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Evaluating Innovation Efficiency in EU Countries: the DEA Approach

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Abstract: Innovation, science and technology, which are among the most important tools for achieving economic growth, prosperity and competitiveness in the local and global business environments, are increasingly gaining attention. Thus, improving the level of innovation efficiency of countries should be one of the EU priorities. The aim of this paper is to analyse the development of the innovation efficiency of EU member states and to assess the use of resources entering their national innovation systems. To determine the efficiency of the EU countries, basic output-oriented DEA models were applied. The data were processed from databases of the World Bank. First, the development and comparative analysis of input variables (government expenditure on education as a percentage of gross domestic product, research & development expenditure as a percentage of gross domestic product, researchers in research & development per million people) and output variables (patent applications, high-technology exports as a percentage of manufactured exports and scientific and technical journal articles) was performed. The level of efficiency of individual EU countries was subsequently quantified via DEA Solver (LV 8.0) software. Based on the scaling method, 5 groups of countries with similar levels of efficiency were identified and presented in the cartogram (efficient countries, above-average efficient countries, average efficient countries, below-average efficient countries, and inefficient countries). Over the period analysed, a total of 6 countries were identified as efficient – France, Germany, Ireland, Italy, Malta, Romania (and the United Kingdom in 2018–2019). Countries such as Sweden, Denmark, Belgium, Finland and Austria recorded the highest values of the selected inputs, but the efficiency score showed average to below-average results. The findings of this study demonstrated that many of the top-ranked nations in global innovation rankings are misusing and underutilizing the resources that enter their national innovation systems. Makers of policies and strategic plans for the innovation efficiency of EU countries will thus have the opportunity to incorporate the results of the study into real proposals and solutions.

Keywords: data envelopment analysis; inputs; national innovation strategy; outputs; research, development.

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1. Introduction. According to the European Commission (2022), Europe has the greatest potential to lead waves of high-tech innovation because of its long and illustrious history of invention. Europe is home to some of the top research institutes and schools in the world, and their invaluable support for innovation, research and education never stops. With 17.5 million students enrolled in postsecondary education, over a million researchers and a rise in licensing, patenting and start-ups, Europe has a powerful talent pool. A fifth of the world's excellent publications are produced in the EU, which makes up 6% of the global population. Additional factors contributing to the EU's leadership in this area include the continent's robust technological base, a thriving start-up ecosystem and policies that support the formation of alliances between businesses and academics through EU policies and programs. Owing to their significant position in the world of innovation and technology, EU member states were selected for this research study.

The aim of this study is to analyse the development of the innovation efficiency of EU member states and to assess the use of resources entering their national innovation systems. Improving the level of innovation efficiency of countries should be one of the EU priorities. However, the initial step is to evaluate the position and efforts of individual member states that participate in achieving common EU goals in the fields of innovation, technology and development. Although extensive research has been carried out on measuring EU member states' level of innovation efficiency, no single study exists that examines the unique combination of DEA input and output variables we created using the most up-to-date data at the time of the research (including 2 years before and after the withdrawal of the United Kingdom from the EU).

The main contribution of this research includes providing an overview of EU member states' innovation efficiency, as it is essential for policy makers to assess the position of countries in relation to other member states. The paper thus emphasizes the importance of developing national innovation strategy policies that are suitable for the actual economic climate and concentrating on the elements that will most effectively convert innovative inputs into innovative outputs. This research has also contributed to confirming the conclusions of several similar studies that have criticized the explanatory value and robustness of global composite indices (e.g., the GII and the SII). The achievement of significantly different positions of countries in the rankings of innovativeness and technological development encouraged us to consider whether the use of alternative data-driven methodologies such as DEA was more appropriate after all.

The paper has the following structure. The second section begins by laying out the theoretical dimensions of the research. The third section describes the research methods, the procedure of selecting suitable input–output indicators and the data used. The key findings of the research conducted are analysed and presented in the fourth section. The following section discusses and compares the findings with those of other authors. The final chapter summarizes the findings of the research and suggests further investigations in this area. The chapter also describes potential research limitations.

2. Literature Review. Innovation is important for achieving the overall goals of concurrent green and digital transformations because it forms markets, transforms economies and causes major changes in the quality of public services. Therefore, innovation, R&D expenditures and technology investments are considered key prerequisites for ensuring competitiveness, progress and sustainable economic growth.

The capacity of a nation to generate innovative outputs by utilizing the components that facilitate innovation activities is known as national innovation efficiency (Erdin & Caglar, 2023). Many published studies (Spanos et al., 2015; Wei & Liu, 2015; Huergo et al., 2016; Dumont, 2017; Guo et al., 2018; Jugend et al., 2020) have described the effects of public and state support for businesses' R&D efforts. Other studies (Radicic et al., 2019; Bianchini et al., 2019) have attempted to analyse the circumstances under which the public should fund R&D activities more intensively. Governments play two roles in innovation: they promote entrepreneurship and manage the innovation climate by creating science and technology regulations (Wang et al., 2016; Levchenko et al., 2018). Both technical advancement and economic growth can be slowed by the ineffective use of innovation resources, even while a healthy national innovation system can promote economic development (Chen et al., 2011; Smoliv et al., 2018; Slavinskaite et al., 2022). To encourage innovation in organizations, governments usually use a combination of nonfinancial (e.g., programs for training, support, or cluster/consortia associations) and financial policy instruments (e.g., grants, discounts or tax breaks) (Dumont, 2017; Chapman & Hewitt-Dundas, 2018; Hushko et al., 2021; Sip et al., 2023). Owing to the unique resources and limitations of various countries and locations, each nation has implemented unique innovation policies and strategies (Lipkova & Braga, 2016). As stated by Cozzens (2012), no policy initiative is appropriate for each country. Innovation policies may be effectively targeted towards regions that require extra strategies to achieve prospective improvements by conducting evaluations of innovation processes. It is important to implement distinct policies that foster the implementation of innovative techniques in areas where efficiency ratings have shown a lack of rigour in the use of their resources (Bresciani et al., 2021; Toloo et al., 2021). On July 5, 2022, the European Commission adopted the New European Innovation Agenda (European Commission, 2022), which aims to establish Europe as the centre of the next wave of technology innovation and start-up companies. It will support Europe's efforts to create and commercialize breakthrough technologies that tackle the most significant problems facing society. Through a cohesive set of 25 actions, the New European Innovation Agenda is aimed at accelerating the development of innovation and expanding throughout the Union. These actions will be carefully tracked and reported on by 2024 in close collaboration with Member State representatives in the European Innovation Council Forum. In this context, it is necessary to analyse the individual efforts and conditions of the 27 member states, which can determine the overall innovation performance of the European Union as a whole.

In general, the subjects determine which perspective is used to measure innovation efficiency. As national efficiency is the primary focus of our study, the previously published research in this area has been compiled into Table 1. Overall, efficiency has long been a question of great interest in a wide range of fields. In the latter part of the 20th century, Farrell (1957) built a fundamental approach for the examination of units' technical efficiency, building on Debreu's (1951) research. This is when the first concepts of technical efficiency assessment were apparent. A few years later, Charnes et al. (1978) updated the author's method and presented it as a linear programming issue; this model is known as the CCR model. The process was expanded in the 1980s by Banker et al. (1984), who created the BCC model that handles many inputs and numerous outputs. The DEA approach has been the focus of numerous studies since the aforementioned authors first presented it to the public, and in recent years, its acceptance has increased (Emrouznejad & Yang, 2018).

