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Advancing DEA-Based Assessment of Innovation Efficiency Through Feature Selection

Jasmina Popovska
University of Ljubljana, Faculty of Public Administration, Slovenia
jp7392@student.uni-lj.si
https://orcid.org/0009-0006-5472-1286

Lan Umek
University of Ljubljana, Faculty of Public Administration, Slovenia
lan.umek@fu.uni-lj.si
https://orcid.org/0000-0003-2730-2597

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ABSTRACT

Purpose: This article investigates innovation efficiency in European Union (EU) countries and addresses methodological inconsistencies in previous research. It evaluates how efficiently national innovation systems (NISs) convert innovation-related inputs into measurable outputs, with the aim of improving the reliability and interpretability of efficiency assessments.

Design/Methodology/Approach: To identify a parsimonious and statistically relevant set of indicators, the study employs Multi-Cluster Feature Selection (MCFS), a hybrid method that combines unsupervised clustering with the supervised Least Absolute Shrinkage and Selection Operator (LASSO). The technique is applied to longitudinal data derived from the European Innovation Scoreboard (EIS), resulting in a consistent subset of thirteen indicators encompassing key stages of the innovation process. Following indicator selection, a two-stage Data Envelopment Analysis (DEA) model is applied to assess efficiency at both the technological/knowledge-production stage and the commercialisation stage. This approach supports differentiation between countries that are efficient in generating knowledge outputs and those that are effective in converting these outputs into economic results.

Findings: The findings indicate substantial variation in innovation efficiency across EU countries. Few countries achieve high efficiency at both stages, highlighting the difficulty of sustaining performance across the entire innovation value chain. The analysis reveals persistent inefficiencies, particularly at the commercialisation stage, consistent with previous research emphasising structural barriers to translating research and development outputs into economic gains. The results also demonstrate that differences in country rankings reported in the literature are often attributable to differences in indicator selection and DEA model specification. Even among studies using similar DEA frameworks, variation in indicator inclusion leads to different classifications of country performance.

Practical Implications: The methodological choices improve comparability across countries and over time, while also reducing complexity. The two-stage DEA structure provides policymakers with further insight into the internal functioning of national innovation systems and the sources of inefficiency, particularly at the commercialisation stage. This enables more targeted policy interventions that distinguish between weaknesses in knowledge production and weaknesses in the economic exploitation of innovation outputs.

Originality/Value: This study contributes to the literature by introducing MCFS into the field of innovation efficiency assessment and by offering a streamlined, empirically justified set of indicators suitable for DEA applications. By combining a data-driven feature selection approach with a two-stage DEA model, the article addresses methodological fragmentation in previous research and provides a more transparent and replicable framework for evaluating national innovation systems.

Keywords: innovation policy, innovation efficiency, innovation indicators, data envelopment analysis, feature selection

Nadgradnja DEA-ocenjevanja inovacijske učinkovitosti z izbiro značilk

POVZETEK

Namen: članek preučuje inovacijsko učinkovitost držav članic Evropske unije (EU) in obravnava metodološke nedoslednosti v dosedanjih raziskavah. Ovrednoti, kako učinkovito nacionalni inovacijski sistemi (NIS) pretvarjajo vložke, povezane z inovacijami, v merljive rezultate, s ciljem izboljšati zanesljivost in interpretabilnost ocen učinkovitosti.

Zasnova/metodologija/pristop: za določitev statistično relevantnega nabora kazalnikov študija uporablja metodo MCFS (*Multi-Cluster Feature Selection* – MCFS), ki je hibridna metoda, ki združuje nenadzorovano razvrščanje v skupine in nadzorovano regresijo (*Least Absolute Shrinkage and Selection Operator* – LASSO). Tehnika je uporabljena na longitudinalnih podatkih iz Evropskega inovacijskega pregleda (*European Innovation Scoreboard* – EIS), kar je privedlo do konsistentnega nabora trinajstih kazalnikov, ki zajemajo ključne stopnje inovacijskega procesa. Po izbiri kazalnikov je uporabljena dvostopenjska metoda podatkovne ovojnice (*Data Envelopment Analysis* – DEA) za oceno učinkovitosti tako na stopnji tehnološke proizvodnje oziroma proizvodnje znanja kot tudi na stopnji komercializacije. Ta pristop omogoča razlikovanje med državami, ki so učinkovite pri ustvarjanju rezultatov znanja, in tistimi, ki so uspešne pri pretvarjanju teh rezultatov v gospodarske učinke.

Ugotovitve kažejo na znatne razlike v inovacijski učinkovitosti med državami članicami EU. Malo držav dosega visoko učinkovitost na obeh stopnjah, kar poudarja težavnost ohranjanja uspešnosti vzdolž celotne inovacijske vrednostne verige. Analiza razkriva trajne neučinkovitosti, zlasti na stopnji komercializacije, kar je skladno z dosedanjimi raziskavami, ki izpostavljajo strukturne ovire pri pretvarjanju rezultatov raziskav in razvoja v gospodarske koristi. Rezultati prav tako dokazujejo, da so razlike v razvrstitvah držav, ki jih opažamo v literaturi, pogosto posledica različnih izborov kazalnikov in specifikacij metode DEA. Tudi med študijami, ki uporabljajo podobne okvire DEA, razlike pri vključitvi kazalnikov vodijo do različnih razvrstitev uspešnosti držav.

Praktične implikacije: metodološke odločitve omogočajo izboljšano primerljivost med državami in skozi čas, hkrati pa zmanjšujejo kompleksnost. Dvostopenjska struktura metode DEA oblikovalcem politik nudi globlji vpogled v notranje delovanje nacionalnih inovacijskih sistemov in vire neučinkovitosti, zlasti na stopnji komercializacije. To omogoča bolj ciljno usmerjene politične intervencije, ki razlikujejo med šibkostmi pri proizvodnji znanja in šibkostmi pri gospodarskem izkoriščanju inovacijskih rezultatov.

Izvirnost/vrednost: študija prispeva k literaturi z uvedbo metode MCFS na področje ocenjevanja inovacijske učinkovitosti in ponuja poenostavljen, empirično utemeljen nabor kazalnikov, primeren za uporabo v okviru metode DEA. S kombinacijo podatkovno zasnovanega pristopa k izbiri spremenljivk in dvostopenjske metode DEA članek obravnava metodološko razdrobljenost v dosedanjih raziskavah ter zagotavlja preglednejši in ponovljiv okvir za vrednotenje nacionalnih inovacijskih sistemov.

Ključne besede: *inovacijska politika, inovacijska učinkovitost, inovacijski kazalniki, analiza ovojnice podatkov, izbira značilk*

JEL: O, P

1 Introduction

Innovation is widely recognized by policymakers and scholars as a key driver of economic growth. Its positive influence of innovation on society and the economy has motivated governments to implement policies and programs promoting innovation (e.g. Innovation Union, Horizon 2020, Horizon Europe, European Institute of Innovation and Technology – EIT Regional Innovation Scheme – RIS program etc.). In 2025 the European Commission (EC) has forecasted to double the budget dedicated to research and development (R&D) and innovation activities to €175 billion for 2028–2034. The 10th Framework Programme for research and innovation will be part of a €409 billion European Competitiveness Fund. As public budgets expand, the EC and national governments face growing pressure to evaluate the efficiency and impact of these investments.

Innovation measurement and policy have been subjects of extensive research, with studies examining various indicators and approaches. The dominant quantitative approach in measuring National Innovation System (NIS) performance is based on composite indicators (e.g. Desai et al., 2002; Archibugi and Coco, 2004; Saltelli, 2007; OECD, 2008; Summary Innovation Index, 2023; Global Innovation Index, 2023; Innovation Output Indicator, 2014). The innovation composite indicators that are used in practice and for policy making purposes by policy makers in the past two decades is the European Union's Summary Innovation Index (SII) that has direct influence on the innovation programs and policies on supranational level in European Union (EU) (ex. EIT RIS program) and it is considered as a more relevant in this paper. SII is a composite indicator used within the European Innovation Scoreboard (EIS). EIS has been the main tool for comparative assessment of the innovation success and performance among European Union (EU) member countries for the past two decades.

According to Lundvall (1992) most relevant performance indicators for NIS should reflect the efficiency and effectiveness in producing, diffusing and exploiting economically useful knowledge. Edquist (2018) advanced this approach by measuring how much innovation output a country achieves relative to its innovation inputs. Similar efficiency-focused studies include Edquist (2014), Edquist and Zabala-Iturriagagoitia (2015), Edquist et al. (2018), Guan and Chen (2012), Hollanders and Celikel-Esser (2007), Cruz-Cazares et al. (2013), Hong et al. (2016), Jankowska et al. (2017), Global Innovation Index (2023) and Ansaloni et al. (2019).

