

Article

Mapping Strategic Innovation Capacity and Sustainable Development in the European Union: Evidence from Grey Clustering

Corina Ioanăș ¹, Bianca-Raluca Cibu ², Paul Diaconu ¹, Florinel-Marian Sgârdea ¹ and Camelia Delcea ^{2,*}

¹ Department of Accounting and Audit, Bucharest University of Economic Studies, 010552 Bucharest, Romania

² Department of Economic Informatics and Cybernetics, Bucharest University of Economic Studies, 010552 Bucharest, Romania

* Correspondence: camelia.delcea@csie.ase.ro; Tel.: +40-769652813

Abstract

This paper evaluates the extent to which European Union member states show alignment between strategic innovation capacity and sustainable development outcomes. To achieve this objective, indicators were collected from Eurostat for two dimensions: strategic capacity for innovation (public expenditure on research and development, human resources in science and technology, and the higher education graduation rate) and sustainable development outcomes (real GDP per capita, employment rate, risk of poverty or social exclusion, and greenhouse gas emissions). Going beyond traditional literature, we develop an analysis based on grey clustering using multiple scenarios to illustrate the complex, non-linear relationships and structural bottlenecks in member states. The stability of the classifications was further examined through threshold sensitivity testing across all scenarios and through 200,000 weight-perturbation simulations for an illustrative boundary case. The results reveal distinct performance typologies: a resilient group of “systemic leaders” (including Denmark, Sweden, and the Netherlands) demonstrating consistent excellence across all applied prioritization scenarios, and a stagnant core facing structural challenges regarding both innovation and sustainability (such as Romania and Hungary). The dynamic analysis covering 2021–2024 suggests that strong innovation-capacity indicators are not necessarily associated with equally strong sustainability-outcome indicators, while certain economies in Central and Eastern Europe show positive convergence trends. Supported by stability simulations conducted across multiple scenarios, the study highlights significant alignment gaps between innovation-capacity indicators and sustainability-outcome indicators across the European Union and offers public policy recommendations to stimulate sustainable cohesion and technology adoption.

Keywords: strategic innovation capacity; sustainable development outcomes; grey clustering; economic convergence; European Union; employment rate



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1. Introduction

Given the recent global challenges, the European Union plays a key role in integrating strategic innovation with sustainable development goals, a synergy that is of great importance to member states. The primary objective of European policies is not only to strengthen strategic innovation capacity, but also to ensure that innovation-related resources are associated with tangible progress toward the Sustainable Development Goals (SDGs). However,

the relationship between innovation-related resources and socio-economic and environmental outcomes is not straightforward. Structural differences among member states and institutional variations often contribute to discrepancies between innovation capacity and sustainable development outcomes.

Innovation is one of the most significant drivers of both socioeconomic progress and economic development [1]. It is indeed a key factor in the sustainable improvement of living standards for people worldwide [2,3]. Furthermore, it supports recovery from various crises and helps stimulate economic development at the macro, meso, and micro levels, contributing to increased economic independence or competitiveness, as well as to the formation of a knowledge-based economy [4,5]. This approach is important because it has the potential to motivate businesses to continuously improve their operations, create new products, or even develop new concepts. Recent global events (the war between Ukraine and Russia or the COVID-19 pandemic) have shown that modern economies have a greater capacity to survive such events [6].

This study aims to examine the extent to which strategic innovation capacity and sustainable development outcomes are aligned across European Union member states by applying different prioritization scenarios within a grey clustering framework. Rather than assuming a direct causal transition from innovation inputs to sustainability outcomes, the paper treats this relationship as a multidimensional classification problem, in which countries may occupy different positions depending on the relative emphasis placed on input-oriented and outcome-oriented indicators. Accordingly, the study is guided by the following research hypotheses:

Hypothesis 1. *European Union member states differ in the degree of alignment between strategic innovation capacity and sustainable development outcomes.*

Hypothesis 2. *Strong strategic innovation capacity does not necessarily correspond to equally strong sustainable development outcomes across all member states.*

Hypothesis 3. *Country classifications are sensitive to the relative analytical weight assigned to innovation-capacity indicators and sustainable-development outcome indicators.*

Hypothesis 4. *Some member states display stable performance profiles across alternative weighting scenarios, whereas others occupy boundary positions that vary according to the assumptions embedded in the composite classification framework.*

In this respect, the study contributes to the literature on EU innovation and sustainability assessment by complementing existing composite indices, such as the European Innovation Scoreboard and the SDG Index. While traditional indices usually rely on linear aggregation, exact-data assumptions, and single ranking outputs, the grey clustering approach allows countries to be grouped into performance typologies under conditions of partial information, multidimensional heterogeneity, and alternative weighting assumptions. Instead of producing one rigid ranking, the proposed framework simulates several prioritization scenarios, ranging from full emphasis on innovation capacity to full emphasis on sustainability outcomes, and thereby highlights patterns of alignment, misalignment, and classification sensitivity among EU member states.

European Union member states are grouped into clusters based on the different weights assigned to these two dimensions. The main methodological contribution of the paper lies in the use of grey clustering to examine country typologies under alternative analytical assumptions. Grey systems theory was developed in 1982 by Professor Deng Julong, who started from the premise that the information used by researchers in analyses is often uncertain, partial, or incomplete [7]. In this study, the grey clustering framework is used to examine patterns of alignment and misalignment between innovation-capacity indicators and sustainable-development outcome indicators. Rather than providing a single statistical ranking, five different scenarios are simulated to show how country classifications vary when the analytical emphasis shifts between the two dimensions. Furthermore, a dynamic analysis spanning four years is introduced, and the stability of the clusters is discussed from a multiple-case perspective.

The paper is divided into six sections. The “Section 1” outlines the role of the European Union in integrating strategic innovation with sustainable development goals, as well as the objective of the research. The “Section 2” serves to define the theoretical foundation, how the field has evolved over time, and what other practical applications of the applied analysis technique have existed. “Section 3” describes the stages of the analysis, the indicators used, how the data were preprocessed, how the formed clusters were validated, and how the mathematical functions were created. “Section 4” presents the results obtained from applying statistical scenarios (for the year 2021), as well as those obtained through dynamic analysis (for the period 2022–2024). “Section 5” describes the typologies identified in the member states of the European Union and offers various policy recommendations to help improve practices. “Section 6” serves to summarize the objective of the paper, present the limitations encountered in its completion, and offer directions for future research.

