0.66	0.06	0.93
RC5	0.27	0.02	0.95
RC6	0.19	0.02	0.96
RC7	0.16	0.01	0.98
RC8	0.14	0.01	0.99
RC9	0.08	0.01	1.0
RC10	0.02	0.0	1.0
RC11	0.02	0.0	1.0
RC12	0.01	0.0	1.0

Eigenvalue decomposition analysis is a fundamental technique in multivariate signal processing and machine learning that allows for the simultaneous diagonalization of multiple matrices to reveal hidden structures and common properties in data sets. The eigenvalues in Table 3 also confirm that only the first 5 PC fully describe the economic model.

The linear combination relationship of each PC on the original variable was calculated in Tables 5–6. They present the ratio of the obtained PC and the initial features. The first PC contains the maximum number of variables, which also explains its high significance for the economic model. The indicators of this component can be conditionally divided into several subcategories: indicators characterizing the current volume of innovations in the economy: Innovation-active firms, Turnover in innovation active firms, share of employees in innovative firms; indicators characterizing the focus of innovation implementation: Firms with Innovation of goods, Business process innovative firms, Firms with innovations in the production. The second PC correlates with Firms with innovations in distribution and logistics, and Firms with innovations in marketing and sales.

The third, fourth, and fifth PC contain only 1 variable each; therefore, Eingenvalues and explained variation are minimal.

Table 6 shows the very low correlation between indicators and PC from 6 to 12. These indicators have a tiny influence and are not included in the final model. Because of that, we didn't include this indicator in the model.

Table 5. Factor loadings (Impact on factors)

	RC1	RC2	RC3	RC4	RC5	RC6	RC7	RC8	RC9	RC10	RC11	RC12
X1	0.87	0.32	0.16	0.24	0.14	0.09	0.07	0.07	0.04	0.09	0.06	–0.05
X2	0.57	0.45	0.02	0.43	0.13	0.04	0.05	0.52	0.04	–0.0	0.0	–0.0
X3	0.29	0.53	0.18	0.37	0.68	0.02	0.05	0.07	0.03	0.0	0.0	0.0
X4	0.39	0.18	0.15	0.87	0.17	0.01	0.04	0.08	0.03	0.0	0.0	0.0
X5	0.78	0.5	0.11	0.18	0.13	0.1	0.17	0.02	0.15	0.0	0.1	0.09
X6	0.63	0.56	0.17	0.14	0.13	–0.01	0.47	0.06	0.06	0.0	0.0	–0.0
X7	0.27	0.92	0.06	0.13	0.12	–0.21	0.06	0.01	–0.03	–0.01	–0.0	–0.0
X8	0.27	0.87	0.06	0.12	0.12	0.33	–0.0	0.15	–0.03	0.01	0.01	0.0
X9	0.43	0.72	0.08	0.22	0.29	–0.02	0.15	0.11	0.35	0.01	–0.0	–0.0
X10	0.17	0.08	0.97	0.11	0.07	0.0	0.03	0.01	0.01	0.0	0.0	0.0
X11	0.9	0.26	0.11	0.26	0.15	0.03	0.01	0.04	0.03	0.07	–0.07	0.05
X12	0.92	0.18	0.15	0.2	0.07	–0.1	0.03	0.14	–0.03	–0.13	–0.02	–0.04

Table 6. Heating map of correlation coefficient between indicators and PC factors

	X1	X10	X11	X12	X2	X3	X4	X5	X6	X7	X8	X9
RC1	0.88	0.46	0.76	0.9	0.65	0.54	0.3	0.77	0.71	0.46	0.28	0.31
RC10	0.02	0.0	0.0	–0.12	0.07	–0.0	–0.0	–0.01	–0.01	0.01	0.02	–0.0
RC11	0.02	0.0	–0.05	–0.08	–0.02	0.0	0.0	0.0	0.01	0.0	–0.0	0.01
RC12	–0.09	–0.0	0.0	–0.05	0.01	–0.0	–0.0	0.0	0.02	–0.0	0.0	–0.0
RC2	0.28	0.8	0.07	0.22	0.4	0.35	0.19	0.45	0.56	0.89	0.82	0.85
RC3	0.17	0.68	0.05	0.21	–0.01	0.03	0.18	0.16	0.11	0.07	0.06	0.06
RC4	0.27	0.20	0.12	0.29	0.47	0.19	0.37	0.18	0.12	0.16	0.11	0.12
RC5	0.14	0.15	0.08	0.14	0.24	0.46	0.17	0.18	0.14	0.15	0.1	0.15
RC6	0.04	0.13	0.03	–0.09	0.1	–0.01	–0.02	0.04	–0.11	–0.26	0.18	–0.01
RC7	0.12	0.10	0.02	0.1	0.6	0.05	0.04	0.09	0.26	0.09	–0.05	0.16
RC8	0.05	–0.02	0.01	0.02	0.24	0.09	0.08	0.01	0.06	0.01	0.2	0.15
RC9	0.01	0.05	0.01	–0.0	0.02	0.04	0.04	0.03	0.07	–0.06	–0.01	0.22

The indicators' influence on a separate component was assessed for a more accurate analysis of each indicator's influence. The inflation coefficients of 5 PCs have only positive values, i.e., they are in a positive relationship.