Table 1. Literature review – research studies indexed in Scopus/WoS

Authors	Inputs	Outputs
Pan et al. (2010)	• Public spending on education (total) • Imports of products services • Spending on R&D (total) • Direct investment stocks abroad • R&D employees across the country (total)	• Patents awarded to citizens (total number) • Partners obtained abroad by citizens (total number) • Scientific articles (total number)
	DEA model used: VRS input-oriented DEA model, Superefficiency DEA model Research sample: selected countries from America, Asia, Europe	
Abbasi et al. (2011)	• R&D scientists • Spending on education • Spending on R&D	• Patents • Royalty incomes and licence fees • Manufacturing and high-tech exports
	DEA model used: VRS output-oriented DEA model Research sample: selected countries from Africa, America, Asia, Europe	
Cai (2011)	• General Expenditures on R&D (GERD) • R&D manpower (total)	• WIPO patents granted • Technical and scientific journal publications • Exports of high-tech and ICT services
	DEA model used: CRS output-oriented DEA model Research sample: selected countries from Africa, America, Asia, Europe	
Chen et al. (2011)	• R&D expenditure stocks • R&D personnel (total)	• Patents pending in the EPO and USPTO • Scientific articles • Copyright and licence fees
	DEA model used: CRS output-oriented DEA model Research sample: selected countries from America, Asia, Europe	
Matei & Aldea (2012)	• One new Ph.D. graduate for every 1,000 people in the 25–34 age group • Copublications in international science per million people • Public spending on R&D as % of GDP • Business spending on R&D as % of GDP • Public–private copublications per million people • PCT patents applications per billion GDP • Community trademarks per billion GDP	• The percentage of total employment that is employed in knowledge-intensive industries (manufacturing and services) • The percentage of total product exports that are made up of medium- and high-tech products • Exports of knowledge-intensive services as a percentage of all service exports • Knowledge-intensive services exports as % total service exports
	DEA model used: Bootstrap based, VRS output-oriented DEA model Research sample: EU member states, Croatia, Iceland, Norway, Switzerland, Turkey	
Guan & Chen (2012)	• Full-time equivalent scientists and engineers (total number) • Additional spending on R&D for innovative projects • Previous accumulated knowledge stock contributing to the downstream commercialization of knowledge • Prior accumulated knowledge stock producing upstream knowledge • Used equivalent full-time labor for non-R&D tasks	• Worldwide scientific publications • Industry added value • New product exports from high-tech industries
	DEA model used: CRS and VRS DEA model, Super efficiency DEA model Research sample: OECD countries	
Carayannis et al. (2016)	• Population with tertiary education • R&D spending	• Technological innovators (product or process) • Nontechnological innovators (marketing or

Authors	Inputs	Outputs
	• Non-R&D innovation spending DEA model used: multistage and multilevel DEA model Research sample: selected European countries and their corresponding regions	organisational) • Sales of new goods entering the market and new products entering the firm
Kontolaimou et al. (2016)	• Business spending on R&D • Labour capital • New technology-based entrepreneurial capital DEA model used: Bootstrap DEA model Research sample: EU member states	• Intellectual property • Exports of high- and medium-tech products
Edquist et al. (2018)	• Public sector R&D spending as a percentage of GDP • Venture capital as a percentage of GDP • Business sector R&D spending as a percentage of GDP • Non-R&D innovation spending as a percentage of turnover DEA model used: advanced and robust nonparametric DEA techniques Research sample: EU member states	• The percentage of SMEs that innovate internally • The number of community trademarks per billion GDP measured in Purchasing Parity Power • The number of community designs per billion GDP measured in Purchasing Parity Power • The percentage of SMEs that develop product of process innovations • The percentage of SMEs that develop marketing or organizational innovations • The impact of exports of medium- and high-tech goods on the trade balance • Exports of knowledge-driven services as a percentage of total service exports • New-to-firm and new-market innovation sales as a percentage of turnover
Jurickova et al. (2019)	• Total researchers • R&D spending DEA model used: CRS output-oriented DEA model Research sample: EU member states	• Scientific journal articles • Patent applications
Barbero et al. (2021)	The same like Edquist et al. (2018) DEA model used: DEA TOPSIS methods Research sample: EU member states, United Kingdom, Switzerland, Norway, Iceland	
Ratner et al. (2022)	• Researchers including technical workers (total number per million people) • R&D spending as a percentage of GDP • Payments for intellectual assets as a percentage of GDP) DEA model used: CRS output-oriented DEA model Research sample: post-Soviet countries (Estonia, Lithuania, Latvia, Moldova, Ukraine, Russia, Kazakhstan, Uzbekistan)	• Exports of high-technology goods as a percentage of GDP and manufactured exports • Intellectual asset use receipts as a percentage of GDP
Andrijauskiene et al. (2023)	• EU R&I investment channeled through the Framework Programs (euro per capita) • Research and development investment (% of GDP) • Intramural R&D investment in the public sector (% of GDP) • Total public investment on education (% of GDP) • Total R&D personnel and researchers by all sectors of performance (% of total employment), etc. DEA model used: BCC, CCR, SBM DEA model Research sample: EU member states	• Total patent applications (direct and PCT national phase entries) by applicant's origin (per million inhabitants) • Total trademark applications (direct and via the Madrid system), by applicant's origin (per million inhabitants) • Total design applications (direct and via the Hague system), by applicant's origin (per million inhabitants)
Xu et al. (2023)	• R&D personnel • R&D expenditures • Imports of high-tech products DEA model used: SBM DEA model Research sample: EU countries	• Research papers • Patent applications • High-tech product exports • CO2 emissions • Nitrogen oxide emissions

Sources: developed by the authors.

Research in this area has shown that the use of the DEA method is appropriate for evaluating the innovative efficiency of countries (Afzal, 2014; Alnafrah, 2021; Barbero et al., 2021; Omrani et al., 2019), considering that DEA is being used to generate weights in an unsupervised manner and that each country's efficiency score is compared with those of all other countries. Moreover, a detailed review of the literature compiled by Narayanan et al. (2022) revealed that more attention should be given to cross-country studies, especially comparative analyses. Research should be devoted both to how effectively individual countries use their available capacities and to how innovation efficiency changes over time.

Nonetheless, a number of organizations and institutions calculate index ratings by evaluating each nation's performance and potential for innovation. The most well-known tools for measuring national innovation performance are the European Innovation Scoreboard (EIS) and the Global Innovation Index (GII) (Erdin & Çağlar, 2023). There has been long-standing criticism of measuring innovation success via traditional indicators and a composite index, as demonstrated by the works of Edquist et al. (2018), Hauser et al. (2018) and Janger et al. (2017). The DEA techniques, computations, and their application have been well developed for today's needs while taking into account many practical facts, including those that occur in the context of organizing the process of innovation.

3. Methodology and research methods. To analyse the development of innovation efficiency in EU countries, DEA modelling in the programme DEA Solver (LV 8.0) was carried out. To select the most suitable technique for identifying substained inputs and outputs, correlation analysis was applied (Eskelinen, 2017). The normality of the sample set was tested via the MVN package and the northern R programming language. Considering the outcomes of the Shapiro–Wilk test, the condition of a normal distribution was met, which confirmed the appropriateness of applying Pearson's correlation coefficient to quantify linear dependence (Royston, 1995). In addition, research methods such as descriptive statistics, analysis, synthesis, comparison, induction, deduction and scaling methods were used.

The research focused on the latest available data from 2021 and analysed the period 2 years before and after the United Kingdom left the EU. The data were processed from the publicly accessible World Bank's official database (World Bank, 2022). The selection of the data (appropriately chosen inputs and outputs forming the structure of the DEA model) was determined on the basis of a detailed review of previously conducted research studies, on which a unique combination of variables was created.