2. Literature Review

Designed specifically to handle systems characterized by uncertainty and incomplete data, grey systems theory proposes a new methodology capable of adapting to small-scale samples [8–12]. This approach has the ability to enable the extraction and generation of valuable insights even from limited datasets, with broad applicability across numerous fields [7,13]. The theory is named based on a chromatic metaphor for the level of knowledge: “white” is used to symbolize the situation where information is fully known, “black” for that which is completely unknown, while “grey” defines systems in which knowledge is partial [14–18].

Thanks to the constant evolution of knowledge, systems science emerged, providing an essential framework for investigating the various connections between objects and phenomena. Its foundations were laid in the late 1940s through general systems theory [19], information theory [20] and cybernetics [21], offering solutions to complex scientific problems [15,22,23]. In this scientific context, grey systems theory has undergone an impressive trajectory of development. A bibliometric analysis covering the period 1982–2021 revealed a phase of slow growth in the first two decades, followed by a remarkable acceleration over the past 20 years, a period marked by extremely rapid progress in research in the field [24]. To reinforce this idea, according to another bibliometric study conducted on a database of papers from 1989 to 2024, it was observed that grey systems allow not only for static evaluation but also for dynamic evaluation, tracking how the entities under analysis migrate between performance groups over several years [25]. Furthermore, it was also identified that the method’s popularity has grown due to its ability to be adapted and combined with other functions, thereby offering high flexibility in classifications.

Over time, this theory has frequently been adopted by researchers to develop and test various hypotheses. For example, H. Liu et al. [26] combined grey clustering with the entropy weighting method to evaluate and identify the factors that influence the quality of teaching in a university setting with regard to the English language. Jiang et al. [27] investigated the fishing hospitality industry in China with the aim of optimizing service quality, using the analytical network decision-making process to identify critical influencing factors. Using the grey clustering model to evaluate various provinces, the researchers demonstrated that both personalized services and online marketing are essential pillars of quality. In a similar context, Dong-Liang et al. [28] investigated the development capacity of the high-tech sector across China by applying an incidence clustering model based on a grey matrix. This method facilitated a detailed assessment of regional differences in research and development, revealing significant structural disparities between regions.

Similarly, Tang and Xie [29] aimed to create a model designed to assess tourism potential by integrating grey cluster theory with a structured index system. By applying this methodological framework, interviews, literature review and factor analysis were integrated, using the hierarchical process to weight the criteria. This revealed marked differences in the utilization of local cultural resources in Huangshan. Karimi and Ahmadian [30] investigated the operational efficiency of bank branches and how they are ranked based on performance. The authors found that this approach can aid in the development and planning of banking policies, and the results are highly useful for identifying best practices. In terms of practical application, Tan et al. [31] developed a model for detecting online rumours using the grey clustering technique, which combines deep learning with manual features. Meanwhile, Tu et al. [32] introduced a relationship-based approach using TOPSIS for optimizing portfolio strategies, while Li [33] developed a system for analyzing students' mental health, utilizing clustering models to identify risk factors and therapeutic solutions.

The analysis considers the economic literature on the interconnections between innovation and sustainability in the context of the European Union. These interconnections can be explained using the National Innovation Systems (NIS) theory, which asserts that a country's capacity for technological progress is influenced not only by the gross volume of resources invested as inputs, but also by the intensity and quality of interactions between universities, the public sector, and the private sector [34,35]. An important public policy instrument designed to synchronize these systems at the EU level is the European Smart Specialization (S3/S4) framework [36]. Initially, it focused strictly on knowledge-based economic growth [37]; the current Smart Specialization for Sustainability agenda positions research and innovation as fundamental factors for achieving the objectives of the European Green Deal and the Sustainable Development Goals (SDGs) [38].

Figure 1 reflects the conceptual framework of the study, highlighting the transition from established macro-theoretical approaches to applied empirical analysis. The integration of concepts such as NIS and Smart Specialization for Sustainability explains the simultaneous assessment of innovation inputs and sustainable development outcomes. These dimensions were not treated as isolated phenomena; the diagram illustrates how public investments and the stock of highly skilled human capital (I_1 – I_3) directly influence a country's ability to generate outcomes regarding socioeconomic and environmental well-being (I_4 – I_7). The Grey Clustering algorithm is used as the mathematical model, with various dynamic prioritization scenarios created (ranging from a 100% focus on innovation to a 100% focus on sustainability).