Only the first 5 PCs have a clearly expressed influence of individual indicators on the model, i.e., we can determine the field of each component and, considering its characteristics, formulate recommendations in this direction. Also, if we combine data on the impact of indicators on a separate component with cumulative variance, then to simplify the created model and interpret its results, we will further consider only the first 5 PCs. The cumulative variance for the 5 PC has a high level of explanation and is equal to 95% (Table 4).

*PC*1 can be interpreted as the Comprehensive Innovation Index. It encompasses six indicators that collectively reflect the innovative capacity of firms within an economy. The *X*1, *X*12*, and X*12 indicators have the most significant impact on *PC*1. Innovation-active firms (*X*1) indicator highlights the number of firms actively engaged in innovation, which is crucial for economic growth and competitiveness. Share of employees in innovative firms (*X*11) measures the proportion of the workforce involved in innovative activities, reflecting the depth of innovation within firms. Turnover in innovation-active firms (*X*12) assesses the financial performance of innovative firms, linking innovation to economic output. These three indicators have a substantial impact of 0.9 on the economic model, suggesting that they are key drivers of innovation and economic vitality.

The Indicator with the middle impact of 0.8 on *PC*1, Business process innovative firms (*X*5) indicate the role in enhancing operational efficiency through innovation.

Firms with innovations in production (*X*6) and Firms with Innovation of goods (*X*2) have a smaller impact of 0.6, reflecting their contribution to product development and diversification.

All these indicators are positively correlated with the increase of *PC*1, suggesting that they collectively enhance the innovative capacity of the economy.

*PC*2 focuses on innovations in distribution, logistics, marketing, and digitalisation. Firms with innovations in distribution and logistics (*X*7) indicator have a significant positive coefficient of 0.9, highlighting the critical role of efficient distribution and logistics in driving economic growth by meeting consumer demands effectively. Firms with innovations in marketing and sales (*X*8) reflect the importance of innovative marketing strategies in reaching consumers and expanding market share. Firms with digital innovations (*X*9) indicate the role of digital technologies in enhancing business operations and customer interactions.

*PC*3 consists of only Firms cooperating on innovation activities (*X*10). The indicator shows the share of companies that cannot independently develop innovations but want to be involved in this process.

*PC*4 consists of Firms with new-to-market innovations (*X*4), highlighting the importance of introducing new products or services to the market.

*PC*5 is solely composed of Firms with Innovation of services (*X*3), indicating its unique contribution to service innovation (Figure 2).

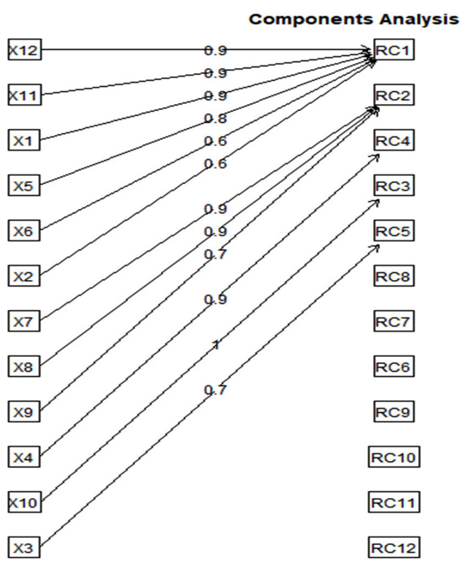

Figure 2. Indicators' incorporation in the components

By representing each PC using factors that have the maximum load, they are combined into one indicator based on calculations. Based on the previous analysis, we can create a system of equations for the economic model (4)–(8):

$$PC1 = 0.9X11 + 0.9X12 + 0.9X1 + 0.8X5 + 0.6X6 + 0.6X2; \tag{4}$$

$$PC2 = 0.9X7 + 0.9X8 + 0.7X9; \tag{5}$$

$$PC3 = X10; \tag{6}$$

$$PC4 = 0.9X4; \tag{7}$$

$$PC5 = 0.7X3. \tag{8}$$

Assigning each *PC* the calculated weights and combining all the *PC*s into one Equation. By transforming the Eqs. (4)–(8), we got the main Equation of the main economic model (9):

$$PCA = 0.726 \times PC1 + 0.115 + PC2 + 0.073 \times PC3 + 0.063 \times PC4 + 0.021 \times PC5. \tag{9}$$