In general, the DEA method is used to quantify the relative efficiency for homogenous decision-making units (DMUs) producing certain outputs that consume certain inputs by giving them scores between 0 and 1. The DEA method's applicability and accuracy can be assured only when every DMU performs an identical or comparable task. It is therefore feasible to determine a shared set of analysis-relevant inputs and outputs. Assume that there is a set of similar production units, denoted as U_1, U_2, ... , U_n. Each unit generates r outputs and simultaneously uses m inputs to calculate the enterprise's efficiency. The input matrix is X = {x_{ij}, i = 1, 2..., n; j = 1, 2..., m}, and the output matrix is Y = {yi_k, i = 1, 2..., n; j = 1, 2..., r}. According to Banker et al. (1984), a unit's efficiency may be broadly described as follows:

$$\text{efficiency (Uq)} = \frac{\text{weighted sum of outputs}}{\text{weighted sum of inputs}} = \frac{\sum_{k=1}^{r} u_k\, y_{qk}}{\sum_{j=1}^{m} v_j\, x_{qj}} \tag{1}$$

The weights in the formula correspond to the j-th input (v_j, j = 1, 2..., m) and the k-th output (u_i, k = 1, 2..., r). DMUs are classified as "efficient" if their score is equal to or greater than 1 and "inefficient" if their score is less than 1. To incorporate all the qualities considered in the model, both the input and output weights must be larger than zero simultaneously. Explanatory information, mathematical equations and formulas for calculating individual DEA models are presented, e.g., in Charnes et al. (1978), Banker et al. (1984), and Aetkyn et al. (2022). Compared with other methods, DEA provides two main benefits over other approaches (Wang et al., 2016). First, using all of the DMUs as a baseline, DEA creates a Pareto-efficient frontier that provides an ordinal ranking of relative efficiency. Second, prior knowledge of the input and output weights is not required by DEA. Two DMUs might be considered equally efficient if they have various input combinations but have the same output.

Choosing the appropriate model orientation (input/output-oriented, nonoriented, or both) and the type of (in)efficiency the model can include (radial/nradial, or both) is crucial when choosing a DEA model. However, other alternative or modified forms of fundamental DEA models are being progressively developed to increase their computing capacity and broaden their application (Narayanan et al. 2022).

Research investigations previously conducted in the relevant field served as the foundation for choosing the final DEA model (Table 1). Assuming that constant returns from scale are not feasible, the premise of continuous returns to scale can only be upheld in the event that every DMU functions at its ideal scale. This assumption is completely fallacious due to a number of issues, including financial limits, imperfect competition, and regulations. As a result, the BCC and CCR output-oriented models were used in this study to show how much a country can optimize its innovation outputs given the resources at its disposal. Highly correlated variables were not included in the model developed because they would not add any significant additional information. Another key assumption was to meet the requirements for the ratio of the variables to the DMUs being compared, as reported by Friedman & Sinuany-Stern (1998). When comparing innovation policy across the 28(27) EU member states, the total number of variables should represent one-third of the total number of DMUs examined. This requirement was also met (Table 2). Table 3 presents the descriptive statistics of the variables creating the structure of the DEA models.

Table 2. Definitions of the input and output variables.

Variable	Definition	Variable	Definition
	Input		Output
GEE	Government expenditure on education, total (as a percentage of GDP) – spending funded by transfers from international sources to government.	PA	Patent applications (number of patents) requests for the exclusive rights to a product or method that offers a novel approach to an existing problem or a new way of doing something. They can be submitted with a national patent office or through the Patent Cooperation Treaty procedure.
R&DE	R&D expenditure (as a percentage of GDP) – capital and current spending in the private nonprofit sector, business enterprise sector, higher education sector and government sector.	STJA	Scientific and technical journal articles (number of journal articles) number of journal articles published in the fields of science and technology (physics, biology, chemistry, mathematics, clinical medicine, biomedical research, engineering, etc.).
R&DR	Researchers in R&D (number of researchers per million people) – people who do study and produce models, techniques, concepts, theories, software and operational procedures.	HTE	High-technology exports (as a percentage of manufactured exports) products having a high R&D intensity, such as those in the aerospace, computer, pharmaceutical, scientific instrument and electrical equipment industries.

Sources: Developed by the authors on the basis of World Bank (2022).

Table 3. Descriptive statistics of the input and output variables (2018–2021).

Variable	Year	GEE	R&DE	R&DR	PA	STJA	HTE
Mean	2018	4.7960	1.6603	3,979	3,659	22,662	14.5381
	2019	4.8236	1.7101	4,137	3,614	23,136	14.5881
	2020	5.1688	1.7682	4,216	3,132	21,251	14.6931
	2021	5.0136	1.7585	4,454	3,008	20,240	14.4060
Median	2018	4.6493	1.3798	3,878	670	10,901	12.2271
	2019	4.6544	1.4286	4,027	734	11,264	12.2771
	2020	4.8766	1.5079	4,195	673	11,328	12.2643
	2021	5.0016	1.4564	4,452	541	10,996	12.2560
Standard deviation	2018	1.0362	0.8766	1,726	9,038	29,637	6.7901
	2019	1.0160	0.8848	1,766	9,013	29,921	6.5132
	2020	1.0694	0.8902	1,792	8,271	27,607	6.7680
	2021	0.8297	0.8918	1,885	7,833	26,465	6.4595
Minimum	2018	3.3192	0.4973	876	2	430	5.2834
	2019	3.2144	0.4762	887	4	416	6.5734
	2020	3.2719	0.4654	941	2	527	5.6189
	2021	2.9846	0.4730	985	1	442	6.0749
Maximum	2018	7.6408	3.3211	7,636	46,617	107,581	33.0708
	2019	7.6385	3.3876	7,727	46,632	108,725	29.6218
	2020	7.9256	3.4896	7,759	42,260	109,379	35.3378
	2021	6.6800	3.4398	8,131	39,822	108,391	30.7356

Sources: Developed by the authors on the basis of World Bank (2022).

In the first three years of the reference period, GEE increased by 0.373% on average in EU countries but declined slightly by 0.155% in the following year, 2021. In 2018, Romania had the least significant share in the growth of this indicator among EU countries; its government expenditure on education made up only 3.3192% of GDP. Surprisingly, Ireland recorded the lowest GEE in the following years (3.1569% on average), followed by Romania, Greece, Luxembourg and Italy. Conversely, GEE made up the highest share of Sweden's GDP every year of the analysed period (7.4712% on average). Above-average results were also achieved by countries such as Denmark, Belgium, Finland and Estonia.

The development of average R&DE in EU countries was very similar to that of the previous indicator GEE. In 2018--2020, there was an average year-to-year increase of 3.1991%, but in the last reference period, the indicator decreased by 0.5458%. The R&DE accounted for the lowest share of GDP in Romania (0.4780% on average), followed by Malta, Latvia, Cyprus and Bulgaria. However, certain countries, such as Sweden (3.409% on average), Belgium, Austria, Germany and Denmark, invested the most in R&D. As reported by Aytekin et al. (2022), the significant portion of GDP assigned to R&D in these countries can be seen as a sign of both macroeconomic and microeconomic development. The abovementioned countries accurately establish goals for innovation and, as a result, reach the desired degree of success.

The number of European researchers per million inhabitants recorded a positive increase from 2018--2021 (annual increase of 5% on average). Overall, the lowest number of researchers was recorded for Romania (922 on average), followed by countries such as Cyprus, Malta, Latvia and Croatia. The highest values of R&DR from EU countries in 2018--2019 were concentrated in Denmark (7,682 on average). However, in the following period, more researchers were concentrated in Sweden (7,945 on average). In the case of this indicator, above-average values were recorded in countries such as Finland, Austria, and the Netherlands.

From 2018–2021, the average PA in EU countries decreased by a total of 651. The greatest decrease was recorded from 2019–2020 (13.3383% on average). The differences in the EU countries are very significant, as evidenced by the values of the standard deviation. In the first analysed year, the fewest PAs were recorded in the case of Malta (2), whereas in the following years, the fewest PAs were recorded in the case of Cyprus (3). On average, fewer than 100 PAs were also reported by countries such as Estonia, Ireland, Lithuania and Latvia. In contrast, Germany presented significantly above-average values every year during the analysed period (43,833 on average). Those above the average limit of 10,000 PAs were France (13,641 on average) and the United Kingdom (12,463 on average), which, by leaving the EU, contributed to the deterioration of the statistics of this indicator.