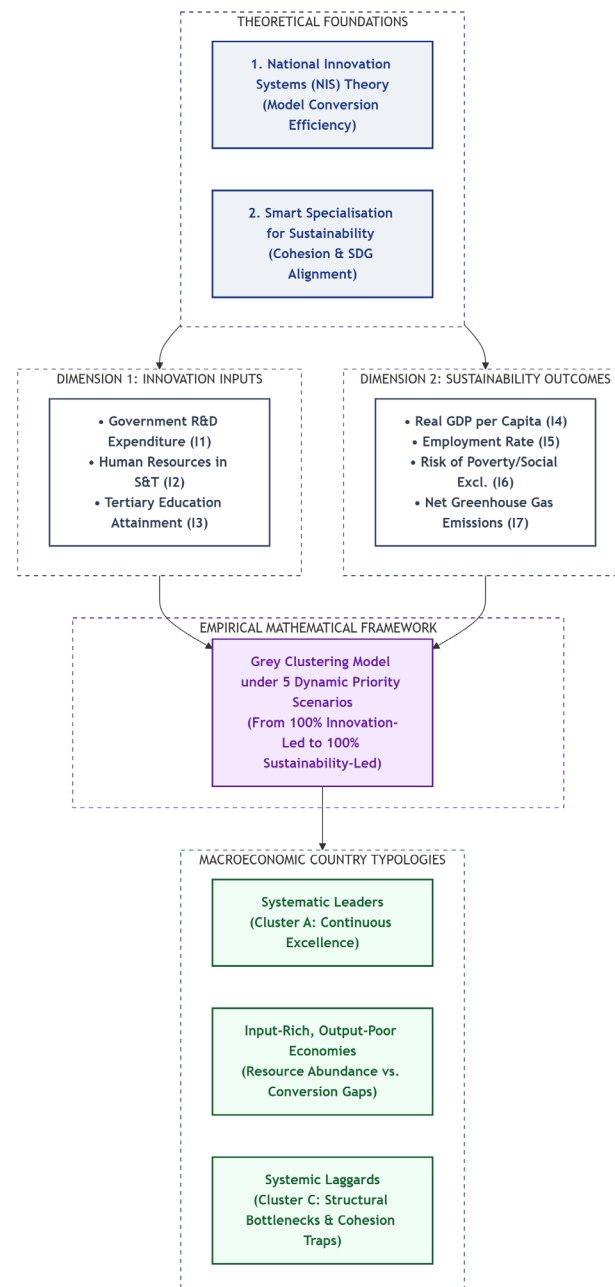


Figure 1. The conceptual framework of the study.

3. Methodology

In this section, the methodological framework used to underpin the research is detailed, structured as a logical sequence of steps designed to ensure the accuracy of the analysis. First, it is necessary to describe the steps taken during the analysis to provide an overview of the workflow, followed by the identification and selection of representative indicators needed to observe the dynamics of the phenomenon under study. Once selected, the process continues with data extraction and preprocessing, a stage dedicated to cleaning and normalizing the information to ensure the accuracy of the results. Subsequently, the methodology focuses on determining the optimal number of clusters, a process in which the selection is guided by performance indicators, where the interpretation follows rules such as “better” = “higher” or “better” = “lower,” as appropriate. Finally, the chapter presents the mathematical foundation using grey clustering functions to organize the data into well-defined categories.

3.1. Research Design and Methodological Transparency

The research design follows a comparative, macro-level, quantitative approach focused on the 27 member states of the European Union. The EU-27 was selected because the member states share a common institutional and policy framework, while still displaying substantial heterogeneity in terms of innovation capacity, socioeconomic performance, and environmental outcomes. This makes the European Union an appropriate empirical setting for examining differences in the alignment between strategic innovation capacity and sustainable development outcomes.

The study relies exclusively on indicators extracted from Eurostat [39] in order to ensure comparability, transparency, and replicability across countries and years. The selected variables were organized into two analytical dimensions. The first dimension, strategic innovation capacity, captures public R&D effort and the availability of advanced human capital through three indicators: government sector R&D expenditure, human resources in science and technology, and the share of the population aged 25–34 with tertiary education. The second dimension, sustainable development outcomes, captures economic, social, and environmental performance through four indicators: real GDP per capita, employment rate, risk of poverty or social exclusion, and domestic net greenhouse gas emissions.

The measurement procedure involved extracting comparable Eurostat data for the years used in the analysis, followed by preprocessing and normalization. Since the indicators are expressed in different units and have different performance meanings, min–max normalization was applied to transform all variables onto a common 0–1 scale. For indicators where lower values indicate better performance, namely the risk of poverty or social exclusion and greenhouse gas emissions, reverse normalization was applied so that all normalized indicators follow the same interpretation, namely higher values indicate better performance.

The methodological choice of grey clustering is consistent with the objective of the study, as the analysis does not seek to produce a single deterministic ranking, but to classify countries into performance typologies under conditions of partial information and multidimensional heterogeneity. The use of alternative weighting scenarios allows the study to assess how classifications change when the analytical emphasis shifts from innovation-capacity indicators to sustainable-development outcome indicators. Therefore, the scenarios should be interpreted as sensitivity-oriented classification assumptions rather than as evidence of a direct causal transition process.

3.2. Steps

To provide a clear overview of the analysis conducted, the steps followed in preparing this article are presented in Figure 2.

First, in the “Identifying Indicators” section, two dimensions are defined: strategic innovation capacity and sustainable development outcomes. Strategic innovation capacity consists of three indicators: I_1 : Government sector R&D expenditure (GERD), I_2 : Human resources in science and technology and I_3 : Population aged 25–34 with tertiary education. The second dimension, outcomes of sustainable development, comprises: I_4 : Real GDP per capita (chain-linked volumes, 2020, euros), I_5 : Employment rate (20–64 years), I_6 : Share of persons at risk of poverty or social exclusion and I_7 : Domestic net greenhouse gas emissions.

In the second section, “Data Extraction and Preprocessing”, the database from which the data was extracted is presented to ensure the accuracy of the analysis. Subsequently, the process by which all indicators are scaled to the same range using the Min-Max normalization technique (on a scale from 0 to 1) is described.