Replacing each *PC* with the factors included in it, and also multiplying the weights of the corresponding component by the corresponding factor, we obtain the Eq. (10):

$$PCA = 0.6534X_1 + 0.4356X_2 + 0.0147X_3 + 0.0567X_4 + 0.5808X_5 + 0.4356X_6 + 0.1035X_7 + 0.1035X_8 + 0.0805X_9 + 0.0730X_{10} + 0.6534X_{11} + 0.6534X_{12}. \tag{10}$$

Based on Eq. (10), the largest weights (≈0.65) have 3 factors: the number of Innovation-active firms, the share of employees in innovative firms, and turnover in innovation-active firms. These indicators represent the volume of innovative products and services in the economy and their rarity in the economy.

4.3. Clustering analysis

To classify countries by their level of innovation, a cluster analysis was conducted based on the 5 obtained PC using the K-means method and the Euclidean distance metric. The optimisation function used aims to minimise the sum of the squares of the Euclidean distances between countries and their cluster centres based on 5 PCs.

Based on the analysis results and the construction of a Scatter Plot Matrix, 5 clusters were identified, as shown in Table 7.

Clusters 0 and Cluster 1 are the smallest in terms of the number of included countries. They are strong in market-oriented innovation but have lagged in overall innovation activity and cooperation.

Cluster 0 includes Cyprus and Malta. These countries are characterized by the highest level of *PC*2 (market-oriented innovations in distribution, logistics, marketing, and digital sales systems), along with good performance in *PC*4 (new-to-market innovations) and *PC*5 (service innovation). However, *PC*1 (overall innovation activity) and *PC*3 (innovation cooperation) are the lowest among all clusters, indicating a weaker overall innovative capacity and limited collaboration in innovation activities.

Cluster 1 covers the Czech Republic and Slovenia. These countries exhibit high levels of *PC*2 (distribution, logistics, marketing, and ICT innovations) and *PC*4 (new-to-market innovations). However, *PC5* (service innovation) is the lowest in this cluster compared to other *PCs*. Notably, Slovenia ranks the lowest in *PC*5 among all analyzed countries, highlighting its limited contribution to service-based innovation (Table 7).

Table 7. Results of clustering countries by level of firm-based innovation in the economy

Cluster		Countries
Cyprus		cluster_0
Malta		
Czechia		cluster_1
Slovenia		
Switzerland	Germany	cluster_2
Spain	France	
Greece	Estonia	
Lithuania	Denmark	
Portugal	Hungary	cluster_3
Italy	Latvia	
Croatia	Poland	
Slovakia		
Netherlands	Finland	cluster_4
Ireland	Luxembourg	
Norway	Sweden	

Cluster 2 represents economies where innovation is deeply embedded across multiple sectors. This cluster groups countries with strong innovation integration into their economies, where the average values across *PC*1, *PC*2, and *PC*3 exceed the overall mean (Table 6). It includes Switzerland, Germany, Spain, France, Greece, Estonia, Lithuania, and Denmark. The presence of these countries suggests a well-established innovation infrastructure, strong cooperation in innovation activities (*PC*3), and a balanced approach to technological and market-oriented innovation.

Cluster 3 consists of moderate performers with stable but non-leading innovation ecosystems. This large cluster includes Portugal, Hungary, Italy, Latvia, Croatia, Slovakia, and Poland. These EU countries demonstrate average or slightly below-average values across all *PC* (Table 7). Their innovation ecosystem is not leading, but they maintain a moderate level of technological and market-driven innovation, with room for growth in innovation penetration and cooperation.

Cluster 4 contains top innovators that outperform in innovation penetration, collaboration, and service-based innovation, with Northern European dominance in this group.

This cluster represents the top innovators in the economy, with average values above the overall mean across all components except *PC*2 (market-oriented innovations in logistics, marketing, and sales digitalisation). It includes the Netherlands, Finland, Ireland, Luxembourg, Norway, and Sweden. A geographical pattern is evident, as most of these countries are located in Northern Europe, suggesting that regional factors contribute to innovation leadership. Their strengths lie in strong innovation penetration (*PC*1), cooperation in innovation activities (*PC*3), and advancements in service-based innovation (*PC*5).

For a more detailed analysis, the description statistics by clusters by *PC* were calculated (Table 8).

Cluster 0 is significantly behind the other clusters in innovative capacity of the economy, with negative mean scores, suggesting a lack of innovation integration. Cluster 0 is consistently weak, with a tight range of values.