During the analysed period, the values of the STJA indicator reached an average level of 21,822. A slight increase of 2.0948% was recorded from 2018--2019. However, in the following year, the values of the indicator decreased by an average of 8.1507% and subsequently by another 4.7572%. The worst and significantly below-average results were recorded in the case of Malta (454 on average), surprisingly Luxembourg (905 on average), Cyprus, Latvia and Estonia. On the other hand, Germany (108,519 on average) and the United Kingdom (100,972 on average) again recorded significantly higher values of STJA than other EU countries did. Italy, France and Spain are considered the largest competitors of these countries.

Although there was an overall nonsignificant average decrease in the HTE from 2018--2021, its development was relatively stable. Until 2020, a year-to-year increase in the indicator was recorded (0.5320% on average). However, in the following year, 2021, its value decreased (1.9543% on average). The lowest share of high-technology exports was recorded in 2018 in the case of Portugal (5,2834 on average). However, the situation changed in the following period, and countries such as Luxembourg, Slovenia, Italy and Spain reached significantly below-average results compared with other EU countries. Surprisingly, highly above-average values of HTE were recorded each year of the analysed period in the case of Malta (32,191 on average), followed by Ireland, France, the Netherlands and the United Kingdom.

4. Results. The results of the application of the output-oriented BCC model (BCC-O) and, for comparison, the results of the output-oriented CCR model (CCR-O) are presented in Table 4.

Table 4. Efficiency scores of EU member states (2018–2021).

Country	2018		2019		2020		2021	
	BCC-O	CCR-O	BCC-O	CCR-O	BCC-O	CCR-O	BCC-O	CCR-O
Austria	0.3925	0.3529	0.4056	0.3370	0.4221	0.3661	0.4166	0.3249
Belgium	0.4054	0.3117	0.4999	0.3700	0.5182	0.4001	0.7643	0.5136
Bulgaria	0.4444	0.3902	0.4598	0.4235	0.4492	0.4173	0.4552	0.4370
Croatia	0.4388	0.3554	0.4181	0.3553	0.4139	0.3771	0.3620	0.3583
Cyprus	0.8849	0.8162	0.7833	0.7751	0.4157	0.4140	0.6682	0.6557
Czechia	0.7148	0.7097	0.7464	0.7108	0.7867	0.7601	0.7336	0.6464
Denmark	0.4196	0.2802	0.4265	0.2674	0.4523	0.3008	0.5100	0.3283
Estonia	0.5535	0.5019	0.5737	0.4840	0.6041	0.5593	0.6768	0.5498
Finland	0.3071	0.2295	0.3263	0.2204	0.3400	0.2448	0.3813	0.2500
France	**1.0000**	0.9619	**1.0000**	0.9888	0.9951	0.9487	**1.0000**	0.9331
Germany	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	1.0000
Greece	0.6363	0.558	0.5781	0.5312	0.4933	0.4931	0.4649	0.4640
Hungary	0.5573	0.5395	0.6270	0.6003	0.6197	0.6082	0.5626	0.4931
Ireland	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	1.0000
Italy	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	1.0000
Latvia	0.8456	0.7272	0.7060	0.6456	0.7218	0.6651	0.5577	0.5418
Lithuania	0.4849	0.4502	0.4527	0.4447	0.3978	0.3954	0.3890	0.3591
Luxembourg	0.2658	0.2632	0.2437	0.2348	0.2085	0.2044	0.2045	0.1877
Malta	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**1.0000**	1.0000
Netherlands	0.7798	0.6905	0.8220	0.7028	0.8461	0.7458	0.8538	0.6807
Poland	0.6719	0.6643	0.6180	0.6064	0.5898	0.5820	0.6039	0.5688
Portugal	0.2772	0.2770	0.3285	0.3253	0.3312	0.3168	0.2983	0.2718
Romania	**1.0000**	0.9475	**1.0000**	**1.0000**	**1.0000**	0.9680	**1.0000**	1.0000
Slovak Republic	0.4697	0.4160	0.4187	0.3959	0.3666	0.3592	0.3598	0.3565
Slovenia	0.2187	0.2040	0.2554	0.2178	0.2477	0.2179	0.2170	0.1684
Spain	0.9348	0.9010	0.9458	0.9133	0.8406	0.8361	0.8600	0.8352
Sweden	0.4945	0.3103	0.5186	0.3092	0.5395	0.3435	0.5427	0.3306
United Kingdom	**1.0000**	**1.0000**	**1.0000**	**1.0000**				
Mean	0.6499	0.6021	0.6484	0.6021	0.6148	0.5750	0.6253	0.5650
Median	0.5968	0.5488	0.5981	0.5658	0.5395	0.4931	0.5626	0.5136
Std. dev.	0.2681	0.2833	0.2590	0.2839	0.2581	0.2706	0.2595	0.2722
Min.	0.2187	0.2040	0.2437	0.2178	0.2085	0.2044	0.2045	0.1684
Max.	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Sources: Developed by the authors based on DEA Solver (LV 8.0).

When the BCC-O and CCR-O models were applied, the nations' acquired scores and rankings were nearly comparable. One of the requirements for correctly using the DEA approach was the lack of extremes in the dataset, which is confirmed by the variances between the median and the average. According to the outcomes of the application of the BCC-O model, a total of 7 countries (France, Germany, Ireland, Italy, Malta, Romania, and the United Kingdom) were identified as efficient in 2018. In the case of the CCR-O model, both

France and Romania were scale inefficient. In the following 2019, the number of efficient EU countries did not change in the case of the BCC-O model, but the CCR-O model included Romania in the group of countries with an efficiency score of 1.0000; the number of inefficient countries was thus reduced from 23–22. In addition to the loss of one of the EU's top innovation leaders in 2020 (United Kingdom), France was also included in the group of inefficient countries. In the case of the BCC-O model, the number of countries with an efficiency score of 1.0000 was thus reduced from the original 7–5 (Germany, Ireland, Italy, Malta, Romania), which represented 22.73% of EU countries. In the given year, worse results were also recorded in the case of the CCR-O model, which identified only 4 efficient countries (Germany, Ireland, Italy, and Malta). In 2021, the situation improved slightly, and EU countries reached values comparable to those in 2019. In total, in the case of the BCC-O model, 6 countries were identified as efficient (France, Germany, Ireland, Italy, Malta, Romania), which represented 28.57% of EU countries. In the case of the CCR-O model, France was scale inefficient, which would decrease the percentage representation of efficient EU countries by 5.84%. Countries such as Luxembourg, Slovenia, Portugal, the Slovak Republic and Croatia achieved the lowest efficiency scores every year of the analysed period. The only exception was 2019, when Finland was surprisingly included in the three least innovatively efficient countries. To visualize the distribution of the variable (average innovation efficiency for the period 2018–2021), the results for individual EU countries are presented in the form of a cartogram (Figure 1). In this context, countries can be classified into 5 groups with comparable levels of innovation efficiency via the scaling method:

- Group No. 1 – efficient countries (BCC-O = 1.0000) – France, Germany, Ireland, Italy, Malta, Romania.
- Group No. 2 – above-average efficient countries (0.86000 > BCC-O > 0.69616) – Spain, the Netherlands, Belgium, and Czechia.
- Group No. 3 – average efficient countries (0.69615 > BCC-O > 0.53227) – Estonia, Cyprus, Poland, Hungary, Latvia, Sweden.
- Group No. 4 – Below-average efficient countries (0.53226 > BCC-O > 0.36839) – Denmark, Greece, Bulgaria, Austria, Lithuania, Finland.
- Group No. 5 – inefficient countries (0.36838 > BCC-O > 0.20450) – Croatia, Slovak Republic, Portugal, Slovenia, Luxembourg.