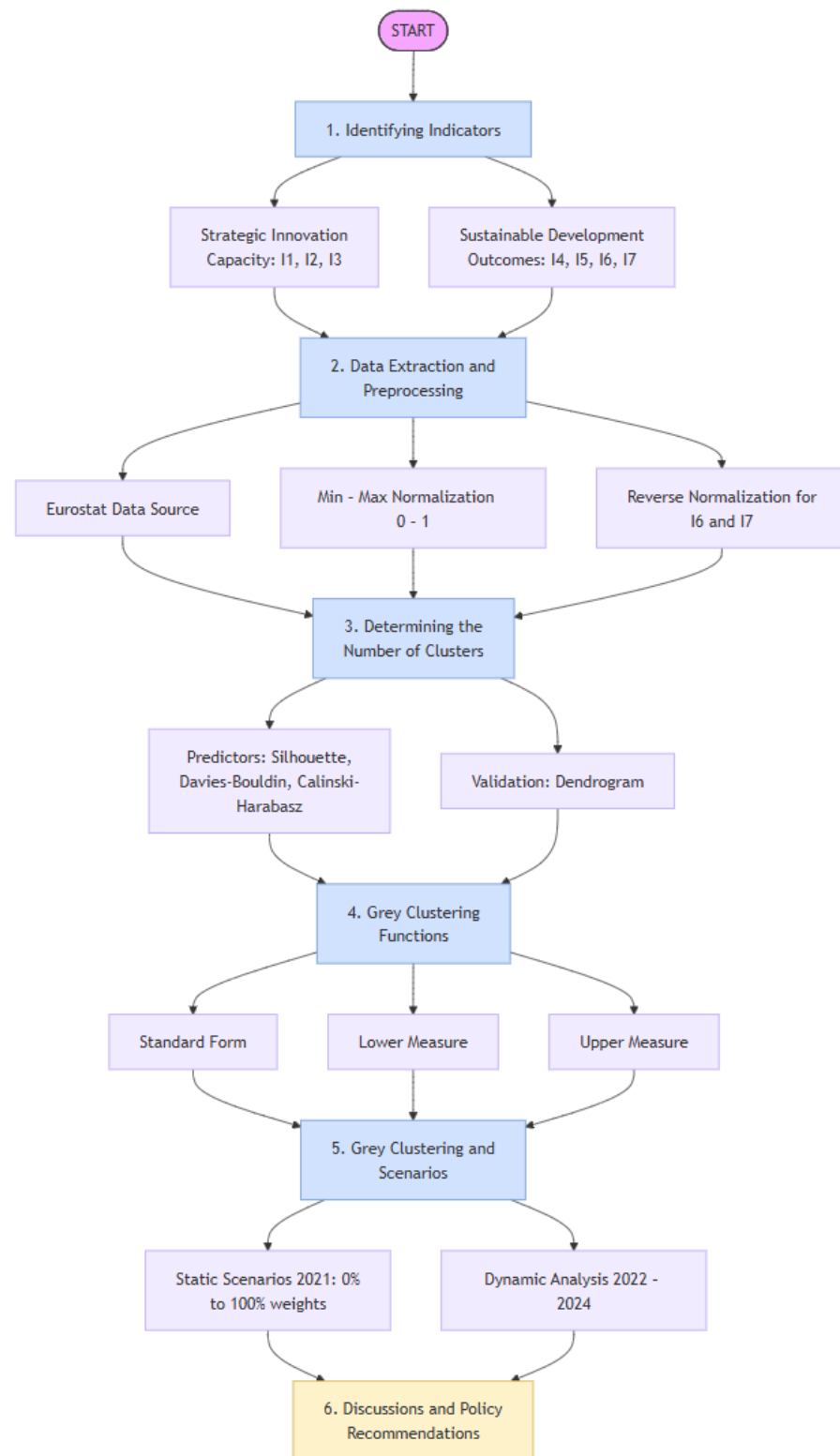


Figure 2. Methodological steps.

The third section, “Determining the Number of Clusters”, describes the process of determining the optimal number of clusters using three statistical measures: the Silhouette index, the Davies-Bouldin index and the Calinski-Harabasz index. The interpretation of these aims to maximize the values for Silhouette and Calinski-Harabasz, and to minimize the value for Davies-Bouldin. Furthermore, the result is additionally validated through the

results of applying the Elbow method and through a dendrogram, which provides a visual representation of the distances between the analyzed states.

The fourth section, “Grey Clustering Functions”, presents the mathematical foundation of the research, with the functions used to organize data into well-defined categories based on turning points. The methodology outlines three forms of clustering functions: the standard form, the lower measure and the upper measure. The resulting framework provides adaptability to the model under conditions of limited or incomplete information.

The fifth section, “Grey Clustering and Scenarios”, illustrates the simulation of five different scenarios for 2021, assigning different weights to the two dimensions. In addition, a dynamic analysis for the period 2022–2024 is described using a balanced scenario (50–50%) for both dimensions.

Finally, in the sixth section, “Discussions and Policy Recommendations”, various classifications of the analyzed countries are presented based on the results obtained. This stage highlights those countries that perform optimally in all scenarios, as well as those that face constant difficulties in transforming innovation capacity into sustainable results.

3.3. Identifying the Representative Indicators

To ensure an appropriate assessment of how strategic potential is translated into sustainable performance, indicators drawn from Eurostat databases have been discussed in the specialized macroeconomic literature. The innovation capacity dimension (I_1 – I_3) represents key factors related to public financial investment in research and development and the structural stock of highly skilled human capital. At the other end of the spectrum, the dimension of sustainable development outcomes (I_4 – I_7) includes aggregate indicators reflecting the classic pillars of sustainability: economic prosperity, labour market inclusion, social resilience to poverty, and direct environmental impact. To avoid repetitive text and to provide a clearer picture of these indicators and how they have been used over time in the literature, this information is presented in Table 1.

Table 1. Rationale and literature support for the selected indicators.

Indicator	Eurostat Code	Dimension	Relevance for the Study	Examples from Previous Literature
Government sector R&D expenditure (GERD)	rd_e_gerdtot	Strategic innovation capacity	Reflects public investment in research and innovation capacity at national level	Used to monitor innovation dynamics and macroeconomic performance in EU countries [40–42]
Human resources in science and technology	tsc00025	Strategic innovation capacity	Captures the availability of skilled labour and scientific capacity supporting knowledge-based development	Applied in studies on creativity, innovation potential, and knowledge economies [43–45]
Population aged 25–34 with tertiary education	edat_lfse_03	Strategic innovation capacity	Measures advanced human capital and educational attainment relevant for innovation systems	Frequently used as a proxy for human capital and demographic educational structure [46,47]
Real GDP per capita (chain-linked volumes, 2020 euro)	sdg_08_10	Sustainable development outcomes	Reflects economic performance and material welfare associated with sustainable development	Incorporated in SDG-oriented assessments and sustainable growth analyses [48–50]
Employment rate (20–64 years)	sdg_08_30	Sustainable development outcomes	Measures labour market inclusion and economic participation	Widely used in studies on resilience, labour markets, and sustainable growth [49,51,52]

Table 1. Cont.