Innovation efficiency, increasingly central in policy debates, refers to the degree to which innovation inputs are effectively transformed into innovation output and as efficient NIS would be considered the one where the output exceeds the input invested in the innovation process (Hollanders and Celikel-Esser, 2007). Most studies operationalize this by separating indicators into inputs (resources, determinants) and outputs (innovations). This input-output framework helps policymakers assess whether weak performance stems from insufficient investment or inefficient resource use (e.g. Mahroum and Al-Saleh, 2013; Edquist et al., 2018; Guan and Chen, 2012; Dutta et al. 2017; Jankowska et al., 2017; Ansaloni et al., 2019; GII efficiency index, 2019). The researchers argue that indicators that reflect the input character of innovation (causes, determinants) and the outputs of the innovative action (actual innovations) need to be considered separately. Additionally, the authors value only the relationship between the two sets of indicators (Edquist et al, 2018). Guan and Chen (2012) conclude that innovation efficiency is related to the concept of productivity and involves comparing the observed output to the maximum potential output obtainable from the input or comparing the observed input to the minimum potential input required to produce the output. Innovation efficiency can thus be understood, in line with the process view in Kemp et al (2003) and the Crépon-Duguet-Mairesse (CDM) framework (Crépon et al., 1998) as the effectiveness with which a country transforms its innovation inputs into outputs.

Among the key determinants of NIS efficiency are the maturity of the national financial system and the management of the national intellectual capital. Gan (2022) shows that mature financial systems improve efficiency by easing access to capital, a finding echoed by Low et al. (2018), who link stock market and banking development to stronger input-output conversion. Natalia et al. (2020) emphasize the role of intellectual capital strategies, classifying countries by their ability to leverage knowledge assets. Countries prioritizing intellectual capital management typically exhibit higher innovation efficiency.

Recent studies have examined the efficiency of NIS using various approaches. Studies have employed Data Envelopment Analysis (DEA) to assess the efficiency of NIS (Narayanan et al., 2022), introducing concepts like cross-productivity for dynamic peer-evaluation (Aparicio et al., 2020). DEA has been widely employed to assess NIS efficiency, considering inputs like innovation environment indicators and outputs such as economic performance or patents (Amatucci et al., 2024; Zhang, 2013; Adamovský and Gonda, 2019). Anderson and Stejskal (2019) employed a single-stage CCR (Charnes, Cooper and Rhodes) DEA model to evaluate the efficiency of innovation diffusion across EU countries.

In most recent studies the authors distinguish between two-stages of innovation process and have proposed two-stage DEA models to evaluate both technological or R&D and economic or commercialisation efficiency (Carayannis et al., 2016; Alnafrah, 2021; Tziogkidis et al., 2020; Anouze et al., 2024). The innovation efficiency research highlights the importance of improving science and technology transformation to enhance NIS efficiency (Zhang, 2013) and provides insights for policymakers to develop strategies for improving their innovation systems.

However, measuring the innovation efficiency of NIS requires a comprehensive set of input and output indicators that can effectively capture the multifaceted nature of innovation processes. Inputs such as R&D expenditure, human capital, IP and investments provide a foundation for innovation activities, while outputs like new product introductions, reflect the effectiveness of these activities. By utilizing a comprehensive set of indicators, policymakers can better assess and enhance the innovation capabilities of their countries. Thus, this paper focuses on identifying the most important and distinct input-output indicators, grounded in NIS theory (e.g. Lundvall 1992; Bačić and Aralica, 2016; Edquist et al. 2018;) and in the CDM framework that explains productivity by innovation output and the output by research investment as input (Crepon et al., 1998), which provide clear insights into the relationship between resources invested and innovations produced. This approach would offer policymakers a more focused and practical tool for decision-making, addressing the need for either increased investment or enhanced resource utilization.

The purpose of this article is to apply novel methods in selection of variables (indicators) and produce a simple tool and comprehensive analytical framework for assessing innovation efficiency of NIS, considering the two separate sub-processes for technological/knowledge production and commercialisation. The main objective is to avoid redundancy and providing actionable insights for policymakers, which involves several key steps:

a. Input-Output Framework: categorizing the indicators into inputs, intermediate outputs (throughputs)and outputs (Kemp et al., 2003). Inputs capture the resources devoted to innovation such as R&D expenditure, innovation-related human capital (e.g. R&D personnel, highly qualified employees and public support for innovation (e.g. subsidies, tax incentives).Intermediate outputs (throughputs) reflect the immediate, technical results of these R&D efforts (e.g., the number and share of new or significantly improved products and processes, the number of innovative and high-tech companies, patents and other intellectual property and investments). These intermediate outputs then serve as inputs to the second stage of the innovation process, where they are transformed through commercialisation activities into final outputs measured by market outcomes (e.g. export intensity, sales from new products etc.).

b. Feature Selection: Ensure that each selected variable captures a distinct aspect of the innovation process to avoid redundancy. Feature selection for unsupervised data is not so common, yet especially useful - this is an application to innovation efficiency data which is something novel. Indicators selection will also depend on reliable data sources, variables need to be available across EU member countries, ensuring comparability with widely recognized and robust data sources (e.g., IUS, Eurostat, OECD). Data processing and data imputation methods are applied to addressing the challenge with missing data and ensure completeness for the analysis.

c. Investment vs. Efficiency: Create a simple tool that helps determine whether the focus of a country should be on increasing investments or improving efficiency in the use of inputs.

2 Literature Review

Studies on innovation efficiency apply diverse input and output indicators. Common inputs include R&D expenditure, personnel costs and patent applications (Ochoa-Urrego and Gonzalez-Correa, 2024; Dobrzanski, 2018). Outputs often include patents granted and scientific publications (Lozano, 2002). Dobrzanski (2018) employed DEA to assess innovation efficiency in Central and Eastern European countries, using R&D spending as input and multiple innovation-related outputs. Barasa et al. (2019) examined the effects of innovation inputs on technical efficiency in African manufacturing firms, considering internal R&D, human capital development and foreign technology adoption. They found that combining absorptive capacity-enhancing inputs with foreign technology is crucial for improving efficiency. Lozano (2002) discusses various indicators used in science and technology policy, including input indicators, output indicators and those related to technological innovation, emphasizing their importance in international comparisons and policy development.

Four input groups dominate innovation efficiency studies:

- R&D Expenditure e.g. total R&D spending, as % of GDP or absolute (Chen et al., 2017; Edquist et al., 2018).
- Human Capital e.g. workforce education and skills, measured by tertiary attainment or researchers per capita (Ilchuk and Mushenyk, 2018; Gunadi et al., 2018).

- Intellectual Property (IPR) e.g. patents, trademarks, or design registrations as innovation proxies (Chen et al., 2017; Edquist et al., 2018; Ilchuk and Mushenyk, 2018; Wei et al., 2017).
- Financial Resources e.g. venture capital and startup funding, often relative to GDP (Gan, 2022; Low et al., 2018).

Outputs typically include:

- New product introductions such as market entry of new goods or services (Chen et al., 2017).
- Sales from new-to-market innovations e.g. share of revenues from innovative products (Chen et al., 2017; Edquist et al, 2018; Janger et al., 2017; Ledeneva, 2020).
- Startups and high-growth firms as new firm creation and fundraising (Vandresse et al., 2024).
- High-tech employment such as jobs generated in high-tech sectors (Ilchuk and Mushenyk, 2018; Ibrahim, 2022).

The existing literature on innovation efficiency measurement, primarily relies on many input and output indicators listed in the Innovation Union Scoreboard (IUS) or Global Innovation Index (GII). No consensus exists on which indicators to retain in the efficiency analysis and although there are existing classifications between inputs and outputs (Aralica et al., 2025) some of them such as patents are treated as inputs or outputs (Ansaloni et al., 2019). Existing frameworks either include overlapping indicators, reducing clarity, or reduce the set too aggressively, risking omission of key information. Furthermore, this could implicate the insights provided to policymakers regarding whether further investments are required or if existing resources should be used more efficiently.

A key research gap lies in the development of a streamlined and non-overlapping set of critical innovation indicators that can directly inform policymakers about the efficiency of innovation investments. Existing frameworks, such as the IUS, do not sufficiently distinguish between inputs and outputs in a manner that enables clear policy guidance on whether additional funding is necessary or if the primary issue lies in the inefficient use of current inputs. The SII and EIS methodology has been subject of many critics since the beginning mainly due to the lack of an appropriate theoretical discussion of the selected individual indicators, its key dimensions and categories where it does not explain relations among its components, the applied methodology in the construction of SII (equal weights, aggregation method, missing values etc.)and especially the absence of a clear definition of the country's innovation performance that is in the focus of the assessment (e.g. Godin, 2003; Grupp and Mogee, 2004; Grupp and Schubert, 2010; Edquist and Zabala-Iturriagagoitia, 2015, Edquist et al., 2018).

3 Methods

This section outlines the methods applied. First, we review prior applications of DEA, the most used approach to assess NIS efficiency. We then describe the Multi-Cluster Feature Selection (MCFS) procedure used to select input and output indicators for the DEA model.