On the basis of the results, a total of 6 countries were identified as efficient: France, Germany, Ireland, Italy, Malta, Romania (and the United Kingdom in 2018--2019). Even though the input and output variables in the cases of Romania, Malta, Ireland and Italy reached the lowest values during the analysed period, their innovation performance is effective. Thus, the process of transforming innovation inputs into outputs in the process is set in an appropriate way. Only Germany, France and the United Kingdom were identified as effective and achieved some of the highest values of the selected output variables. Conversely, economies that were less developed and had simpler innovation mechanisms were shown to be more efficient. According to Edquist et al. (2018), a possible explanation for these apparently incongruous outcomes is that a considerable number of these small EU countries allocate comparatively limited resources to inputs, yet they are able to make better and more effective use of the resources they do have. One possible reason for this phenomenon could be that countries with limited resources for innovation often acquire and implement inventions and embodied knowledge from other countries. Lower innovation input costs are associated with this type of absorption, but it may also be more effective because it may spare the inherent risk associated with the growth of these innovations, leading to a quicker and less expensive adaptation of the new knowledge than in the country where it originated.

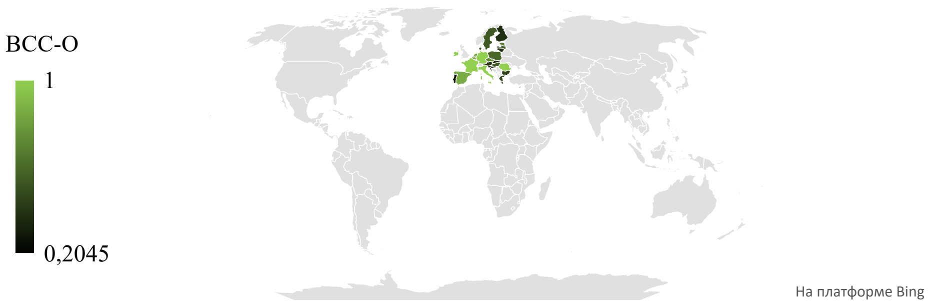

Figure 1. Cartogram of EU countries from the perspective of innovation efficiency (2018--2021 average)
Sources: developed by the authors.

Overall, EU member states have good innovation environments, high levels of resources and adequate combinations of national innovation system components that can produce economically useful innovations. In the case of inefficient DMUs (countries), it was also possible to determine the reference values of the output variables, which is considered one of the greatest advantages of the DEA method. Since we applied the output-oriented BCC model in the study, Table 5 shows the real values of the input variables and then their recommended values that would lead to the desired efficiency frontier. The output target values were quantified through vectors of optimal values of the variables and output values of the efficient production units. The projection was made on the basis of the most recent actual data and results from 2021. For example, Spain classified in Group No. 2 (above-average efficient countries) would have to increase PA by approximately 218%, the STJA by 140% and the HTE by 140% of the original (actual) values to reach the desired efficiency frontier of 1.0000, under the condition of no change in inputs. The Netherlands should be able to generate 247% (PA) and 17% (STJA, HTE) more innovation outputs under the given conditions; Belgium, 426% (PA) and 31% (STJA, HTE); Czechia, 633% (PA) and 36% (STJA, HTE). In this case, the abovementioned countries would have reached the efficiency frontier of 1.0000 and would be classified into Group No. 1 (efficient countries).

Table 5. Projections of each country onto the efficient frontier analysed by the BCC-O DEA model.

Country	PA (Output_1)			STJA (Output_2)			HTE (Output_3)		
	Data	Projection	Diff. (%)	Data	Projection	Diff. (%)	Data	Projection	Diff. (%)
Austria	1,872	5,955	218	13,083	31,406	140	11.0064	26.4208	140
Belgium	799	4,200	426	16,361	21,406	31	21.3797	27.9721	31
Bulgaria	165	1,579	857	3,589	7,883	120	10.9134	23.9731	120
Croatia	77	3,933	5,008	4,593	12,689	176	9.6066	26.5382	176
Cyprus	1	277	27,642	1,315	3,710	182	15.9690	23.8989	182
Czechia	541	3,963	633	15,720	21,427	36	20.3523	27.7412	36
Denmark	1,090	5,681	421	14,689	28,805	96	13.7672	26.9965	96
Estonia	25	390	1,461	1,603	2,368	48	20.6288	30.4820	48
Finland	1557	5,686	265	10,996	28,834	162	10.2937	26.9927	162
Greece	394	7,597	1,828	11,471	24,675	115	12.2560	26.3630	115
Hungary	433	2,105	386	6,985	12,414	78	16.2479	28.8777	78
Latvia	104	447	330	1,479	2,651	79	16.9802	30.4446	79
Lithuania	81	783	867	2,459	6,321	157	11.5086	29.5838	157
Luxembourg	112	548	389	882	4,513	412	6.0749	29.7037	389
Netherlands	2,080	7,225	247	31,824	37,271	17	21.9774	25.7393	17
Poland	3,377	8,660	156	35,033	58,012	66	9.4444	15.6391	66
Portugal	711	15,116	2,026	15,383	51,572	235	6.2503	20.9545	235
Slovak Republic	146	1,661	1,038	5,414	15,047	178	9.0013	25.0161	178
Slovenia	222	3,223	1,351	3,585	16,522	361	6.2089	28.6159	361
Spain	1,308	9,501	626	58,958	68,556	16	9.3926	10.9217	16
Sweden	1,771	7,699	335	21,107	38,891	84	13.9300	25.6667	84

Sources: Developed by the authors based on DEA Solver (LV 8.0).

However, countries should focus on how to create more innovative outputs while simultaneously not deviating more from each other in terms of competitiveness and sustainable economic growth. Tackling innovation gaps is crucial for economic, social and territorial cohesion, as well as the possibility of delivering wider economic and social benefits. Thus, the New European Innovation Agenda aims to strengthen regional cohesion and enable deep technological innovation.

5. Discussion. The overall efficiency scores of the EU member states that have been determined are similar to those of other studies, such as Carayannis et al. (2016). The authors used the multiobjective DEA technique to evaluate 23 EU countries, and the findings indicate that there are significant deviations from the predicted norm in terms of innovation efficiency. Kontolaimou et al. (2016) developed a classification of EU nations according to innovation efficiency and technology gap metrics. This disclosed characteristic is related to a country's ability to absorb knowledge, its strategic direction, and the impacts of knowledge spillover. As a consequence of these findings, Germany, Switzerland, the Netherlands, Denmark, Austria, Iceland, and Italy make up the group of European best innovators. The empirical research was built via information from the Global Entrepreneurship Monitor and the Innovation Union Scoreboard. Edquist et al. (2018) used the well-known summary innovation indicator (SII) composite indicator to analyse the innovation performance of all

28 national innovation systems in the EU. The authors claim that the SII is not a useful indicator of innovation performance, and they have created a substitute that is enhanced by a sophisticated and reliable nonparametric DEA approach. According to the bootstrapped efficiency score for 2015, Slovenia, Poland, the United Kingdom, Malta, Austria, France, Denmark, Italy, Portugal, and Spain had the top 10 EU national innovation systems. Jurickova et al. (2019) examined the efficiency of EU (28) countries over the years 2005--2016. For measurement, they used DEA and an output-oriented CRS model. On the basis of these results, most of the countries were scale inefficient, with the exceptions of Cyprus, Luxembourg, Malta and Romania. The results of a study by Gavurova et al. (2019), who assessed the innovation potential of EU countries between 2010 and 2015, identified Bulgaria, Romania Cyprus, Croatia, and the United Kingdom as the most efficient. Barbero et al. (2021) determined which EU countries had the greatest and worst-performing innovation systems via DEA-TOPSIS. The findings showed that nations with high innovation scales frequently overinvest in innovation inputs on the basis of the same data from the European Innovation Scoreboard for the years 2010, 2013, and 2016. As a result, there are scale inefficiencies caused by declining returns, which diminish production levels. Four groups of EU countries were identified by comparing the rankings of innovation performance and innovation inputs: a) high innovation inputs and high innovation performance (France, the Netherlands, Denmark, Germany, Austria); b) high innovation inputs and low innovation performance (Sweden, Finland, Switzerland, Estonia, Belgium, Iceland, the Czech Republic, Ireland, the United Kingdom, Norway, Slovenia); c) low innovation inputs and high innovation performance (Portugal, Luxembourg, Spain, Cyprus, Slovakia, Italy, Malta, Greece); and d) low innovation inputs and low innovation performance (Lithuania, Poland, Croatia, Hungary, Bulgaria, Romania, Latvia). In accordance with the findings of Aytekin et al. (2022), the Netherlands, Germany, and Sweden were the most important countries in terms of global innovation efficiency. Nevertheless, Lithuania, Greece, and North Macedonia were ranked as the last three inefficient countries. Andrijauskiene et al. (2023) measured the European Union's innovation efficiency via patents, trademarks, and design applications. The findings showed that the general EU innovation efficiency situation has improved over time. However, there were noticeable differences across the member states, demonstrating that Luxembourg is an absolute innovation efficiency leader, whereas Greece and Portugal achieved the lowest average efficiency scores.