Table 8. Centers of the clusters

	PC1	PC2	PC3	PC4	PC5
Cluster_0	–0.810	2.000	–1.060	0.736	0.950
Cluster_1	0.021	1.043	0.814	1.206	–1.860
Cluster_2	0.711	–0.133	–0.810	–0.201	0.317
Cluster_3	–0.290	–0.240	0.065	–0.182	–0.781
Cluster_4	0.257	–0.417	1.195	0.059	0.789

Cluster 1 is the most stable, with the lowest SD (0.12) of *PC*1, and performs similarly across countries. It is close to the mean, confirming average performance. Countries in this cluster are very similar in innovation, with a narrow range close to zero.

The 2nd cluster of leading countries is pushing the mean of *PC*1 up. The values of the 1st PC responsible for the innovative capacity of the economy are clearly distinguished. It stands out as the top-performing group in innovation, but with high variability among countries. Cluster 2 has *PC*1 extreme variability, meaning some countries are exceptional innovators, while others are just above average. The 2nd cluster has a large deviation from the average in the upper quantile; the maximum deviation of the 0.5th quantile is 0.47 for *PC*1.

Cluster 2 has the highest spread; it includes the countries with the largest deviation from the average. It contains both top innovators and average performers. Romania has the lowest indicator of the innovative capacity of the economy, which significantly deviates from the values of other countries. It is (–1.15) and part of the 3rd cluster. Although the SD for the cluster as a whole (0.476) is less than in the 2nd cluster, in the 1st quantile, it is greater than in the 2nd quantile. Cluster 2 has the highest spread, containing top innovators and average performers.

Based on Mean Analysis (Table 9), Cluster 4 performs well, aligning with high innovation trends but slightly below Cluster 2. Cluster 4 has notable diversity, and leans towards stronger innovation trends. Cluster 2 is stable, as the median and mean indicate above-average performance.

Countries in Clusters 1 and 3 are close to average in mean values but show variability in performance.

Table 9. The description statistics by clusters by PCs

Cluster	Mean	Median	Min	Max	0.75-quantile	Standard deviation (SD)
				*PC*1		
cluster_0	–0.810	–0.810	–1.020	–0.600	–0.710	0.297
cluster_1	0.021	0.021	–0.069	0.112	0.068	0.128
cluster_2	0.711	0.534	0.083	1.720	1.136	0.569
cluster_3	–0.290	–0.161	–1.152	0.258	0.091	0.476
cluster_4	0.257	0.435	–0.649	0.821	0.652	0.600
				*PC*2		
cluster_0	2.000	2.000	0.988	3.012	2.704	1.431
cluster_1	1.043	1.043	0.5101	1.575	1.493	0.752
cluster_2	–0.133	–0.225	–1.304	1.532	0.428	0.860
cluster_3	–0.240	–0.220	–0.800	0.449	0.201	0.441
cluster_4	–0.417	–0.479	–1.740	0.680	0.152	0.844

End of Table 9

Cluster	Mean	Median	Min	Max	0.75-quantile	Standard deviation (SD)
	PC3					
cluster_0	–1.060	–1.060	–1.450	–0.671	–0.864	0.550
cluster_1	0.814	0.814	0.348	1.279	0.973	0.658
cluster_2	–0.810	–0.516	–2.478	–0.287	–0.319	0.748
cluster_3	0.065	0.183	–0.361	0.546	0.253	0.326
cluster_4	1.195	1.038	0.656	2.342	1.783	0.607
	PC4					
cluster_0	0.736	0.736	0.201	1.270	0.966	0.755
cluster_1	1.206	1.206	0.166	2.246	1.898	1.470
cluster_2	–0.201	–0.649	–1.469	1.247	0.889	0.950
cluster_3	–0.182	–0.114	–1.206	0.829	0.232	0.637
cluster_4	0.059	0.112	–1.872	1.778	0.918	1.191
	PC5					
cluster_0	0.950	0.950	0.066	1.835	1.350	1.250
cluster_1	–1.860	–1.860	–2.279	–1.440	–1.614	0.592
cluster_2	0.317	0.362	–0.826	0.815	0.452	0.519
cluster_3	–0.781	–0.637	–1.730	–0.030	–0.699	0.623
cluster_4	0.789	0.845	0.190	1.415	1.087	0.512

The illustration of the described clusters is visible in Figure 3.