3.1 Previous DEA Studies

DEA is a non-parametric method that measures relative efficiency using multiple inputs and outputs (Bhat et al., 2001). It applies linear programming to construct efficiency frontiers. Innovation efficiency improves when a country produces more outputs with the same inputs, or the same outputs with fewer inputs. The basic DEA models can be solved using linear programming, typically requiring multiple runs for each Decision-Making Unit (DMU) (Appa and Williams, 2002). Innovation efficiency is measured as the level of resource use in producing innovation outputs. A unit improves its efficiency when it generates more outputs with the same number of inputs or with fewer inputs with the same number of outputs. DEA is particularly useful in contexts where the process is complex and involves several factors, making it suitable for evaluating innovation systems that transform resources into innovative outputs (Hashimoto and Haneda, 2008; Carayannis et al., 2016). The flexibility of DEA allows researchers to analyse different dimensions of innovation efficiency, including technological advancements, R&D activities and overall system performance (Kotsemir, 2013; Xu et al., 2020). The application of the BCC (Banker, Charnes and Cooper) model within DEA frameworks has been prevalent in assessing technological innovation efficiency across various sectors. This model allows for variable returns to scale, making it particularly relevant for innovation systems where outputs may not increase proportionally with inputs (Wang et al., 2019; Wang and Mu, 2019).

DEA applications have evolved from simple one-stage models to two-stage and network approaches. Early work ranked countries by overall innovation efficiency, while later studies distinguished between knowledge production and commercialisation (Guan and Chen, 2012; Liou, 2009). Recent advances include multi-objective DEA (Carayannis et al., 2016), bootstrapped network DEA (Alnafrah, 2021), multi-directional efficiency analysis combined with Partial Least Squares (PLS) regression (Tziogkidis et al., 2020) and dynamic network DEA with inter-temporal effects (Anouze et al., 2024).

Two-stage and network DEA models allow for separate assessment of technological development/knowledge production and technological/knowledge commercialisation phases - acknowledging the multi-stage nature of NIS based on Schumpeter’s (1934) definition of innovation. Studies like Guan and Chen (2012) and Liou (2009) provide insights into the structural complexity of innovation processes across countries. Carayannis et al. (2016) applies a multi-objective DEA model formulated for multi-stage innovation process; followed by a multicriteria ordinal regression to analyse environmental factors. Tziogkidis et al. (2020) implement a Multi-Directional Efficiency Analysis (MEA) - a DEA variant that computes separate efficiency scores for each innovation input and output, addressing the issue of compensability and an iterative PLS regression approach to gauge each country's output sensitivity to input improvements. Anouze et al. (2024) apply a dynamic-network DEA - a two-stage DEA model that accounts for interlinked sub-processes and dynamic (inter-temporal) effects. The NIS is modelled as a network where Stage 1 converts innovation inputs into intermediate outputs and Stage 2 converts those into final innovation outcomes. In addition to the aforementioned, the two-stage DEA models have been discussed by other authors as well such as Cai and Hanley (2012), Cullmann et al. (2011), Lv (2011), Wu et al. (2010), Kaihua and Mingting (2014) and Chun et al. (2015), that consider that NIS are composed of the two key sub-processes or phases. Thus, Technological development/Knowledge production sub-process transforms R&D inputs into technology/knowledge outcomes that become inputs in the Technological/Knowledge commercialisation sub-process that transforms them in commercial results. Other methodological advancements include the use of the Malmquist productivity index to capture dynamic changes over time and bootstrapped DEA for bias correction.

3.2 Multi-Cluster Feature Selection (MCFS)

Variable selection critically shapes DEA results: too many variables reduce discrimination, while omitting key one's biases scores. Researchers have applied methods such as Principal Component Analysis (PCA), Efficiency Contribution Measure (ECM), regression-based selection, bootstrapping and stepwise approaches. PCA is widely used to reduce dimensionality and mitigate multicollinearity. Adler and Yazhemsky (2010) demonstrated its efficacy, particularly when input correlations exceed 0.8. However, PCA's transformation of variables compromises interpretability and may exclude temporally relevant features. The ECM method, as analysed by Nataraja and Johnson (2011), evaluates each variable's marginal impact on DEA efficiency. It performs well under low inter-variable correlations (<0.2) with sufficiently large datasets (N≥300). While ECM is computationally efficient and intuitive, it lacks the capacity to model underlying structural groupings or temporal changes. Regression-based variable selection techniques estimate the relationship between inputs/outputs and DEA scores, commonly employing OLS or logistic models. These approaches assume linearity and often falter with small samples or multicollinearity. Bootstrapping methods (e.g., Simar and Wilson, 2007) resample data to assess the stability and statistical significance of DEA results under varying model specifications. While statistically rigorous, bootstrapping is computationally intensive and impractical for high-dimensional, time-dependent analyses. The stepwise approach (Wagner and Shimshak, 2007) sequentially adds or removes variables based on changes in DEA efficiency scores. Although simple and interpretable, this method is prone to overfitting and may yield unstable results with correlated or high-dimensional variables. Jenkins and Anderson (2003) proposed statistical correlation-based reduction strategies to eliminate redundant variables. These methods, while reducing dimensionality, may inadvertently discard features with significant explanatory power.

In the research on NIS Innovation Efficiency and applied DEA, only few articles incorporate statistical methods to improve indicator selection and model robustness, but mainly to address multicollinearity and correlations, such as Correlation analysis or Principal Component Analysis (PCA). To address some of the limitations of these methods, we have chosen to apply a feature selection and not a feature creation method. This study applies MCFS, which preserves interpretability while capturing latent structural patterns and consistency over time – advantages over traditional methods. To our knowledge, MCFS has not yet been applied to indicator selection in innovation efficiency. We implemented a sophisticated pipeline for MCFS over time, designed to extract meaningful variables from complex international datasets. No previous study has tried to apply MCFS for selection of indicators within innovation efficiency context, which affect the reliability of statistical inference in the DEA application.

The aim is to identify input, intermediate output and output indicators that best differentiate countries year by year. The process first determines the optimal number of clusters using KMeans and silhouette scores (Rousseeuw, 1987), with a minimum cluster size constraint. This score evaluates how similar each sample is to its own cluster versus other clusters, providing a heuristic for the best partitioning. Importantly, a minimum cluster size constraint is enforced to avoid unstable or meaningless clusters, a practical adaptation for real-world datasets where country-level data might be sparse or uneven. We then examined different values of the number of clusters and selected the one with the highest silhouette score that also respects the cluster size constraint. Once clusters are assigned for a given year, the script employs LASSO regression (Tibshirani, 1996) to perform feature selection. For each cluster, a binary target vector is created (countries in cluster = 1, others = 0) and Lasso is used to model this classification using all features. We use LASSO and not regression as it excludes some of the features i.e. sets regression coefficients to exactly zero. This results in sparse solutions where unimportant features are effectively excluded. By aggregating the absolute value of coefficients across all clusters and years, the script produces cumulative importance scores for each feature. This method combines the local interpretability of Lasso with the global structure provided by clustering, aligning with the principles of MCFS as described by Cai et al. (2010).

After feature importance scores are accumulated for each feature in all years, we applied a dual-threshold heuristic to select the most informative subset. One criterion is based on the elbow method, which identifies the point of greatest drop in sorted feature scores, akin to a breakpoint in marginal gains. The second threshold considers the cumulative explained importance, selecting the smallest number of features that account for 90% of total importance. By choosing the minimum of these two cutoffs, we balanced between including too many redundant variables and excluding subtle but relevant indicators. MCFS is an unsupervised feature selection method. Based on a multi-cluster assumption, it aims at finding meaningful features using sparse reconstruction of spectral basis using LASSO.

Algorithm: Multi-Cluster Feature Selection Over Time

Dataset:

$D = \{X_y \mid y \in \{2018, 2020, 2022, 2024\}\}$, where $X_y \in R^{27*d}$ for each year y; and d is the number of features.

Feature groups:

$G = \{G_1, G_2, G_3\}$, where each group G_k contains d_k features (columns). These groups are inputs, intermediate outputs and outputs.