The findings of this paper are consistent and comparable with those of the abovementioned studies. Research in this area has shown that many of the top innovation leaders (according to the GII and SII international rankings) were identified as inefficient in the utilization of the resources entering the national innovation system. Countries do not use inputs effectively, and their strategic policies for innovation efficiency are not set up correctly. Even so, the main drivers of state support for innovation in enterprises should be the creation and growth of more innovative enterprises, which in turn leads to positive externalities such as increased productivity (Afcha & García-Quevedo, 2016; Bilan et al., 2019); generating or increasing foreign exchange transactions (Vokoun, 2016); or increasing the number of skilled laborers (Castillo et al., 2020; Danova et al., 2021). Vanino et al. (2019) assert that supplementary elements exist that bolster public endorsement of innovation. These elements are linked to market failures such as businesses' difficulties with funding their R&D projects (Cano-Kollmann et al., 2017; Cabinova et al., 2018), information asymmetry issues (Hewitt-Dundas & Roper, 2018; Kwilinski et al., 2023a), and network-related problems (Kang & Park, 2012; Kwilinski et al., 2023b). The benefits of this assistance may include a decrease in informational asymmetries, a promotion of costly R&D projects and fewer failures in the market (Spanos et al., 2015).

6 Conclusions. DEA modelling was used to analyse the development of innovation efficiency in EU countries and indicate the extent to which countries may optimize their innovation outputs given the resources at their disposal. Using the BCC and CCR DEA models, the efficiency of EU countries was determined on the basis of data processed from the World Bank's official database (2018–2021). First, the development and comparative analysis of input variables (government expenditure on education as a percentage of gross domestic product, research & development expenditure as a percentage of gross domestic product, researchers in research & development per million people) and output variables (patent applications, high-technology exports as a percentage of manufactured exports and scientific and technical journal articles) was performed. The level of efficiency of individual EU countries was subsequently quantified via DEA Solver (LV 8.0) software. On the basis of the scaling method, 5 groups of countries with similar levels of efficiency were identified and presented in the cartogram (efficient countries, above-average efficient countries, average efficient countries, below-average efficient countries, and inefficient countries).

A surprising result is that countries such as Sweden, Denmark, Belgium, Finland, and Austria presented the highest values of the selected input variables, but the efficiency score quantified by the DEA models reported average to below-average results. However, in the EIS and GII rankings, these countries are among the top leaders not only of the EU but also of the world. The results of this study contribute to the growing motivation for rethinking the foundations of innovation theory and practice, including the definition, operationalization, and interpretation of the abovementioned indices, which strongly influence the formulation of countries' national innovation strategies.

On the basis of the results, a total of 6 countries were identified as efficient: France, Germany, Ireland, Italy, Malta, Romania (and the United Kingdom in 2018--2019). Even though the input and output variables in the cases of Romania, Malta, Ireland and Italy reached the lowest values during the analysed period, their innovation performance is effective. The process of transforming innovation inputs into outputs is set in an appropriate way. Only Germany, France and the United Kingdom were identified as effective and achieved some of the highest values of the selected output variables. Thus, we suggest several key policy implications that can be learned from these innovation leaders. The policy makers and strategic planners for EU innovation efficiency should incorporate the results of the study into realistic proposals and solutions to improve the current situation while taking inspiration from the policies of countries with the highest or above-average levels of innovation efficiency.

EU member states need to pay increased attention to policy issues related to the availability of highly skilled labour, especially in science and technology. Therefore, nations with low global innovation performance should work to advance their knowledge of science and technology and develop strategies to take the lead in these fields. EU member states can also be inspired by global innovators such as Japan, South Korea, and Taiwan for ideas on how to enhance their own national innovation strategies. These countries concentrate on spending for education, reverse engineering and building clusters, associations or conglomerates of sizable businesses. They can easily obtain investments, loans from domestic and international sources, and preferential treatment from the government. Moreover, solid ties with research and development organizations such as universities and high-tech export businesses are constantly maintained.

Despite the fact that certain results were obtained, the study has several limitations that could serve as a basis for further investigation. Since the research needs to be expanded with more pertinent input/output variables, the data from the World Bank database may represent a substantial constraint for subsequent measurements. The data that are used in the DEA analysis determine the final findings; therefore, to ensure sufficient results, techniques and statistical samples must be compared. Additionally, advanced techniques are needed that allow us to account for important factors, including sectoral structure, diversity, level of globalization, size of the company, and institutional conditions, to explain these results properly and thoroughly. These techniques need to be investigated further to enrich the conclusions obtained.

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References

1. Abbasi, F., Hajihoseini, H., & Haukka, S. (2011). Use of Virtual Index for Measuring Efficiency of Innovation Systems: A Cross-Country Study. *International Journal of Technology Management and Sustainable Development, 9*(3), 195–212. [GoogleScholar] [CrossRef]

2. Afcha, S., & García-Quevedo, J. (2016). The Impact of R&D Subsidies on R&D Employment Composition. *Industrial and Corporate Change, 25*(6), 955–975. [GoogleScholar] [CrossRef]

3. Afzal, M. N. I. (2014). An Empirical Investigation of the National Innovation System (NIS) Using Data Envelopment Analysis (DEA) and the TOBIT Model. *International Review of Applied Economics*, *28*(4), 507–523. [GoogleScholar] [CrossRef]

4. Alnafrah, I. (2021). Efficiency Evaluation of BRICS's National Innovation Systems Based on Bias-Corrected Network Data Envelopment Analysis. *Journal of Innovation and Entrepreneurship*, *10*(1), 1–28. [GoogleScholar] [CrossRef]

5. Andrijauskiene, M., Ioannidis, D., Dumciuviene, D., Dimara, A., Bezas, N., Papaioannou, A., & Krinidis, S. (2023). European Union Innovation Efficiency Assessment Based on Data Envelopment Analysis. *Economies*, *11*(6), Article 163. [GoogleScholar] [CrossRef]