Indicator	Eurostat Code	Dimension	Relevance for the Study	Examples from Previous Literature
Share of persons at risk of poverty or social exclusion	sdg_01_10	Sustainable development outcomes	Captures social vulnerability and inclusion aspects of sustainability	Used in analyses of social vulnerability and sustainability assessment [50,52,53]
Domestic net greenhouse gas emissions	sdg_13_10	Sustainable development outcomes	Reflects environmental pressure and climate sustainability performance	Applied in studies examining SDG convergence and environmental sustainability [54,55]

It is important to note that the measure of sustainable development outcomes used in this study is not intended to provide a comprehensive and integrated representation of sustainability. Given that the methodological objective of this study was to construct an interpretable grey clustering framework based on a limited number of comparable macroeconomic indicators, the selected variables were designed to represent dimensions of sustainable performance, rather than the full complexity of the concept of sustainable development. This approach is consistent with the literature regarding the construction of composite indices [56].

The model developed incorporates indicators related to economic prosperity, social inclusion, and environmental protection, in line with the approaches outlined in the literature on sustainable development [57]. In this way, both real GDP per capita and the employment rate represent the economic dimension, while the risk of poverty or social exclusion captures the social component, and net greenhouse gas emissions reflect the pressure on the environment. These dimensions are not intended to be interchangeable, but rather as complementary manifestations of the outcomes of sustainable development observed at the macroeconomic level.

3.4. Data Extraction and Preprocessing

It is important to note that all the indicators used in the analysis are on different scales, especially since some of them have different meanings. For example, there are cases where “better” = “lower,” but also cases where “better” = “higher”. To resolve this, the indicators will be normalized using the min-max normalization technique on the 0–1 scale. To do this, the following formula will be applied [58]:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

In the formula mentioned above, x represents the indicator to be normalized, $\min(x)$ is the minimum value of the indicator, $\max(x)$ is the maximum value of the indicator, and x' reflects the new value obtained by applying the min-max normalization process.

Since it is observed that not all indicators follow the “higher” = “better” principle, but that there are two indicators of the “lower” = “better” type (indicators I_6 and I_7) the min-max normalization method will be applied to their inverted values, so that, when the grey clustering procedure is applied, the meaning of all indicators is the same, namely “higher” = “better” (Table 2). The inverted values are obtained by subtracting the current value from the maximum value of each indicator.

Although macroeconomic literature offers numerous alternative variables for measuring performance at the European level, the selection of these seven specific indicators was based on the need to avoid multicollinearity within the grey clustering algorithm. In

grey systems theory, which is structurally designed for analyzing datasets with partial information and small samples, including an excessive number of dependent or redundant variables can dilute the discriminatory power of the grey weighting functions [59,60]. This was the reason for opting to select “macro-proxy” key indicators capable of reflecting the system’s dynamics.

Table 2. Description of the indicators.

Code	Dimension	Eurostat Code	Indicator Name	Measurement Unit	Indicator Type
I ₁	Strategic innovation capacity	rd_e_gerdtot	Government sector R&D expenditure (GERD)	% of GDP	better = greater
I ₂	Strategic innovation capacity	tsc00025	Human resources in science and technology	% of labour force	better = greater
I ₃	Strategic innovation capacity	edat_lfse_03	Population aged 25–34 with tertiary education	% of population	better = greater
I ₄	Sustainable Development Outcomes	sdg_08_10	Real GDP per capita (chain-linked volumes, 2020, euro)	EURO/inhabitant	better = greater
I ₅	Sustainable Development Outcomes	sdg_08_30	Employment rate (20–64 years)	% of population	better = greater
I ₆	Sustainable Development Outcomes	sdg_01_10	Share of persons at risk of poverty or social exclusion	%	better = lower
I ₇	Sustainable Development Outcomes	sdg_13_10	Domestic net greenhouse gas emissions	Index	better = lower

To construct the strategic innovation capacity dimension, government expenditure on research and development (GERD) and the stock of highly skilled human capital were chosen over proxies such as the number of patents or private sector research expenditure (BERD). This choice was made because public spending and educational infrastructure are a structural foundation upon which private innovation develops [61]; furthermore, the number of patents is an indicator that tends to asymmetrically favour countries with an industrial structure traditionally focused on heavy technology, while human capital indicators provide a more homogeneous and equitable measure of innovation potential based on knowledge across all member states [62]. With regard to the outcomes of sustainable development, the model was designed to assess final impact outcomes (economic, social, and environmental). Alternatives such as public social spending or the energy intensity of the economy were excluded, as they represent process indicators or financial effort (system inputs), not final achieved states [63]. To ensure a focused assessment of the alignment between innovation capacity and sustainable development outcomes, the model analyzed material well-being, social inclusion, and direct ecological cost [64], thereby ensuring a close conceptual link between innovation inputs and sustainable development outputs.

3.5. Establishing the Number of Clusters

In order to perform grey clustering, it is important to first determine the optimal number of clusters to be formed. To this end, the scores obtained using the Silhouette, Davies-Bouldin and Calinski-Harabasz indices were selected as predictors.

First, the Silhouette index is calculated using the following formula [65]:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

In this context, $s(i)$ represents the Silhouette index, $a(i)$ is the average distance between point i and the other points in the same cluster, and $b(i)$ is also the average distance, but this time between point i and all the other points in the nearest cluster that is different from the cluster of point i .

The effectiveness of clustering is evaluated by calculating the indicator for various values of the number of clusters. Since the logic behind this indicator is that “better” = “greater”, the final selection will be based on the number of clusters that yields the maximum value.

The second index calculated is the Davies-Bouldin index, which is determined using the formula [66]:

$$DBI = \frac{1}{k} \sum_{i=1}^k R_i$$

with:

$$R_i = \max_{j \neq i} R_{ij}$$

$$R_{ij} = \frac{S_i + S_j}{M_{ij}}$$

DBI represents the value of the Davies-Bouldin index, where S_i is the variance of cluster i , S_j is the variance of cluster j and M_{ij} represents the distance between the centroids of clusters i and j .