Parameters:

– Minimum cluster size: $N_{min} = 3$
– Cluster range: $K_{min} = 2$, $K_{max} = 10$
– Lasso regularization parameter: $\lambda > 0$ (default: $\lambda = 1.0$)
– Cumulative explained importance threshold: $\alpha \in (0, 1]$ (default: $\alpha = 0.90$)

Process:

1. For each feature group $G_k \in G$ (with $d_k = | G_k |$, i. e. number of features):
2. For each year $y \in \{2018, 2020, 2022, 2024\}$:
   a. Extract group-specific feature matrix: $X_y (G_k) \in R^{27*dk}$ (select columns for G_k only)
   b. Determine optimal number of clusters K^*_y:
      – For each $K \in [K_{min}, K_{max}]$:
      – Fit KMeans: $C_K = \text{KMeans}(X_y (G_k), K)$
      – Compute silhouette score s_K
      – If any cluster has fewer than N_{min} samples, set $s_K := -\infty$
      – Choose $K^*_y = \text{argmax}_K\, s_K$
   c. Assign clusters:
      – Obtain cluster labels C_y for K^*_y clusters
   d. For each cluster $l = 1, \ldots, K^*_y$:
      – Construct binary target $z_{y,l}$ (indicator for cluster membership)
      – Fit Lasso regression:

$$\hat{\beta}_{y,l} = arg\,\min_{\beta} \frac{1}{2 * N\,y} \left\| z_{y,l} - X_y(G_k) \cdot \beta \right\|_2 + \lambda \cdot \|\beta\|_1 = arg\,\min_{\beta} \frac{1}{54} \left\| z_{y,l} - X_y(G_k) \cdot \beta \right\|_2 + \lambda \cdot \|\beta\|_1$$

      (since $N_y = 27$, denominator is $2*N_y = 54$). Here $||_2$ stands for Eucledean (sum of squares) and $||_1$ for Manhattan norm (sum of absolute values)
      – Store absolute coefficients $a_{y,l} = |\hat{\beta}_{y,l}| \in R^{dk}$

3. Aggregate feature importance across all years and clusters: For each feature f = 1, ..., d_k

$$I_f = \sum_{y \in \{2018,2020,2022,2024\}} \sum_{l=1}^{K^* y} a_{y,l}$$

4. Feature selection with dual-threshold heuristic:

   Let I_f be the importances sorted in decreasing order: $I_1 \geq I_2 \geq \ldots \geq I_{dk}$.

   a. Elbow method:

      $f_{elbow} = \text{argmax}_{f=1,\ldots,dk-1} (I_f \geq I_{f+1})$

   b. Cumulative explained importance (α):

      Find smallest n_α such that $\frac{\sum_{F=1}^{n_\alpha} I_f}{\sum_{f=1}^{d_k} I_f} \geq \alpha$

   c. Final feature set:

      Let $n^* = \min(f_{elbow}, n_\alpha)$

      Select $F^* = \{f_1, \ldots, f_{n^*}\}$

Results:

For each group G_k: selected features $G_k^* \subseteq \{1, \ldots, d_k\}$

3.3 Selected indicators – MCFS results

This analysis adopts the indicator definitions and statistics from the European Innovation Scoreboard (EIS) 2024 to ensure comparability. Definitions and data sources are provided in European Innovation Scoreboard 2024 Methodology Report published by the Directorate-General for Research and Innovation, European Commission on 8th of July 2024 at the following link. All indicators were included in the feature selection except impact indicators, as the study focuses on inputs and outputs; assessing impact lies beyond its scope. Table 1 presents the indicators, their categorisation into inputs, intermediate outputs and outputs and the subset selected through MCFS.

Table 1: EIS Indicators list and selected indicators with MCFS

Code	Indicator	Category	Selected with MCFS
1.1.1	New doctorate graduates in science, technology, engineering and mathematics (STEM) per 1000 population aged 25-34	Input	Yes
1.1.2	Percentage population aged 25-34 having completed tertiary education	Input	No
1.1.3	Percentage population aged 25-64 participating in lifelong learning	Input	No

Code	Indicator	Category	Selected with MCFS
1.2.1	International scientific co-publications per million population	Intermediate	No
1.2.2	Scientific publications among the top 10% most cited publications worldwide as percentage of total scientific publications of the country	Intermediate	No
1.2.3	Foreign doctorate students as a percentage of all doctorate students	Input	No
1.3.1	Broadband penetration	Input	No
1.3.2	Individuals who have above basic overall digital skills (% share)	Input	No
2.1.1	R&D expenditure in the public sector (percentage of GDP)	Input	Yes
2.1.2	Venture capital expenditures (percentage of GDP)	Intermediate	Yes
2.1.3	Direct government funding and government tax support for business R&D (percentage of GDP)	Input	Yes
2.2.1	R&D expenditure in the business sector (percentage of GDP)	Input	Yes
2.2.2	Non-R&D innovation expenditures (percentage of turnover)	Input	Yes
2.2.3	Innovation expenditures per person employed	Input	No
2.3.1	Enterprises providing training to develop or upgrade ICT skills of their personnel	Input	No
2.3.2	ICT specialists (as a percentage of total employment)	Input	No
3.1.1	SMEs introducing product innovations (percentage of SMEs)	Intermediate	No
3.1.2	SMEs introducing business process innovations (percentage of SMEs)	Intermediate	Yes
3.2.1	Innovative SMEs collaborating with others (percentage of SMEs)	Intermediate	Yes
3.2.2	Public-private co-publications per million population	Intermediate	No
3.2.3	Job-to-job mobility of Human Resources in Science & Technology	Input	No
3.3.1	PCT patent applications per billion GDP (in PPS)	Intermediate	Yes
3.3.2	Trademark applications per billion GDP (in PPS)	Intermediate	No
3.3.3	Design applications per billion GDP (in PPS)	Intermediate	Yes
4.1.1	Employment in knowledge-intensive activities (percentage of total employment)	Intermediate	Yes

Code	Indicator	Category	Selected with MCFS
4.1.2	Employment in innovative enterprises	Intermediate	No
4.2.1	Exports of medium and high technology products as a share of total product exports	Output	No
4.2.2	Knowledge-intensive services exports as percentage of total services exports	Output	Yes
4.2.3	Sales of new-to-market and new-to-enterprise innovations as percentage of turnover	Output	Yes
4.3.1	Resource productivity	Impact	No
4.3.2	Air emissions by fine particulate matter (PM2.5) in Industry	Impact	No
4.3.3	Development of environment-related technologies, percentage of all technologies	Impact	No

Source: Own and EC, 2024

The European Innovation Scoreboard (EIS) reports normalized scores over an eight-year period. Owing to missing data, this study uses four biennial years such as 2018, 2020, 2022and 2024, combined with data processing and imputation. The original dataset contained thirty-two indicators covering research, innovation and economic performance from 2017 to 2024. Only every second year was retained because many key indicators are measured biennially (e.g., digital skills, non-R&D innovation expenditures, SME innovation activities, employment in innovative enterprises and sales of new-to-market products). Missing values were primarily filled using Eurostat and other official sources. If a single value was missing, regression-based imputation estimated it from other years. Indicators missing all observations for a country were excluded for example, Job-to-job mobility of Human Resources in Science and Technology. The final dataset comprises thirteen indicators, each with official names and codes, measured biennially from 2018 to 2024. The full dataset is provided in Appendix 1.

3.3.1 Inputs

Thirteen input indicators initially captured education and human capital (e.g., STEM doctorate graduates, tertiary education, lifelong learning), digital infrastructure and skills (broadband, digital literacy), R&D funding (public and business expenditures, tax support) and organizational readiness (ICT training, ICT specialists). MCFS retained *five*: STEM doctorate graduates, public R&D expenditure, direct government support for business R&D, business R&D expenditure and non-R&D innovation expenditures. The retained features emphasize countries' financial and human investments in innovation, suggesting that these indicators were more effective in distinguishing clusters of countries over time. This reflects their strong correlation with innovation system performance and their ability to capture systemic capacity differences across nations. More behavioural or enabling indicators like digital skills and ICT employment may have shown lower variability or discriminative power in relation to innovation clustering.

3.3.2. Intermediate Outputs

Intermediate output indicators are considered to be results of knowledge production stage and inputs for commercialisation stage. EIS does not distinguish this group of indicators and they have different categorisation as either inputs or outputs. We have consulted several studies and categorise them based on the two phases of innovation process.

Twelve intermediate output indicators initially captured different aspect of research output, commercialisation, or knowledge work, such as including publications, citations, SME innovations, co-publications, patents, trademarks, design applications, venture capital and high-tech employment. MCFS retained *six*: venture capital expenditures, SMEs with process innovations, collaborating innovative SMEs, PCT patent applications, design applications and employment in knowledge-intensive activities. These indicators collectively represent a focus on commercial innovation, intellectual property generation and networked business innovation, especially within small and medium-sized enterprises. The selection reflects the tendency for these indicators to vary meaningfully between countries, enabling robust clustering. Conversely, scientific publication indicators may have been dropped because high-performing countries often converge on publication volume, making these metrics less useful for distinguishing innovation typologies in a clustering context.

3.3.3 Outputs

Three output indicators captured economic returns: exports of high-tech products, exports of knowledge-intensive services and sales from innovation. MCFS retained two: knowledge-intensive services exports and innovation-driven sales. These outputs showed stronger discriminatory power across countries, highlighting diverse strategies in capitalising on innovation investments. The exclusion of high-tech product exports might suggest that this variable either overlaps with other export measures or that its variance across countries was not aligned well with clustering patterns. The retained indicators reflect both service-oriented knowledge economies and firm-level innovation outcomes, signalling distinct innovation models and economic impacts across national systems.