6. Aytekin, A., Ecer, F., Korucuk, S., & Karamasa, C. (2022). Global Innovation Efficiency Assessment of EU Member and Candidate Countries Via DEA-EATWIOS Multi-Criteria Methodology. *Technology in Society, 68*(2), 1–11. [GoogleScholar] [CrossRef]
7. Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some Models for Estimating Technical Scale Inefficiencies in Data Envelopment Analysis. *Management Science, 30*(9), 1078–1092. [GoogleScholar] [CrossRef]
8. Barbero, J., Zabala-Iturriagagoitia, J. M., & Zofío, J. L. (2021). Is More Always Better? On the Relevance of Decreasing Returns to Scale on Innovation. *Technovation, 107*, Article 102314. [GoogleScholar] [CrossRef]
9. Bianchini, S., Llerena, P., & Martino, R. (2019). The impact of R&D subsidies under Different Institutional Frameworks. *Structural Change and Economic Dynamics,* 50, 65‒78. [GoogleScholar] [CrossRef]
10. Bilan, Y., Lyeonov, S., Lyulyov, O., & Pimonenko, T. (2019). Brand Management and Macroeconomic Stability of the Country. *Polish Journal of Management Studies, 19*(2), 61–74. [GoogleScholar] [CrossRef]
11. 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 & Social Change*, *172*(2021), 121040. [GoogleScholar] [CrossRef]
12. Cabinova, V., Onuferova, E., Gallo, P. Jr., Gallo, P., & Gallo, J. (2018). A Comparative Analysis of Modern Performance Methods in Economic Practice. *Montenegrin Journal of Economics, 14*(4), 85–96. [GoogleScholar] [CrossRef]
13. Cai, Y. (2011). Factors Affecting the Efficiency of the BRICS' National Innovation Systems: A Comparative Study Based on DEA and Panel Data Analysis. *Discussion Papers, 2011*(52), 1–24. [GoogleScholar] [CrossRef]
14. Cano-Kollmann, M., Hamilton, R., & Mudambi, R. (2017). Public Support for Innovation and the Openness of Firms' Innovation Activities. *Industrial and Corporate Change, 26*(3), 421‒442. [GoogleScholar] [CrossRef]
15. Carayannis, E. G., Grigoroudis, E., & Goletsis, Y. (2016). A Multilevel and Multistage Efficiency Evaluation of Innovation Systems: A Multiobjective DEA Approach. *Expert Systems with Applications, 62,* 63‒80. [GoogleScholar] [CrossRef]
16. Castillo, V., Garone, L. F., Maffioli, A., Rojo, S., & Stucchi, R. (2020). Knowledge Spillovers Through Labour Mobility: An Employer–Employee Analysis. *The Journal of Development Studies, 56*(3), 469‒488. [GoogleScholar] [CrossRef]
17. Cozzens, S. E. (2012). Editor's Introduction: Distributional Consequences of Emerging Technologies. *Technological Forecasting and Social Change, 79*(2), 199‒203. [GoogleScholar] [CrossRef]
18. Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the Efficiency of Decision Making Units. *European Journal of Operational Research, 2*(6), 429–444. [GoogleScholar] [CrossRef]
19. Chapman, G., & Hewitt-Dundas, N. (2018). The Effect of Public Support on Senior Manager Attitudes to Innovation. *Technovation*, *69*, 28‒39. [GoogleScholar] [CrossRef]
20. Chen, C. P., Hu, J. L., & Yang, C. H. (2011). An International Comparison of R&D Efficiency of Multiple Innovative Outputs: The Role of the National Innovation System. *Innovation: Management, Policy and Practice, 13*(3), 341–360. [GoogleScholar] [CrossRef]
21. Danova, M., Kravcakova Vozarova, I., & Sira, E. (2021). Innovations in Human Resources Management: Impact on Economic Growth. *Marketing and Management of Innovations*, 3, 53–65. [GoogleScholar] [CrossRef]
22. Debreu, G. (1951). The Coefficient of Resource Utilization. *Econometrica, 19*(3), 273–292. [GoogleScholar] [CrossRef]
23. Dumont, M. (2017). Assessing the Policy Mix of Public Support to Business R&D. *Research Policy, 46*(10), 1851‒1862. [GoogleScholar] [CrossRef]
24. Edquist, Ch., Zabala-Iturriagagoitia, J. M., Barbero, J., & Zofío, J. L. (2018). On the Meaning of Innovation Performance: Is the Synthetic Indicator of the Innovation Union Scoreboard Flawed? *Research Evaluation, 27*(3), 196–211. [GoogleScholar] [CrossRef]
25. Emrouznejad, A., & Yang, G. L. (2018). A Survey and Analysis of the First 40 Years of Scholarly Literature in DEA: 1978 – 2016. *Socio-Economic Planning Sciences, 2018*(6), 4–8. [GoogleScholar] [CrossRef]
26. Erdin, C., & Çağlar, M. (2023). National Innovation Efficiency: A DEA-Based Measurement of OECD Countries. *International Journal of Innovation Science, 15*(3), 427–456. [GoogleScholar] [CrossRef]
27. Eskelinen, J. (2017). Comparison of Variable Selection Techniques for Data Envelopment Analysis in a Retail Bank. *European Journal of Operational Research, 259*(2), 778–788. [GoogleScholar] [CrossRef]
28. European Commission (2022). Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Region: A New European Innovation Agenda. [Link]
29. Farrell, M. J. (1957). The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society. Series A, 120*(3), 253‒290. [GoogleScholar] [CrossRef]

30. Friedman, L., & Sinuany-Stern, Z. (1998). Combining Ranking Scales and Selecting Variables in the DEA Context: The Case of Industrial Branches. *Computers & Operations Research, 25*(9), 781–791. [GoogleScholar] [CrossRef]

31. Gavurova, B., Halaskova, M., & Korony, S. (2019). Research and Development Indicators of EU28 Countries from Viewpoint of Super-Efficiency DEA Analysis. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis* 67(1), 225–242. [GoogleScholar] [CrossRef]

32. Guan, J., & Chen, K. (2012). Modelling the Relative Efficiency of National Innovation Systems. *Research Policy, 41*(1), 102−115. [GoogleScholar] [CrossRef]

33. Guo, D., Guo, Y., & Jiang, K. (2018). Governance and Effects of Public R&D Subsidies: Evidence from China. *Technovation*, *74–75*, 18−31. [GoogleScholar] [CrossRef]

34. Hauser, C., Siller, M., Schatzer, T., Walde, J., & Tappeiner, G. (2018). Measuring regional innovation: A Critical Inspection of the Ability of Single Indicators to Shape Technological Change. *Technological Forecasting and Social Change, 129*, 43–55. [GoogleScholar] [CrossRef]

35. Hewitt-Dundas, N., & Roper, S. (2018). Exploring Market Failures in Open Innovation. *International Small Business Journal: Researching Entrepreneurship, 36*(1), 1−26. [GoogleScholar] [CrossRef]

36. Huergo, E., Trenado, M., & Ubierna, A. (2016). The Impact of Public Support on Firm Propensity to Engage in R&D: Spanish Experience. *Technological Forecasting and Social Change, 113*, 206−219. [GoogleScholar] [CrossRef]

37. Hushko, S., Kulishov, V., Hangoni, T., Puriy, H., Kuzysin, B., & Sip, M. (2021). Global Work Mobility in the Integration Conditions. *Quality – Access to Success, 22*(183), 72–77. [GoogleScholar] [CrossRef]

38. Janger, J., Schubert, T., Andries, P., Rammer, C., & Hoskens, M. (2017). The EU 2020 Innovation Indicator: A Step Forward in Measuring Innovation Outputs and Outcomes? *Research Policy, 46*(1), 30–42. [GoogleScholar] [CrossRef]

39. Jugend, D., Fiorini, P. D., Armellini, F., & Ferrari, A. G. (2020). Public Support for Innovation: A Systematic Review of the Literature and Implications for Open Innovation. *Technological Forecasting and Social Change, 156*, 119985. [GoogleScholar] [CrossRef]

40. Jurickova, E., Pilik, M., & Kwarteng, M. A. (2019). Efficiency Measurement of National Innovation Systems of the European Union Countries: DEA Model Application. *Journal of International Studies, 12*(4), 286–299. [GoogleScholar] [CrossRef]

41. Kang, K. N., & Park, H. (2012). Influence of Government R&D Support and Inter-Firm Collaborations on Innovation in Korean Biotechnology SMEs. *Technovation, 32*(1), 68−78. [GoogleScholar] [CrossRef]