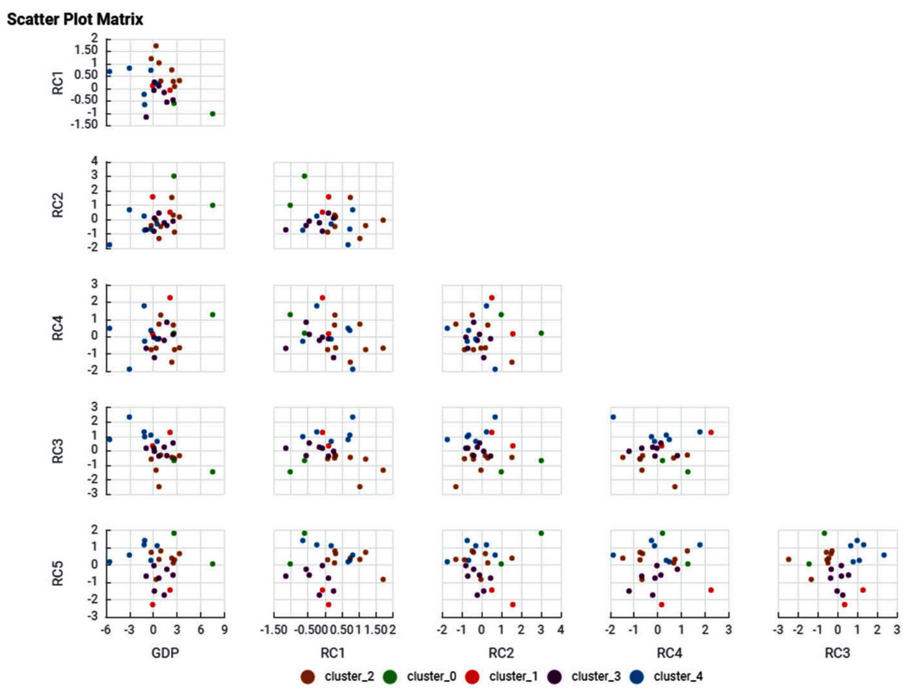

Figure 3. Clusters with GDP

Next, based on the created PCs, the authors constructed a linear correlation model to identify the fundamental components' influence on countries' GDP growth (Table 10).

Table 10. GDP growth for countries

Variable	Coeff.	Std. Err.	P>|t|
*PC*1	1.146	0.056	0.004
*PC*2	0.852	0.035	0.002
*PC*3	0.273	0.035	0.001
*PC*4	1.245	0.038	0.004
*PC*5	−0.095	0.034	0.004
Intercept	0.943	0.035	0.000

All PCs contain p-value <0.05, which explains that all variables are significant predictors of the linear regression model (11).

$$GDP = 0.943 + 1.146PC1 + 0.852PC2 + 0.273PC3 + 1.245PC4 - 0.095PC5. \quad (11)$$

The PCA analysis revealed that the first five PCs explain 95% of the total variance in the data, allowing for an efficient reduction of the model complexity without losing information relevance. The *PC*1 was identified as a reflection of the Innovation Index, which integrates the most significant indicators of innovativeness, such as the share of innovative firms, their turnover, and employee engagement. This component had the strongest positive impact on the economic model and can be considered a key indicator of innovation potential.

The *PC*2 reflected digitalisation and market innovation, such as logistics, marketing, and sales. The remaining *PC*3–*PC*5 covered specific types of innovation: collaborative innovation, new-to-market innovation, and service innovation.

Further clustering of countries by component revealed five different levels of innovation development: from highly digitalised but lacking in collaboration (Cyprus, Malta) to innovation leaders (Sweden, the Netherlands, Finland), characterised by the full integration of innovation into the economy. These results reveal a clear link between the structure of innovation and the growth potential of GDP and can be valuable in shaping policies and strategies to promote innovation and sustainable economic growth.

5. Discussions

The results showed a significant impact of innovation on GDP growth in the countries and significant differences between Member States. The three-step analysis allowed not only to quantify the impact of innovation on the economy, but also to identify the structural factors influencing the intensity of this impact.

One of the main insights of the study is that the impact of innovation is not homogeneous across the countries (Bottazzi & Peri, 2003; Sojoodi & Baghbanpour, 2024), with innovation making a significant contribution to economic growth only in contexts where a favourable environment for its development exists. This is borne out by the high-performing countries: Germany, Denmark, Finland, the Netherlands, Sweden, and Ireland. These countries have strong innovation ecosystems that successfully combine public and private investment in R&D, a highly skilled workforce, and a policy environment that fosters innovation.

Meanwhile, cluster analysis has highlighted countries where innovation potential remains limited. These countries often face insufficient R&D investment and lower capacity to commercialise innovation (Boeing et al., 2022). This shows that innovation alone does not guarantee economic growth – it is important to create the conditions that allow innovation to be transferred to the market and generate added value (Raghutla & Kolati, 2023).

The econometric analysis shows that the impact of innovation on GDP is significant but uneven, with some countries experiencing a stronger impact and others a weaker or delayed one. This can be attributed to different rates of adoption of innovations, and, further, the extent of diffusion. Such results align with previous studies' findings that emphasise context's importance in analyzing innovation's impact (Sawng et al., 2021; Sojoodi & Baghbanpour, 2024).