3.4 Applied two-stage DEA

This study applies a Variable Returns to Scale (VRS) output-oriented DEA, following prior work (Cullmann et al., 2011; Guan and Chen, 2012; Matei and Aldea, 2012; Carayannis et al., 2015, 2016). Many authors advocate VRS over Constant Returns to Scale (CRS), particularly when evaluating entities of different sizes (Hudec and Prochádzková, 2013) or when scale efficiency is critical (Cook and Zhu, 2008). VRS better reflects real-world conditions where doubling inputs does not necessarily double outputs due to inefficiencies, coordination costs, or structural constraints. However, we additionally employ DEA CRS model in order to compare the results from both models and to assess the presence of scale inefficiencies.

An output-oriented model was selected to evaluate how effectively EU countries maximize innovation outputs given their resources. In NIS, inputs such as R&D spending are policy-determined and less flexible in the short run (Guan and Chen, 2012). By contrast, policymakers can influence commercialisation and adoption policies, making output orientation more informative. As Carayannis et al. (2016) note, output orientation avoids penalizing countries with modest R&D inputs but strong innovation outcomes, particularly relevant for smaller EU economies. In a two-stage DEA, this orientation also enables analysis of downstream inefficiencies without assuming full control over upstream resources (Jovanović et al., 2022). Table 2 summarizes methodological choices in comparable DEA studies on NIS efficiency.

In our output-oriented DEA, DMUs are NISs of the 27 EU countries, where NISk, k = 1, 2, …, 27, as for each NIS we perform DEA for 2018-2020, 2020-2022 and 2022-2024 where each DMU in each year is treated as if it were a distinct DMU. The DEA considers the time lag of two years for inputs to transform in intermediates and intermediates to transform in commercial results, similar to the previous studies that apply two-stage DEA. The inputs from 2018 are analysed in the knowledge production efficiency for 2020 and the intermediates from 2022 are used for the analysis of commercialisation efficiency in 2024. Below we present the two-Stage DEA Efficiency Analysis for 27 EU member countries, for the period 2020-2024. The variables (inputs, intermediate outputs, outputs) used in the analysis were selected based on the results of the MCFS algorithm.

Table 2: Selected scientific articles for comparison of DEA methodology

Scientific articles	This article	Edquist et al. (2018)	Carayannis et al. (2016)	Anouze et al. (2024)	Guan and Chen (2012)	Hudec and Procházková (2013)	Liou (2009)
Indicators Selection method	Yes, MCFS	No	No	No	No	No	No
Data sources	IUS	IUS	IUS, WIPO	GII	OECD, IMD	OECD, Eurostat	OECD
Period	2020-2024	2014-2015	2007-2011	2016-2021	1999-2003	2004-2010	2000-2005
Two-stage DEA	Yes	No, one	Yes	Yes	Yes	Yes	Yes
Applied Method	VRS output-oriented DEA	Input oriented, CRS DEA?	MOLP-DEA, VRS, input oriented - stage 1, output oriented - stage 2	DNDEA-VRS, non-oriented	PLSR, VRS and CRS	CRS and VRS, input-oriented	Malmquist DEA
Analysed NISs	EU-27 countries	EU-28 countries	EU-23 countries	23 oil countries	OECD-22 countries	EU-19 countries	15 OECD countries

Source: Own

Dataset

Years: Y = {2018, 2020, 2022, 2024}

Countries: C = {c_1, c_2, ..., c_{27}}

For each year y, built matrices:

- Inputs: $X_y \in R^{27\times5}$ (countries × inputs)
- Intermediate outputs: $M_y \in R^{27\times6}$ (countries × intermediate outputs)
- Outputs: $O_y \in R^{27\times2}$ (countries × outputs)

Process

DEA Stage 1: Technological/Knowledge Production Process (Inputs into Intermediate Outputs)

For each year y in {2018, 2020, 2022}:

1. Applied output-oriented DEA using X_y as inputs and M_{y+2} as outputs. To account for time lags, inputs from 2018 correspond to intermediate outputs for 2020, inputs from 2020 align with intermediate outputs for 2022, etc.
2. Obtained efficiency scores $E_{c,y}(1)$ for all c in C.

DEA Stage 2: Technological/Knowledge Commercialisation Process (Intermediate Outputs into Outputs)

For each year y in {2020, 2022, 2024}:

1. Applied output-oriented DEA using M_y as inputs and O_{y+2} as outputs. To account for time lags, intermediate outputs from 2020 correspond to outputs for 2022, etc.
2. Obtained efficiency scores $E_{c,y}(2)$ for all c in C.

Results

For each country c and each year y:

- Stored and reported pair of efficiency scores: ($E_{c,y}(1)$, $E_{c,y}(2)$)

The dataset used for the DEA analysis was constructed using variables identified by the MCFS algorithm, ensuring the most relevant features were included in each stage. The program used for calculating the relative efficiency scores is the Frontier Analyst 4.0.

4 Results

The key findings are presented in two parts, the first part is focusing on the results of the applied MCFS and the second part is using the selected indicators to calculate the relative innovation efficiency of the selected EU-27 countries for each year based on two-stage DEA model. The efficiency scores calculated with output-oriented DEA with VRS and CRS for the two-stages and time lag of two years are presented for each EU member country for 2020 (based on inputs from 2018), 2022 (based on inputs/intermediates from 2020) and 2024 (based on intermediates from 2022) in the Table 3 below.

Table 3: DEA Efficiency scores per country per stage, VRS and CRS

Method	VRS				CRS			
Stage	Stage 1		Stage 2		Stage 1		Stage 2	
Country	2020	2022	2022	2024	2020	2022	2022	2024
AT	100.00	100.00	73.50	67.65	67.70	90.60	69.20	63.80
BE	95.71	100.00	88.05	92.59	61.80	80.10	69.10	77.60
BG	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
CY	100.00	100.00	100.00	100.00	100.00	100.00	93.40	83.20
CZ	72.98	82.82	86.39	74.19	26.00	58.90	82.60	73.30
DE	100.00	100.00	100.00	100.00	91.00	82.90	80.30	91.80
DK	100.00	100.00	100.00	100.00	100.00	100.00	75.60	88.20
EE	100.00	100.00	77.76	88.67	48.60	100.00	68.50	72.90
EL	83.42	100.00	100.00	100.00	50.20	79.40	100.00	100.00
ES	58.50	72.78	100.00	100.00	53.20	72.70	100.00	100.00
FI	100.00	100.00	95.92	100.00	100.00	100.00	71.90	93.30
FR	88.49	90.91	87.77	88.57	61.70	85.60	63.60	66.10
HR	100.00	72.99	100.00	100.00	100.00	64.00	80.10	79.70
HU	66.43	98.83	100.00	98.63	59.30	89.40	97.90	96.50
IE	100.00	100.00	100.00	100.00	89.20	100.00	100.00	100.00
IT	98.83	100.00	90.89	76.69	61.70	97.20	82.60	71.20
LT	69.76	72.36	51.33	80.56	66.80	71.80	50.80	79.90
LU	100.00	100.00	100.00	100.00	100.00	100.00	61.90	53.70
LV	100.00	100.00	82.54	100.00	100.00	100.00	66.90	100.00
MT	100.00	100.00	76.86	100.00	100.00	100.00	40.60	100.00
NL	100.00	100.00	98.82	90.68	100.00	100.00	66.30	62.90
PL	60.11	100.00	85.31	82.96	60.10	100.00	83.80	82.10
PT	61.82	74.01	84.41	95.64	32.80	50.80	83.50	89.30
RO	100.00	100.00	100.00	100.00	48.60	100.00	100.00	100.00
SE	100.00	100.00	100.00	90.18	100.00	100.00	70.70	66.40
SI	71.01	78.47	100.00	100.00	47.30	61.70	100.00	96.60
SK	53.65	55.37	100.00	100.00	40.40	51.20	100.00	100.00

Source: Own

Before interpreting the efficiency results, several methodological points warrant discussion. First, regarding the proportion of efficient units: under DEA VRS, 55.6% of countries achieved full efficiency in Stage 1 in 2020, rising to 66.7% in 2022, while in Stage 2, 51.9% and 55.6% were efficient in 2022 and 2024, respectively. These relatively high proportions are common in DEA applications with small samples and reflect both the VRS assumption and the dimensionality of our model. The CRS specification provides a stricter efficiency benchmark by assuming proportional returns to scale. Under CRS, the number of fully efficient countries decreases substantially: in Stage 1, efficient countries fall from 15 (VRS) to 10 (CRS) in 2020 and from 18 to 13 in 2022; in Stage 2, efficient countries decrease from 14 to 7 in 2022 and from 15 to 8 in 2024. This pattern is consistent with theoretical expectations, as CRS penalises both very small and very large DMUs that may operate at suboptimal scale.

We retain VRS as our primary specification as innovation systems exhibit well-documented scale effects whereby doubling R&D inputs does not necessarily double outputs (Fritsch and Slavtchev, 2007) and EU member states vary substantially in size, from Malta to Germany, making constant returns implausible. The VRS results show stronger concordance with established benchmarks such as the SII and GII. Nevertheless, the CRS results are reported throughout for comparative purposes and to identify scale inefficiencies.