42. Kontolaimou, A., Giotopoulos, I., & Tsakanikas, A. (2016). A Typology of European Countries Based on Innovation Efficiency and Technology Gaps: The Role of Early-Stage Entrepreneurship. *Economic Modelling, 52,* 477−484. [GoogleScholar] [CrossRef]

43. Kwilinski, A., Lyulyov, O., & Pimonenko, T. (2023a). Environmental Sustainability within Attaining Sustainable Development Goals: The Role of Digitalization and the Transport Sector. *Sustainability, 15*(14), 1–14. [GoogleScholar] [CrossRef]

44. Kwilinski, A., Lyulyov, & O., Pimonenko, T. (2023b). Unlocking Sustainable Value through Digital Transformation: An Examination of ESG Performance. *Information, 14*(8), 1–18. [GoogleScholar] [CrossRef]

45. Levchenko, V., Kobzieva, T., Boiko, A., & Shlapko, T. (2018). Innovations in Assessing the Efficiency of the Instruments for the National Economy De-Shadowing: The State Management Aspect. *Marketing and Management of Innovations*, 4, 361–371. [GoogleScholar] [CrossRef]

46. Lipkova, L., & Braga, D. (2016). Measuring Commercialization Success of Innovations in the EU. *Marketing and Management of Innovations*, 4, 15–30. [GoogleScholar]

47. Matei, M. M., & Aldea, A. (2012). Ranking National Innovation Systems According to their Technical Efficiency. *Procedia - Social and Behavioral Sciences, 62*(2012), 968–974. [GoogleScholar] [CrossRef]

48. Narayanan, E., Ismail, W. R., & Mustafa, Z. (2022). A Data-Envelopment Analysis-Based Systematic Review of the Literature on Innovation Performance. *Heliyon, 8*(2022), 1–15. [GoogleScholar] [CrossRef]

49. Omrani, H., Valipour, M., & Mamakani, S. J. (2019). Construct a Composite Indicator Based on Integrating Common Weight Data Envelopment Analysis and Principal Component Analysis Models: An Application for Finding Development Degree of Provinces in Iran. *Socio-Economic Planning Sciences*, 68, 100618. [GoogleScholar] [CrossRef]

50. Pan, T. W., Hung, S. V., & Lu, W. M. (2010). DEA Performance Measurement of the National Innovation System in Asia and Europe. *Asia-Pacific Journal of Operational Research, 27*(3), 369–392. [GoogleScholar] [CrossRef]

51. Radicic, D. (2019). Effectiveness of Public Procurement of Innovation versus Supply-Side Innovation Measures in Manufacturing and Service Sectors. *Science and Public Policy, 46*(5), 732−746. [GoogleScholar] [CrossRef]

52. Ratner, S. V., Balashova, S. A., Lychev, A. V. (2022). The Efficiency of National Innovation Systems in Post-Soviet Countries: DEA-Based Approach. *Mathematics, 10*, 1–23. [GoogleScholar] [CrossRef]

53. Royston, P. (1995). Remark AS R94: A Remark on Algorithm AS 181: The W-test for Normality. *Applied Statistics, 44*(4), 547–551. [GoogleScholar] [CrossRef]

54. Slavinskaite, N., Lapinskiene, G., Hlawiczka, R., & Vasa, L. (2022). Financial Innovation Management: Impact of Fiscal Decentralization on Economic Growth of the Baltic Countries. *Marketing and Management of Innovations*, 1, 257–271. [GoogleScholar] [CrossRef]
55. Smoliy, L., Revutska, A., & Novak, I. (2018). Influence of Innovation Factor in Economic Dynamics in Europe. *Marketing and Management of Innovations*, 1, 247–258. [GoogleScholar] [CrossRef]
56. Spanos, Y. E., Vonortas, N. S., & Voudouris, I. (2015). Antecedents of Innovation Impacts in Publicly Funded Collaborative R&D Projects. *Technovation, 36-37*, 53–64. [GoogleScholar] [CrossRef]
57. Sip, M., Kuzysin, B., Sabolik, M, & Valco, M. (2023). Human Dignity in Inpatient Care: Fragments of Religious and Social Grounds. *Religions, 14*(6), 1–16. [GoogleScholar] [CrossRef]
58. Toloo, M, Keshavarz, E. & Hatami-Marbini, A. (2021). Selecting Data Envelopment Analysis Models: A Data-Driven Application to EU Countries. *Omega, 101*(2021), Article 102248. [GoogleScholar] [CrossRef]
59. Vanino, E., Roper, S., & Becker, B. (2019). Knowledge to Money: assessing the Business Performance Effects of Publicly Funded R&D Grants. *Research Policy, 48*(7), 1714–1737. [GoogleScholar] [CrossRef]
60. Vokoun, M. (2016). Innovation Behaviour of Firms in a Small Open Economy: The Case of the Czech Manufacturing Industry. *Empirica, 43*(1), 111–139. [GoogleScholar] [CrossRef]
61. Wang, S., Fan, J., Zhao, D., & Wang, S. (2016). Regional Innovation Environment and Innovation Efficiency: The Chinese Case. *Technology Analysis & Strategic Management, 28*(4), 396–410. [GoogleScholar] [CrossRef]
62. Wei, J., & Liu, Y. (2015). Government Support and Firm Innovation Performance: Empirical Analysis of 343 Innovative Enterprises in China. *Chinese Management Studies, 9*(1), 38–55. [GoogleScholar] [CrossRef]
63. World Bank (2022). Indicators. [Link]
64. Xu, K., Mei, R., Liang, L., & Sun, W. (2023). Regional Convergence Analysis of Sustainable Innovation Efficiency in European Union Countries. *Journal of Environmental Management*, *325*, Article 116636. [GoogleScholar] [CrossRef]

Оцінювання ефективності інновацій у країнах ЄС: підхід DEA

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Інновації, наука та технології, які є одними з найважливіших інструментів для досягнення економічного зростання, добробуту та конкурентоспроможності в локальному та глобальному бізнес-середовищі, дедалі більше привертають увагу. Таким чином, підвищення рівня ефективності інновацій у країнах має бути одним із пріоритетів ЄС. Метою статті є аналіз розвитку ефективності інновацій у країнах-членах ЄС та оцінка використання ресурсів, які надходять до їхніх національних інноваційних систем. Для визначення ефективності країн ЄС були застосовані базові орієнтовані на результати моделі DEA. Вибірка дослідження сформовано на основі даних Світового банку. У статті проведено порівняльний аналіз вхідних змінних (державні витрати на освіту у відсотках від валового внутрішнього продукту, витрати на дослідження та розробки у відсотках від валового внутрішнього продукту, кількість науковців у сфері досліджень і розробок на мільйон осіб) та вихідних змінних (кількість патентних заявок, обсяги високотехнологічного експорту у відсотках від експорту продукції виробничого сектору, кількість наукових і технічних статей у журналах). Рівень ефективності окремих країн ЄС кількісно оцінено з використанням програмного забезпечення DEA Solver (LV 8.0). На основі методу масштабування визначено та представлено у картограмі 5 груп країн із подібними рівнями ефективності. За аналізований період такі країни було віднесено до ефективних – Франція, Німеччина, Ірландія, Італія, Мальта, Румунія (та Сполучене Королівство у 2018–2019 роках). Такі країни, як Швеція, Данія, Бельгія, Фінляндія та Австрія, демонстрували найвищі значення вибраних вхідних показників, але коефіцієнт ефективності показав середні або нижчі за середні результати. Результати цього дослідження підтвердили гіпотезу, що багато з країн, які займають топові позиції у світових рейтингах інновацій, неправильно використовують та недооцінюють ресурси, які надходять до їхніх національних інноваційних систем. Політикам та розробникам стратегічних планів для підвищення ефективності інновацій у країнах ЄС буде надано можливість інтегрувати результати цього дослідження у реальні пропозиції та рішення.

Ключові слова: аналіз охоплення даних; вхідні змінні; національна інноваційна стратегія; вихідні змінні; дослідження, розробки.