The optimal number of clusters is selected based on the premise that this metric follows the “better” = “lower” principle. For this reason, lower values are preferred, as they indicate a more precise segmentation of the data [66,67].

Similar to the Silhouette index and the Calinski-Harabasz index, it follows a “better” = “higher” principle, thus suggesting that one should aim for maximized values of this criterion when choosing the number of clusters. The formula used for this index is [68]:

$$CH = \frac{RSC/(k-1)}{DSC/(n-k)}$$

In the formula, RSC is the separation rate between clusters, DSC is the dispersion within a cluster, k represents the number of clusters being analyzed, and n is the number of data points in the dataset.

In addition to the indices described above, a graph (dendrogram) will also be used to ensure that the chosen number of clusters is optimal [69,70]. This graph will be a two-dimensional representation in which the countries included in the analysis are plotted on the x-axis and the distances between them are plotted on the y-axis.

3.6. Determining the Grey Clustering Functions

In order to develop the grey clustering functions that will be used in the clustering process of the set of grey elements, it is necessary to establish a theoretical framework. This framework is designed to provide the information needed to understand the steps

underlying the implementation of such an analysis. In addition to this objective, this subsection will also explain various terms that have been identified over the years in the specialized literature as specific to grey clustering and grey systems theory [71,72].

Over time, the literature has shown that it is highly beneficial to combine clustering and outlier detection functions in situations where the available information is limited or even incomplete [25,60,73,74]. The method is based on the fact that turning points help to classify the constituent elements as effectively as possible. These points are identified using certain similar elements, either through the analysis of grouped objects, without including them in the clustering. This approach provides the classification with adaptability and flexibility. However, it should be noted that the definition of the functions is influenced by the analysts' judgement, which indicates that experts' knowledge regarding this technique is essential to ensure the accuracy of this methodology [75,76].

In the following, the methodology adopted by Li et al. [77] and Liu et al. [60] in their papers will be followed. Given a set of n objects, these are to be grouped into s classes based on m criteria. Applying grey clustering, the observed values for each object i with respect to indicator j are assigned to grey class k (where $i \in \{1, \dots, n\}$, $j \in \{1, \dots, m\}$ and $k \in \{1, \dots, s\}$).

As a preliminary remark, it is necessary to note that the weighting function for the subclass k associated with the indicator j (noted $f_j^k(\bullet)$) can be represented in several forms:

- Standard form: observed graphically in Figure 3 and mathematically via Equation (1). Within this framework, the points $x_j^k(1, \dots, 4)$ define the inflection points. From an analytical perspective, an increase in the value of x in the first stage ($x_j^k(1)$ to $x_j^k(2)$) supports an increase in the probability of the object being classified into the cluster. The segment defined by $x_j^k(2)$ and $x_j^k(3)$ represents the region of maximum stability, where the function reaches the value 1. Finally, as x approaches the upper limit $x_j^k(4)$, the probability of belonging to the cluster gradually decreases.

$$f_j^k(x) = \begin{cases} 0, & x \notin [x_j^k(1), x_j^k(4)] \\ \frac{x - x_j^k(1)}{x_j^k(2) - x_j^k(1)}, & x \in [x_j^k(1), x_j^k(2)] \\ 1, & x \in [x_j^k(2), x_j^k(3)] \\ \frac{x_j^k(4) - x}{x_j^k(4) - x_j^k(3)}, & x \in [x_j^k(3), x_j^k(4)] \end{cases} \quad (1)$$

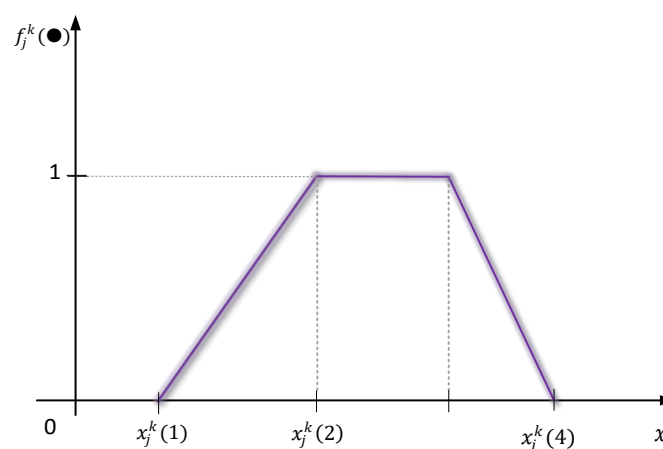


Figure 3. Standard form for the grey clustering function.

- Lower measure: it is shown in Figure 4 and defined mathematically by Equation (2). This function is specific to indicators for which performance is highest at low values.

For any value of x in the interval $[0, x_j^k(3)]$, the function takes the value 1, indicating that the object has a maximum probability of being included in the respective Grey class, with the indicator value being sufficiently small to be considered ideal. Once x exceeds the inflection point $x_j^k(3)$ and moves toward $x_j^k(4)$, the membership degree begins to decrease. Within this interval, as the indicator value increases, the object becomes less and less representative of that class. For any value of x that exceeds the maximum threshold $x_j^k(4)$, the function becomes 0, which means that the object no longer meets the membership criteria for that specific class.

$$f_j^k(x) = \begin{cases} 0, & x \notin [0, x_j^k(4)] \\ 1, & x \in [0, x_j^k(3)] \\ \frac{x_j^k(4) - x}{x_j^k(4) - x_j^k(3)}, & x \in [x_j^k(3), x_j^k(4)] \end{cases} \quad (2)$$

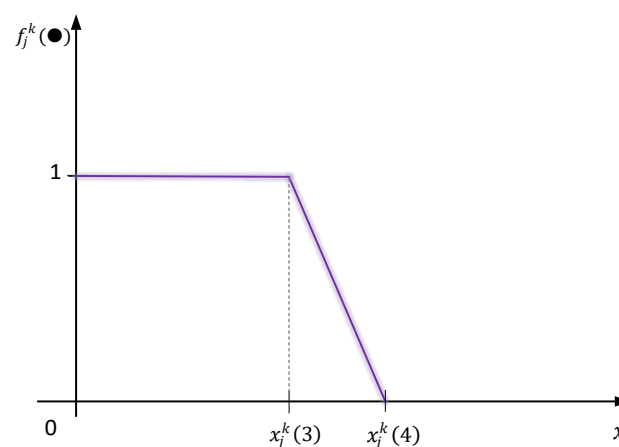


Figure 4. Grey clustering function of lower measure.