Regarding the number of indicators, our two-stage model includes 5 input and six intermediate output variables in Stage 1 and 6 intermediate output and 2 final output variables in Stage 2 for 27 DMUs. While DEA discriminatory power decreases as the variable-to-DMU ratio increases, the MCFS procedure was specifically employed to select only the most relevant indicators, balancing information content against the dimensionality constraints inherent in small-sample applications. Our MCFS analysis identified a concise subset of 13 EIS indicators: five inputs, six intermediates and two outputs, capturing all stages of the innovation process. This is the smallest complete set among the reviewed articles that still capture the two main phases of the innovation process (see Table 5).

Innovation efficiency is not expected to shift considerably in the short term, as national policies and mid-term strategies (e.g., R&D roadmaps, digital agendas, smart specialization strategies) are stable. Innovation systems show structural inertia due to the long-term nature of R&D investments, human capital formation and institutional learning. As Edquist (2011) notes, the effectiveness of innovation policy is "not instantaneous" but shaped by medium- to long-term feedback loops. Consequently, national performance rankings tend to remain stable. The European Innovation Scoreboard (2024) similarly observes that performance differences persist over time, with countries rarely shifting categories quickly. Over the last seven years, only a few countries (e.g., Estonia's move to Strong Innovator) have changed tiers and these shifts reflect sustained policy-driven growth rather than short-term fluctuations.

High DEA efficiency scores in both stages in 2022-2024, characterise innovation systems that are simultaneously close to the best-practice frontier in both knowledge generation and commercialisation efficiency or at least do not exhibit a pronounced bottleneck in either stage. A group of countries (e.g. BG, CY, DE, DK, EL, FI, IE, LU, LV, MT, RO) operates at or extremely close to the joint two-stage frontier, achieving 100 through full efficiency in both knowledge production and commercialisation. In large and research-intensive systems, such frontier positions are consistent with strong research capacity and effective downstream translation; however, frontier efficiency should be interpreted as a relative measure of proportional input-output performance rather than as a direct indicator of innovation system maturity. When comparing the DEA VRS with DEA CRS scores for 2022-2024, there is a noticeable decrease of scores across the countries, with only persistent high scores in the case of BG, IE, LV, MT and RO. The number of efficient countries in Stage 1 falls from 18 to 13 and in Stage 2 from 15 to 8. This pattern is consistent with theoretical expectations, as CRS penalises both very small and very large DMUs that may operate at suboptimal scale, furthermore the CRS specification provides a stricter efficiency benchmark by assuming proportional returns to scale.

By contrast, values below “100” arise where inefficiency in one or both stages strongly constrains overall system performance. This pattern is evident in 2022-2024 in countries’ DEA VRS scores such as for AT, BE, EE, ES, FR, HR, HU, IT, LT, PL, PT, SI, SK where there is either full efficiency in one stage but with weaknesses in the other, or in both stages. Many EU Member States (e.g. AT, BE, EE, IT, PL) operate close to the frontier in knowledge production and cross-country variation is driven almost entirely by differences in commercialisation performance. When compared to the DEA CRS scores in 2022-2024, countries such as CY, DK, EE, FI, LU, LV, MT, NL, PL and SE still keep high production efficiency compared to their lower commercialisation efficiency. A few countries such as EL, ESand SK, have higher commercialisation efficiency compared to production efficiency based on both their DEA VRS and CRS scores in 2022. This highlights the central role of downstream innovation mechanisms in shaping NIS efficiency.

According to our DEA VRS, seven countries (BG, CY, DE, DK, IE, LU, RO) are efficient in both knowledge production and commercialisation. For Germany and Denmark, the results indicate strong science-industry linkages that are consistent with well-coordinated innovation governance. Ireland combines above-EU sales impacts and high knowledge-intensive services (KIS) exports, alongside a large multinational footprint, which may support translation of innovation to markets. Luxembourg remains a leading European fund domicile and both are recognised as European hubs that are attracting as well scaleups across Europe as reported in the “The scale-up gap” (European Investment Bank, EIB, 2024). For Bulgaria and Romania, efficiency reflects effective use of limited inputs; however, absent higher R&D investment levels, sustained output growth may be constrained. Here, policy should prioritize raising input levels to prevent long-term output stagnation despite current efficiency.

Fourteen countries achieve full efficiency in knowledge production in our DEA VRS, but several such as Austria, Netherlands, Sweden, score lower on commercialisation-proximate indicators. These countries are demonstrating robust R&D capacity, their strong research bases could be offset by structural rigidities and lack of scaling capital that slow the commercialisation of innovations. Italy (IT) and France (FR) show similar imbalances. These patterns align with EU-wide evidence of a late-stage finance gap that constrains scaling, not only in smaller markets (EIB, 2024) and highlight a systemic European bottleneck: abundant research capacity does not automatically yield market-scale innovation.

In our DEA VRS, Poland and Greece move to full efficiency by 2022; Czechia, Hungary, Portugal, Spain, Slovenia improve but remain inefficient in knowledge production, while Croatia declines. We present these as model-based efficiency movements; attributing them to reforms would require complementary policy-process evidence. EIS trend summaries (2017-2024) show heterogeneous movements across these countries, consistent with our finding that indicator choices and timing materially affect rankings.

Five EU countries: Croatia, Greece, Slovenia, Slovakia and Spain are weaker in knowledge production but score well on commercialisation. This suggests strong firm-level monetisation despite limited frontier R&D and could reflect reliance on adaptation of external technologies (ex. digitalisation) and focus on EU cohesion funds or foreign direct investment to scale innovations. In Greece, EU-backed equity initiatives (e.g., EquiFund) have expanded seed and venture markets, potentially supporting commercialisation; however, systematic evidence linking these instruments to national-level sales impacts requires further study. These systems demonstrate that applied innovation pathways can yield strong commercialization outcomes even without deep domestic research pipelines, though long-term sustainability requires reinforcing R&D foundations. A deeper institutional or sectoral analysis would be required to clarify this, as there could be an anomaly or misalignment in national innovation inputs.

For Czechia, Lithuania, Portugal, our DEA VRS indicates inefficiency in both stages during the observed periods. These countries need comprehensive reforms, simultaneously strengthening research foundations and building market pathways. Detailed structural diagnostics (sectoral mix, policy coordination) are beyond our dataset and would require dedicated country studies.

EIS 2024 reports a ten-point improvement in EU innovation performance (2017–2024), with substantial gains in several ‘widening’ economies; Cyprus and Estonia improve strongly, while most Member States rise to varying degrees. Against this background, our DEA VRS suggests convergence in several South-East European systems (BG, CY, RO), alongside divergence for some higher-income countries on commercialisation-oriented metrics. We stress that such movements depend on indicator sets and time cuts. Overall, our results are consistent with high-level assessments that the EU’s primary bottleneck lies in commercialisation and scaling rather than R&D and idea generation: the Draghi report states that innovation is blocked at the next stage and EU is failing to translate innovation into commercialisation, while EIB reports persistent late-stage finance gaps for European scale-ups especially in France and Sweden. These findings provide insights beyond the EIS, highlighting best practices among efficient countries and drawing attention to systemic weaknesses in others.

The coexistence of high innovation efficiency and very low SII scores in few EU countries (e.g. BG, RO) reflects a structural property of DEA rather than an anomaly in the results. In a two-stage DEA framework, efficiency is a relative, scale-dependent measure of input-output proportionality, not an indicator of absolute innovation strength. Given their exceptionally low innovation input levels, these countries are benchmarked against similarly resource-constrained peers and therefore attain frontier efficiency when outputs are commensurate with inputs. This classification indicates limited input waste, not strong or mature innovation systems. The consistently low SII values confirm that absolute innovation outcomes remain weak, underscoring that high DEA efficiency scores in this context signals small but proportionally efficient systems rather than innovation leaders.

This interpretation has important policy implications. For low-input countries, high DEA efficiency combined with low absolute performance indicates that weak innovation outcomes are driven primarily by insufficient scale (under-investment in R&D, human capital and innovation infrastructure) rather than by inefficient resource utilisation. Policy priorities should therefore focus on expanding the innovation input base rather than on correcting process-level bottlenecks. This distinction helps policymakers determine whether policy priorities should focus on expanding the innovation input base or on correcting process-level bottlenecks.

The dual VRS/CRS analysis provides additional diagnostic value. Countries showing large VRS-CRS efficiency gaps in Stage 2 may be operating at sub-optimal scale in their commercialisation activities, suggesting that policy interventions should focus on scaling mechanisms rather than efficiency improvements per se. Conversely, countries with similar VRS and CRS scores but below-frontier performance face genuine technical inefficiency requiring process-level reforms. These findings provide insights beyond the EIS by distinguishing between absolute performance levels and relative efficiency, highlighting best practices among efficient countries, drawing attention to systemic weaknesses in others and identifying whether underperformance stems from scale limitations or resource misallocation.