The validity of the hypothesis is confirmed by the data collected, the methodology applied, and the results of empirical research. The use of Eurostat and OECD data ensures a reliable statistical basis, PCA helped to identify the most important determinants of innovation, the three-step methodology verified the relationship between the maturity of innovation ecosystems and GDP growth, Cluster analysis, which is a direct means of testing the hypothesis, showed that countries with high levels of innovation grouped into clusters coincide with groups with high GDP growth. The study's conclusions directly confirm the hypothesis: countries with a developed innovation ecosystem achieve higher GDP growth, so the hypothesis is acceptable when its validity is assessed in the context of the region and period examined in the study.

It is important to note that the integrated measurement framework proposed in the study has proven to be an effective tool for achieving a holistic view of the relationship between innovation and economic growth. This methodological approach can be applied in future studies to assess the effectiveness of policy measures across countries.

In summary, this study confirms that innovation is an important factor for economic growth, but its impact depends on several interrelated factors. To achieve sustainable and balanced economic growth across the EU, developing policies to promote innovation tailored to specific national needs and conditions is essential. Such a strategy would help to reduce the gap between the countries and strengthen the EU's overall global competitiveness.

6. Conclusions

The study aimed to comprehensively assess innovation's impact on GDP growth in the EU and related countries, using an integrated assessment framework and a three-step analysis methodology. The results obtained allowed us to identify direct links between innovation performance and economic development and look deeper into the structural, institutional, and sectoral differences between countries. Thus, PCA has proven to be an effective tool for revealing the key factors determining countries' innovativeness level, even with limited data available. The study confirms the robustness of the model and its suitability for practical application in economic assessment and forecasting.

Countries' innovation ecosystems are characterised by a high degree of heterogeneity. The study shows that high-performing countries have developed mature and productive innovation ecosystems that contribute significantly to GDP growth. Meanwhile, in other countries, like the Eastern and Southern European regions, innovation potential remains untapped due to structural weaknesses such as limited funding, weak R&D infrastructures, low uptake of innovation, and weak business-research collaboration.

The most important source of innovativeness is the business sector. The innovative activity of firms has a decisive impact on the national innovation rate. A more detailed decomposition of these factors into service and value-chain innovations allows a consistent assessment of the contribution of each type of innovation to economic value.

The analytical model developed has a high predictive potential. The integrated approach allows for identifying the obvious and indirect factors affecting the innovation-to-GDP ratio. Following this, policymakers need to adopt tailor-made innovation strategies that reflect individual countries' economic, social, and sectoral structural characteristics. Such strategies would help to maximise innovation potential and reduce the innovation gap between countries.

The analysis concluded that the following factors contribute significantly to forming the indicator: 1. level of cooperation; 2. service innovations; 3. value chain innovations for distribution and logistics, marketing, and sales.

The link between the first and second components is quite strong: innovation does not have a significant effect without marketing and service. The indicators at the production process level confirm this. At the same time, the growth rate of labour productivity should be higher than the average growth rate in the company's industry. The analytical model presented in the paper shows that the method allows us to identify the significant parameters and to move on to the indirect factors that account for the variations in the data and should be used to forecast sustainable development of individual economies.

It ensures a high degree of accuracy in the calculations and allows management to manage costs most efficiently and prioritise management decisions correctly.

In summary, the three-step analysis methodology has provided a systematic and empirical basis for the impact of innovation on economic growth. The results provide a solid basis for further innovation application and point out the way forward for countries to achieve long-term sustainable development.

Research has some limitations. The authors analysed the impact of innovation on the economies of the EU and the countries concerned, Norway and Switzerland. Further research is possible in two directions: the impact of innovation could be explored by including more countries concerned or in another region.

References

Aghion, P., & Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, *60*(2), 323–351. https://doi.org/10.2307/2951599

Ambos, B., Brandl, K., Perri, A., Scalera, V. G., & Van Assche, A. (2021). The nature of innovation in global value chains. *Journal of World Business*, *56*(4), Article 101221. https://doi.org/10.1016/j.jwb.2021.101221

Antonucci, T., & Pianta, M. (2002). Employment effects of product and process innovation in Europe. *International Review of Applied Economics*, *16*(3), 295–307. https://doi.org/10.1080/02692170210136127

Boeing, P., Eberle, J., & Howell, A. (2022). The impact of China's R&D subsidies on R&D investment, technological upgrading and economic growth. *Technological Forecasting and Social Change*, *174*, Article 121212. https://doi.org/10.1016/j.techfore.2021.121212

Bottazzi, L., & Peri, G. (2003). Innovation and spillovers in regions: Evidence from European patent data. *European Economic Review*, *47*(4), 687–710. https://doi.org/10.1016/S0014-2921(02)00307-0

Bresciani, S., Puertas, R., Ferraris, A., & Santoro, G. (2021). Innovation, environmental sustainability and economic development: DEA-Bootstrap and multilevel analysis to compare two regions. *Technological Forecasting and Social Change*, *172*, Article 121040. https://doi.org/10.1016/j.techfore.2021.121040