- Upper measure, illustrated in Figure 5 and given by the mathematical relationship (3). This is applied to those indicators for which higher values indicate a stronger affiliation with a particular class. For any value of x that is less than the threshold $x_j^k(1)$, the function returns 0, as values below this level are considered insufficient to be included in that class. In the interval between the inflection points $x_j^k(1)$ and $x_j^k(2)$, the degree of cluster membership increases progressively, so the probability that the object is associated with that class becomes increasingly higher. For any value of x equal to or greater than the threshold $x_j^k(2)$, the function reaches and maintains the value 1, indicating full membership, since any result exceeding this inflection point is ideal for the criterion under analysis.

$$f_j^k(x) = \begin{cases} 0, & x < x_j^k(1) \\ \frac{x - x_j^k(1)}{x_j^k(2) - x_j^k(1)}, & x \in [x_j^k(1), x_j^k(2)] \\ 1, & x \geq x_j^k(2) \end{cases} \quad (3)$$

It is important to note that in order to determine the belongingness of an object to one of the classes, the maximum value of the function obtained for each of the considered situations is taken into account.

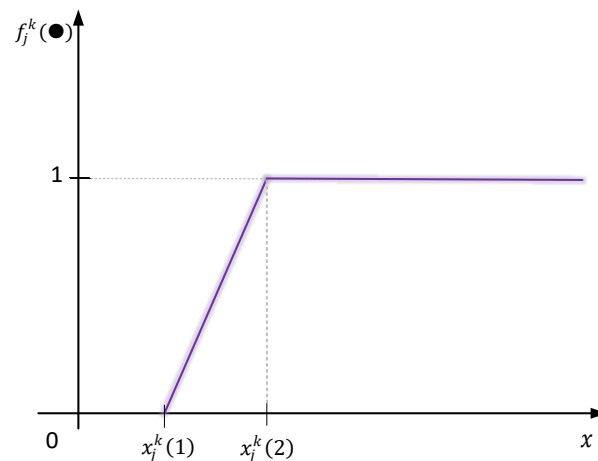


Figure 5. Grey clustering function of upper measure.

In order to assign an object i , from a set of n objects, to one of the considered clusters, having an observed value of the object i for criterion j denoted by x_{ij} , and considering that the grey clustering functions used are known, denoted, as previously shown, by $f_j^k(\bullet)$, as well as the weight associated with criterion j , denoted by η_j , the grey clustering coefficient for the weighted variable corresponding to object i belonging to grey class k is given by [59,60,71,78]:

$$\sigma_i^k = \sum_{j=1}^m f_j^k(x_{ij})\eta_j$$

A final step in determining the membership of a given object to one of the considered clusters consists of applying the condition [59,60,71,78]:

$$\max_{1 \leq k \leq s} \{ \sigma_i^k \} = \sigma_i^{k^*}$$

which indicates the assignment of object i to cluster k^* , where k^* represents the selected cluster [79].

3.7. Threshold Specification and Sensitivity Analysis

Because grey clustering membership functions depend on predefined turning points, the specification of threshold values represents an important modelling decision. In this study, the baseline thresholds were defined on the normalized 0–1 scale in order to distinguish between lower, intermediate, and upper performance regions. The values 0.30, 0.40, 0.60, and 0.70 were used to delimit gradual transitions between performance classes rather than to impose strict binary separations. This choice is consistent with the logic of grey clustering, where objects may show partial affiliation to more than one class before being assigned to the class with the highest grey clustering coefficient.

At the same time, threshold selection should not be treated as a purely objective parameter. Since alternative turning points may affect membership degrees and, in some cases, final cluster assignment, an additional threshold sensitivity analysis was conducted. The baseline configuration was compared with three alternative specifications: T1, T2, and T3, as can be observed from Table 3. These alternatives were selected as small-to-moderate perturbations around the baseline thresholds in order to test whether the results remain stable when the transition zones between adjacent performance classes are slightly modified.

The sensitivity analysis was performed by recalculating the grey clustering coefficients and country assignments under each threshold specification, while keeping the same normalized indicators and weighting scenarios. Stability was assessed by comparing

the resulting country classifications with those obtained under the baseline threshold configuration. This procedure allows the robustness of the typologies to be evaluated not only with respect to weighting assumptions, but also with respect to the turning-point assumptions embedded in the grey membership functions.

Table 3. Threshold specifications used in the sensitivity analysis.

Specification	Thresholds *	Logic
Baseline	0.30/0.40/0.60/0.70	Original configuration
T1	0.28/0.38/0.62/0.72	Slightly wider transition margins
T2	0.32/0.42/0.58/0.68	Slightly narrower transition margins
T3	0.25/0.40/0.60/0.75	Wider outer margins, with the same central interval

* All thresholds are defined on the normalized 0–1 scale.

3.8. Scenarios

This section describes the simulated scenarios used to examine how country classifications vary when the analytical emphasis shifts between strategic innovation capacity and sustainable development outcomes. These scenarios are important for observing how the relative weighting of the two dimensions influences the hierarchy and stability of the resulting clusters. They should therefore be interpreted as alternative classification assumptions rather than as evidence of a direct transition process from innovation inputs to sustainability outcomes.

To begin with, five distinct scenarios were created for the 2021 data, progressively varying the weight assigned to the coefficients, as follows:

- Scenario 1: 100% to strategic innovation capacity, 0% to sustainable development outcomes.

This scenario focuses exclusively on resources invested in research and education. The weight is distributed equally among indicators I_1 , I_2 and I_3 , while the remaining indicators are ignored (I_4 – I_7). The results help identify countries' performance strictly from the perspective of innovation potential.