5 Discussion

This section compares our results with previous DEA studies, focusing on indicator selection and its impact on findings. Our results align with earlier work and theory by Lundvall and Edquist, in emphasizing the importance of innovation efficiency for assessing national innovation performance. Yet, prior research shows no consensus on which indicators to include or how to classify them as inputs or outputs. By applying a systematic feature selection method, this study provides new clarity on indicator choice and categorization. Recent DEA applications (Liou, 2009; Guan and Chen, 2012; Hudec and Procházková, 2013; Carayannis et al., 2016; Edquist et al., 2018; Anouze et al., 2024) rely on ad hoc indicator selection, drawing from prior studies or authors' assumptions without systematic testing. In contrast, our use of MCFS offers an empirically grounded approach. Table 4 compares the indicators used across studies. The comparison of articles regarding selected indicators is presented in Table 4.

Table 4: Comparison of articles regarding selected EIS indicators

Selected EIS indicators								
Code	Category	This article	Edquist et al. (2018)	Carayannis et al. (2016)	Anouze et al. (2024)	Guan and Chen (2012)	Hudec and Procházková (2013)	Liou (2009)
1.1.1	Input	Yes		Yes		Similar	Similar	Similar
1.1.2	Input	No						
1.1.3	Input	No		Yes				
1.2.1	Intermediate	No		Yes				
1.2.2	Intermediate	No		Yes	Yes	Similar	Similar	Similar
1.2.3	Input	No						
1.3.1	Input	No						
1.3.2	Input	No						
2.1.1	Input	Yes	Yes	Yes	Similar	Similar	Similar	Similar
2.1.2	Intermediate	Yes	Yes, but input	Yes		Similar, but external	Similar, but external	
2.1.3	Input	Yes	Yes					
2.2.1	Input	Yes	Yes		Similar	Similar, but external	Similar, but external	
2.2.2	Input	Yes						
2.2.3	Input	No						
2.3.1	Input	No						
2.3.2	Input	No						
3.1.1	Intermediate	No	Yes, but output					
3.1.2	Intermediate	Yes	Yes, but output					
3.2.1	Intermediate	Yes		Yes		Similar, but external	Similar, but external	Similar

Selected EIS indicators								
Code	Category	This article	Edquist et al. (2018)	Carayannis et al. (2016)	Anouze et al. (2024)	Guan and Chen (2012)	Hudec and Prochádzková (2013)	Liou (2009)
3.2.2	Intermediate	No						
3.2.3	Input	No						
3.3.1	Intermediate	Yes		Yes	Similar	Similar	Similar	Similar
3.3.2	Intermediate	No	Yes, but output	Yes, but output				
3.3.3	Intermediate	Yes	Yes, but output					
4.1.1	Intermediate	Yes		Yes	Similar	Similar	Similar	
4.1.2	Intermediate	No						
4.2.1	Output	No	Yes	Yes	Similar	Similar	Similar	
4.2.2	Output	Yes	Yes		Similar			
4.2.3	Output	Yes	Yes	Yes				
4.3.1	Impact	No						
4.3.2	Impact	No						
4.3.3	Impact	No						

Source: Own

None of the reviewed studies employ an identical set of indicators, except Hudec and Prochádzková (2013), who replicated Guan and Chen (2012) on a different country sample. Input indicators are the most consistently included: public R&D expenditure (2.1.1) appears in all studies, while business R&D (2.1.3) and total investment (2.2.1) are also widely adopted. Early-stage human capital and infrastructure indicators show weaker consensus. For instance, 1.1.1 and 1.1.3 appear only in Carayannis et al. (2016) and Liou (2009), while 1.1.2, 1.3.1and 1.3.2 are typically excluded, suggesting that these are perceived as less critical to innovation output transformation in DEA-based models.

Intermediate indicators, especially collaboration and knowledge-flow measures, are inconsistently treated. Patent applications (3.3.1) is widely included except in Edquist et al. (2018), showing convergence. By contrast, 3.1.1 and 3.2.2 are often omitted or reclassified (e.g., as outputs) in multistage frameworks such as Carayannis and Edquist. Output indicators show stronger convergence: knowledge-intensive services exports (4.2.2) and high-tech product exports (4.2.1) appear in most studies as proxies for commercialisation. Edquist et al. (2018) and Carayannis et al. (2016) differ by treating some outputs (e.g., 3.1.2, 3.3.3) as transitional outcomes or feedback signals. For example, Edquist argues for a critical reassessment of composite indicators like the Summary Innovation Index (SII) and instead promotes output/input efficiency analysis through robust DEA techniques. Liou (2009) uses a two-stage DEA to distinguish between technological knowledge creation and commercialisation, aligning with Guan and Chen's interpretation. In both cases, national innovation productivity is decomposed to better detect policy levers. Impact indicators (4.3.1- 4.3.3) are universally excluded, reflecting scepticism about their utility for DEA. While Anouze et al. (2024) and Carayannis et al. (2016) note the importance of long-term socioeconomic effects, they argue such outcomes are better analysed with longitudinal or regression methods than static DEA.

Our MCFS analysis identified a concise subset of 13 EIS indicators: five inputs, six intermediates and two outputs, capturing all stages of the innovation process. This is the smallest complete set among the reviewed articles that still capture all three main phases of the innovation process. The other studies such as those by Edquist et al. (2018), Guan and Chen (2012)and Carayannis et al. (2016) tend to use broader or more complex indicator sets, often expanding to include overlapping or transitional indicators, or indicators outside of IUS.

Our set overlaps most with Edquist et al. (2018), Carayannis et al. (2016)and Anouze et al. (2024), with structural similarities also to Guan and Chen (2012) and Hudec and Procházková (2013). Other studies include between 5 and 8 of our selected indicators and additionally include 2 and 4 EIS indicators that have been omitted based on our analysis. Importantly, based on the MCFS we have achieved our objective to build a concise set of indicators and excludes a range of indicators that, while present in some earlier studies, have demonstrated weaker empirical reliability or pose difficulties in interpretability within DEA frameworks.

Two widely used indicators scientific publications (1.2.2) and high-tech exports (4.2.1) were excluded here. The rationale for excluding scientific publications stems from their limited direct role in the commercialisation process. As Freeman and Soete (1987) argue, innovation is only realized once it reaches the market through a first commercial transaction. Although publications contribute to the broader research ecosystem, their conversion into commercially viable products or services is indirect and uncertain (Pavitt, 1991; OECD, 2005). Regarding indicator 4.2.1, while high-tech exports are often used as proxies for innovation output, they aggregate results from legacy technologies and unrelated sectors, potentially overstating recent innovation activity. In contrast, indicator 4.2.3 directly reflects revenues from new or significantly improved products, providing a more precise measure of commercial innovation performance (European Commission, 2024; Edquist, 1997). Therefore, 4.2.3 is considered a more targeted indicator of market-driven innovation success in this analysis.

Liou (2009) adopts a broader strategy, adding variables such as firm size, industrial structure and absorptive capacity. Our approach deliberately avoids such extensions to maintain analytical clarity and comparability with EIS. Compared to Edquist et al. (2018), which applies a one-stage DEA, this study reaffirms the importance of assessing efficiency in NIS rankings and similarly finds Sweden inefficient in commercialisation. However, although the selected set of indicators has similarities with this article approach, it excludes an important aspect of the human resources in innovation activities and patent applications, that appears more like an effort to measure the technology/ knowledge commercialisation phase and on the other side includes indicators that our selection model has omitted, such as 3.1.1, 3.3.2and 4.2.1. Patent applications is one of the indicators that is mostly present in innovation efficiency studies due to the high potential for companies to transform patents into commercial products and services by maintaining long-term competitive advantage on the market. Patents provide a mechanism for appropriating returns on R&D investments, enabling firms to maintain a sustained competitive advantage in knowledge-intensive markets (Griliches, 1990; Hall et al., 2005). Although not all patents result in marketable products, their legal protection, disclosure function and association with innovation outputs make them a reliable proxy for inventive activity with commercialisation potential (Jaffe and Trajtenberg, 2002; OECD, 2009).

Patent counts are frequently employed in DEA-based innovation efficiency models to capture the intermediate or output stages of the innovation process (Guan and Chen, 2012; Carayannis et al., 2016), especially when assessing the capacity of NIS to generate exploitable intellectual property. Several studies (e.g. Edquist et al., 2018; Guan and Chen, 2012; Hudec and Prochádzková, 2013) recategorize certain Input indicators as either external or intermediate, reflecting methodological differences in interpreting the innovation system structure.

Cross-study comparison is difficult: most assessments cover different country groups, periods, variables, or DEA variants. To illustrate the impact of indicator and methodological choices, we reviewed country rankings across recent DEA studies (Table 5). This comparison is not intended to validate our model but to demonstrate how rankings shift when indicators or samples vary. Countries appearing in multiple studies are often classified inconsistently for example they are efficient in one and inefficient in another, thus highlighting the decisive role of methodological design. Our approach aligns most closely with Carayannis et al. (2016), yet even here differences in indicator selection lead to divergent rankings, confirming that choice of variables strongly shapes conclusions about national innovation efficiency.