Damanpour, F. (1992). Organizational size and innovation. *Organization Studies*, *13*(3), 375–402. https://doi.org/10.1177/017084069201300304

Dempere, J., Qamar, M., Allam, H., & Malik, S. (2023). The impact of innovation on economic growth, foreign direct investment, and self-employment: A global perspective. *Economies*, *11*(7), Article 182. https://doi.org/10.3390/economies11070182

Destefanis, S., & Rehman, N. U. (2023). Investment, innovation activities and employment across European regions. *Structural Change and Economic Dynamics*, *65*, 474–490. https://doi.org/10.1016/j.strueco.2023.03.013

Dokas, I., Panagiotidis, M., Papadamou, S., & Spyromitros, E. (2023). Does innovation affect the impact of corruption on economic growth? International evidence. *Economic Analysis and Policy*, *77*, 1030–1054. https://doi.org/10.1016/j.eap.2022.12.032

Ersin, Ö., Ustabaş, A., & Acar, T. (2022). The nonlinear effects of high technology exports, R&D and patents on economic growth: A panel threshold approach to 35 OECD countries. *Romanian Journal of Economic Forecasting*, *25*(1), 26–44.

Esko, S., Zeromskis, M., & Hsuan, J. (2013). Value chain and innovation at the base of the pyramid. *South Asian Journal of Global Business Research*, *2*(2), 230–250. https://doi.org/10.1108/SAJGBR-03-2012-0020

European Commission. (2021). *European Innovation Scoreboard 2021*. Publications Office of the European Union. https://op.europa.eu/en/publication-detail/-/publication/bd128c04-0b93-11ec-adb1-01aa75ed71a1/

Eurostat. (2024). *Community innovation survey 2022 – key indicators*. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Community_Innovation_Survey_2022_-_key_indicators

Fagerberg, J., & Verspagen, B. (2002). Technology-gaps, innovation-diffusion and transformation: An evolutionary interpretation. *Research Policy*, *31*(8–9), 1291–1304. https://doi.org/10.1016/S0048-7333(02)00064-1

Fernández-Cerezo, A., & Montero, J. M. (2021). *A sectoral analysis of the future challenges facing the Spanish economy* (Documentos Ocasionales No. 2133). Banco de España. https://www.bde.es/f/webbde/SES/Secciones/Publicaciones/InformesBoletinesRevistas/ArticulosAnaliticos/21/T4/Files/do2133e.pdf

Geronikolaou, G., & Papachristou, G. A. (2008). *Venture capital and innovation in Europe*. SSRN. https://doi.org/10.2139/ssrn.1309186

Grafström, J., Söderholm, P., Gawel, E., Lehmann, P., & Strunz, S. (2023). Government support to renewable energy R&D: Drivers and strategic interactions among EU Member States. *Economics of Innovation and New Technology*, *32*(1), 1–24. https://doi.org/10.1080/10438599.2020.1857499

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. In Z. Griliches (Ed.). *R&D and productivity: The econometric evidence* (pp. 287–343). https://www.nber.org/system/files/chapters/c8351/c8351.pdf

Guzman, J., Murray, F., Stern, S., & Williams, H. (2024). Accelerating innovation ecosystems: The promise and challenges of regional innovation engines. *Entrepreneurship and Innovation Policy and the Economy*, *3*(1), 9–75. https://doi.org/10.1086/727744

Hajighasemi, A., Oghazi, P., Aliyari, S., & Pashkevich, N. (2022). The impact of welfare state systems on innovation performance and competitiveness: European country clusters. *Journal of Innovation & Knowledge*, *7*(4), Article 100236. https://doi.org/10.1016/j.jik.2022.100236

Hall, B. H., Mairesse, J., & Mohnen, P. (2010). Measuring the returns to R&D. In B. H. Hall & N. Rosenberg (Eds.), *Handbook of the economics of innovation* (Vol. 2, pp. 1031–1082). Elsevier. https://doi.org/10.1016/S0169-7218(10)02008-3

Hardi, I., Ray, S., Attari, M. U. Q., Ali, N., & Idroes, G. M. (2024). Innovation and economic growth in the top five southeast Asian economies: A decomposition analysis. *Ekonomikalia Journal of Economics*, *2*(1), 1–14. https://doi.org/10.60084/eje.v2i1.145

Harrison, R., Jaumandreu, J., Mairesse, J., & Peters, B. (2014). Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. *International Journal of Industrial Organization*, *35*, 29–43. https://doi.org/10.1016/j.ijindorg.2014.06.001

Häggmark, T., & Elofsson, K. (2022). The drivers of private and public eco-innovations in six large countries. *Journal of Cleaner Production*, *364*, Article 132628. https://doi.org/10.1016/j.jclepro.2022.132628