Our results mirror Carayannis et al. (2016) and other studies in showing that fewer countries achieve efficiency in commercialisation than in knowledge production, underscoring the EU's persistent difficulty in translating R&D into economic gains. This finding echoes the Draghi Report (2024), which highlights Europe's structural barriers to scaling innovation: "we are failing to translate innovation into commercialisation and innovative companies that want to scale up in Europe are hindered at every stage by inconsistent and restrictive regulations" (Draghi, 2024, Part A, p. 6). By contrast, Hudec and Prochádzková (2013), building on Guan and Chen (2012), produced unexpected efficiency rankings across the two stages, raising concerns about indicator alignment and modelling assumptions.

Table 5: Innovation efficiency results for countries analysed in the compared articles

Stage 1: Technological development/knowledge production stage efficiency							
Country	This article (for 2022)	Edquist et al. (2018)*	Carayannis et al. (2016)	Anouze et al. (2024)	Guan and Chen (2012)	Hudec and Prochádzková (2013)	Liou (2009)
DE	Efficient	Inefficient	0.95	0.85	0.92	Efficient	Efficient
DK	Efficient	Efficient	Efficient	Inefficient	Inefficient	0.92	
ES	Inefficient	Efficient	0.89	Inefficient	Efficient	Efficient	Efficient
FI	Efficient	Inefficient	Efficient	0.90	Efficient	0.98	0.99
FR	Inefficient	Efficient	0.80		Inefficient	Inefficient	Efficient
IT	Efficient	Efficient	0.96		0.83	0.80	Efficient
NL	Efficient	Efficient	Inefficient	Inefficient	0.84	Efficient	Efficient
SE	Efficient	Inefficient	Inefficient	Efficient	0.85	Efficient	
BG	Efficient	Efficient	Inefficient				
RO	Efficient	Efficient	Inefficient	Inefficient			
Stage 2: Technological development/knowledge commercialisation stage efficiency							
Country	This article (for 2024)	Edquist et al. (2018)*	Carayannis et al. (2016)	Anouze et al. (2024)	Guan and Chen (2012)	Hudec and Prochádzková (2013)	Liou (2009)
DE	Efficient	Inefficient	Efficient	Inefficient	Efficient	Efficient	Efficient
DK	Efficient	Efficient	Inefficient	Efficient	Inefficient	Inefficient	
ES	Efficient	Efficient	Inefficient	Efficient	Efficient	Efficient	Efficient
FI	Efficient	Inefficient	Inefficient	0.85	Inefficient	Inefficient	0.99
FR	88.57	Efficient	Efficient		Efficient	Efficient	Efficient
IT	Inefficient	Efficient	Inefficient		Efficient	Efficient	Efficient
NL	90.68	Efficient	Efficient	Inefficient	Efficient	Efficient	Efficient
SE	90.18	Inefficient	Efficient	Efficient	Inefficient	0.85	
BG	Efficient	Efficient	Efficient				
RO	Efficient	Efficient	Efficient	Efficient			

* Edquist et al. (2018) used one stage model

Source: Own

6 Conclusions

This paper advances the measurement of NIS efficiency by applying a two-stage DEA model to 27 EU countries for 2018-2024. To improve indicator selection in DEA, this study applies MCFS - a novel and interpretable method particularly suited for dynamic, high-dimensional international datasets. Unlike traditional approaches, MCFS captures latent structures and ensures consistency over time, making it especially valuable for longitudinal analyses. A dedicated pipeline was developed to extract statistically meaningful indicators over time, marking the first application of MCFS in the context of innovation efficiency assessment. The method combines unsupervised clustering with Lasso-based supervised selection, enabling robust indicator differentiation across countries and years. Variables are assessed separately within input, intermediate and output groups to maintain clarity and methodological precision throughout the time series.

6.1 Key Findings

- A compact set of 13 EIS indicators (5 input, six intermediates, two output) was selected, covering all stages of innovation with the smallest complete set among reviewed studies.
- This set overlaps most with Edquist et al. (2018), Carayannis et al. (2016) and Anouze et al. (2024)and shares elements with Guan and Chen (2012) and Hudec and Procházková (2013).
- Frequently used indicators such as scientific publications (1.2.2) and high--tech exports (4.2.1), were excluded due to weaker commercial relevance or redundancy, with innovation-driven sales (4.2.3) preferred as a clearer commercialisation measure.
- Unlike broader frameworks (e.g., Liou, 2009), which include firm structure or absorptive capacity, this study maintains analytical clarity and alignment with EIS.
- Across studies, variations in DEA models, periods, country samples and indicator classifications yield inconsistent rankings. Even studies with similar methods (e.g., Carayannis et al., 2016) produce different results due to indicator choice.
- Some authors reclassify inputs as intermediate or external indicators, contributing to variability.
- Our cross-study ranking comparison (Table 5) illustrates how methodological and indicator choices strongly shape perceptions of which NISs are efficient.

6.2 Policy Insights

Between 2020 and 2024, many EU countries sustained high efficiency in knowledge production, while commercialisation remains a bottleneck. Since innovation is central to economic resilience, balanced performance across both stages is essential. DEA results show that investment alone does not ensure efficiency; effectiveness depends on how well inputs are converted into outputs. To sustain full-cycle innovation performance, countries should design policies for:

- strengthening coordination and linkages between universities, research institute sand firms;
- supporting scaling of startups and innovation-driven enterprises;
- improving monitoring of R&D input conversion into economic impacts.

Countries with strong knowledge production but weak commercialisation should focus on translational policies, while those with the opposite profile should strengthen their R&D infrastructure.

This simplified DEA framework can guide policymakers in benchmarking against top performers, identifying stage-specific weaknesses and designing more targeted EU and national policies. It also complements strategic diagnoses such as the Draghi Report (2024), which emphasizes Europe's difficulty in scaling research into market impact. Countries aiming to enhance policy learning often adopt best practices based on empirical evidence. To design better policies, it is essential to understand how environmental factors affect the efficiency of technological/knowledge production and commercialisation systems. Therefore, selecting an appropriate methodological framework is crucial for policymakers to gather insights and understand processes within NIS. Solving the DEA model for each inefficient NIS yields improvement targets that highlight where countries should adjust input or output levels to enhance performance and close efficiency gaps, emphasizing the importance of prioritizing key factors that most influence innovation outcomes.

6.3 Limitations and Future Research

DEA provides valuable insights but has methodological constraints. There are certain limitations due to its complexity and availability of data. Additionally, the conceptual model presented in this article oversimplifies the complex and dynamic nature of NIS omitting intertemporal dependencies and delayed effects of innovation investments. The model does not consider that some outputs such as patents often appear years after inputs such as R&D expenditures, which limits how accurately it reflects real-world timelines. The two-stage DEA faces limitations in both stages – efficiency scores may be distorted by outliers and noise. Indicator selection is subject to statistical constraints and risks such as double counting or insufficiently distinguishing between inputs, intermediaries and outputs. There is a shortage of empirical research that investigates feature selection for innovation efficiency of NIS. Although MCFS as unsupervised feature selection method has clear advantages over methods like PCA, which is feature construction method, as a next step a more detailed comparison of the approaches in terms of robustness is needed. In addition, the SII and EIS are criticized by many scholars due to lack of theoretical background and issues in the construction of the composite indicator for innovation performance. This is beyond the purpose of this paper and would be subject to follow-on research how to create a sound innovation performance indicator and how to combine both efficiency and performance indicators to have a unique indicator for a holistic assessment of NISs. A further methodological limitation concerns the ratio of variables to decision-making units in the DEA specification. With 27 DMUs and eleven variables in the DEA Stage 1: Technological/Knowledge Production Process, the model operates close to the threshold beyond which DEA is known to suffer from upward bias in efficiency scores and a loss of discriminatory power, as a greater proportion of DMUs are projected onto the efficiency frontier by construction rather than genuine performance. Although the MCFS procedure was explicitly designed to produce the most parsimonious indicator set that still captures all stages of the innovation process, this constraint remains inherent to any small-sample DEA application. Finally, it is important to emphasise that the efficiency scores reported in this study reflect the efficient use of available resources and scale efficiency relative to other EU member states within the sample and should not be interpreted as identifying absolute innovation leaders. DEA is a comparative, frontier-based method: a country classified as efficient has simply made proportionally effective use of its inputs relative to its peers, not that its innovation system is strong in absolute terms. This distinction is particularly noticeable given that the EU continues to fall short of its 3% of GDP R&D expenditure target and lags the South Korea, Japan and United States, in R&D intensity. Against this backdrop, high relative efficiency in a low-input environment signals limited resource waste rather than innovation leadership. Policymakers should therefore read the DEA results alongside absolute performance metrics, such as the Global Innovation Index, to obtain a complete picture of both the efficiency and the scale of national innovation systems.

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