Kučera, J., & Fiľa, M. (2022). R&D expenditure, innovation performance and economic development of the EU countries. *Entrepreneurship and Sustainability Issues*, *9*(3), 227–241. https://doi.org/10.9770/jesi.2022.9.3(14)

Liu, L., Anwar, A., Irmak, E., & Pelit, I. (2022). Asymmetric linkages between public-private partnership, environmental innovation, and transport emissions. *Economic Research – Ekonomska Istraživanja*, *35*(1), 6519–6540. https://doi.org/10.1080/1331677X.2022.2049979

Liu, Y., Chen, Y., Lu, H., Zhong, W., Yuan, G. C., & Ma, P. (2024). Orthogonal multimodality integration and clustering in single-cell data. *BMC Bioinformatics*, *25*, Article 164. https://doi.org/10.1186/s12859-024-05773-y

Maradana, R. P., Pradhan, R. P., Dash, S., Gaurav, K., Jayakumar, M., & Chatterjee, D. (2017). Does innovation promote economic growth? Evidence from European countries. *Journal of Innovation and Entrepreneurship*, *6*, Article 1. https://doi.org/10.1186/s13731-016-0061-9

Mewes, L., & Broekel, T. (2022). Technological complexity and economic growth of regions. *Research Policy*, *51*(8), Article 104156. https://doi.org/10.1016/j.respol.2020.104156

Organisation for Economic Co-operation and Development. (n.d.). *Science, technology and innovation scoreboard* [Dataset]. https://www.oecd.org/en/data/datasets/science-technology-and-innovation-scoreboard.html

Organisation for Economic Co-operation and Development. (2018). *The measurement of scientific, technological and innovation activities.* https://www.oecd.org/en/publications/the-measurement-of-scientific-technological-and-innovation-activities_24132764.html

Paula, F. D. O., & Ferreira da Silva, J. (2021). R&D spending and patents: Levers of national development. *Innovation & Management Review*, *18*(2), 175–191. https://doi.org/10.1108/INMR-11-2019-0142

Pijnenburg, K., & Kholodilin, K. A. (2014). Do regions with entrepreneurial neighbours perform better? A spatial econometric approach for German regions. *Regional Studies*, *48*(5), 866–882. https://doi.org/10.1080/00343404.2012.697143

Prajogo, D. I., McDermott, P., & Goh, M. (2008). Impact of value chain activities on quality and innovation. *International Journal of Operations & Production Management*, *28*(7), 615–635. https://doi.org/10.1108/01443570810881785

Raghutla, C., & Kolati, Y. (2023). Public-private partnerships investment in energy as new determinant of renewable energy: The role of political cooperation in China and India. *Energy Reports*, *10*, 3092–3101. https://doi.org/10.1016/j.egyr.2023.09.139

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, *98*(5), S71–S102. https://doi.org/10.1086/261725

Roper, S., Du, J., & Love, J. H. (2008). Modelling the innovation value chain. *Research Policy*, *37*(6–7), 961–977. https://doi.org/10.1016/j.respol.2008.04.005

Sawng, Y. W., Kim, P. R., & Park, J. (2021). ICT investment and GDP growth: Causality analysis for the case of Korea. *Telecommunications Policy*, *45*(7), Article 102157. https://doi.org/10.1016/j.telpol.2021.102157

Simmie, J., Sennett, J., Wood, P., & Hart, D. (2002). Innovation in Europe: A tale of networks, knowledge and trade in five cities. *Regional Studies*, *36*(1), 47–64. https://doi.org/10.1080/00343400120099852

Symeonidis, G. (1996). *Innovation, firm size and market structure: Schumpeterian hypotheses and some new themes* (OECD Economics Department Working Papers No. 161). OECD. https://www.oecd.org/content/dam/oecd/en/publications/reports/1996/01/innovation-firm-size-and-market-structure_g17a13c7/603802238336.pdf

Sojoodi, S., & Baghbanpour, J. (2024). The relationship between high-tech industries exports and GDP growth in the selected developing and developed countries. *Journal of the Knowledge Economy*, *15*(1), 2073–2095. https://doi.org/10.1007/s13132-023-01174-3

Schumpeter, J. A. (1934). *The theory of economic development*. Harvard University Press.

Wei, Y. (2022). Regional governments and opportunity entrepreneurship in underdeveloped institutional environments: An entrepreneurial ecosystem perspective. *Research Policy*, *51*(1), Article 104380. https://doi.org/10.1016/j.respol.2021.104380

Zhao, P., Lu, Z., Kou, J., & Du, J. (2023). Regional differences and convergence of green innovation efficiency in China. *Journal of Environmental Management*, *325*, Article 116618. https://doi.org/10.1016/j.jenvman.2022.116618