- Scenario 2: 75% to strategic innovation, 25% to sustainable development outcomes.

Similar to the previous scenario, this one prioritizes innovation capacity, but this time it also includes a minor component for evaluating sustainable results. This scenario was introduced to test whether adding a moderate weighting for sustainable results alters the ranking based on innovation investments.

- Scenario 3: 50% to strategic innovation, 50% to sustainable development outcomes.

This approach helps outline how input-oriented and outcome-oriented indicators are jointly reflected in country classifications, providing a balanced view of the alignment between the two analytical dimensions.

- Scenario 4: 25% to strategic innovation, 75% to sustainable development outcomes.

This time, the focus is on concrete results, assessing how effective countries are at generating sustainable benefits, with less weight given to innovation inputs. This scenario highlights countries that manage to achieve excellent results even if they do not have the highest scores when it comes to innovation inputs.

- Scenario 5: 0% to strategic innovation, 100% to sustainable development outcomes.

In this scenario, the assessment is based strictly on performance in sustainable development, completely disregarding investments in innovation. This ranking allows for the identification of those countries that are leaders in terms of social and economic well-being and environmental protection, regardless of their strategic capacity for innovation.

Figure 6 shows Scenario 3 applied to the dynamic analysis of data from the 2022–2024 period. Scenario 3 was selected as the benchmark for the dynamic component because it assigns equal analytical weight to strategic innovation capacity and sustainable development outcomes. This balanced specification is the most appropriate for observing the joint evolution of input-oriented and outcome-oriented indicators over time, without privileging one dimension over the other.

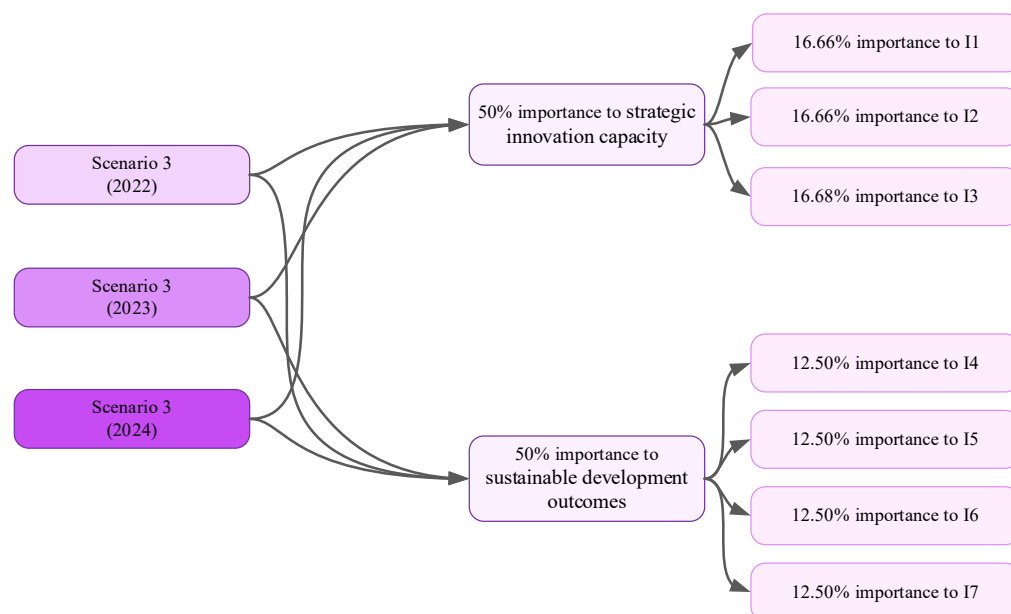


Figure 6. Scenario 3 applied for the dynamic analysis of data from 2022 to 2024.

The other four scenarios were designed primarily as cross-sectional sensitivity specifications for the base year 2021. Their purpose is to show how country classifications change when the composite weighting assumptions shift toward either innovation capacity or sustainable development outcomes. They should not be interpreted as temporal stages in a real transition process. For this reason, extending the dynamic analysis to all five scenarios would combine two sources of variation: changes in the underlying country indicators over time and changes in the weighting assumptions. To maintain interpretability, the dynamic analysis keeps the weighting structure constant and uses Scenario 3 as a balanced reference framework.

The scenario maintains a 50–50% ratio between the two main dimensions. For the innovation dimension (I_1 – I_3), the 50% weight was distributed so as to total the desired percentage: I_1 and I_2 each receive 16.66%, while I_3 receives 16.68%. For the sustainability dimension (I_4 – I_7), the four indicators each receive an equal weight of 12.50%, accounting for the remaining 50% of the model’s total weight. By repeatedly applying this fixed weighting structure for 2022, 2023, and 2024, the analysis identifies whether countries remain stable or change position within the performance typology over time.

4. Grey Clustering Analysis

The following section presents the results of applying the grey clustering model to assess innovation capacity and sustainable development outcomes in the European Union. To determine the optimal number of clusters, the Silhouette, Davies-Bouldin and Calinski-Harabasz performance indices are used to ensure an accurate segmentation of the member states. The specific features of grey clustering are described, and the results obtained for the base year 2021 under the five weighting scenarios are subsequently detailed, followed by a dynamic analysis tracking the evolution of countries over the 2022–2024 period.

4.1. Establishing the Number of Clusters

The optimal number of clusters was determined by jointly analyzing the Silhouette, Davies–Bouldin, and Calinski–Harabasz indices.

As shown in Table 4 and Figure 7, the highest Silhouette coefficient was obtained for $k = 3$ (0.2842), indicating the best balance between intra-cluster cohesion and inter-cluster separation among the analyzed alternatives.

Table 4. Values for the indicators used.

k	Silhouette	Davies–Bouldin	Calinski–Harabasz
2	0.2355	1.2849	8.7546
3	0.2842	1.0113	10.1483
4	0.2268	1.3729	9.3970
5	0.2336	1.1682	9.1542
6	0.2301	0.9856	8.9846
7	0.2389	0.9556	9.1480
8	0.1919	1.0496	7.8370
9	0.2447	0.8953	8.7220

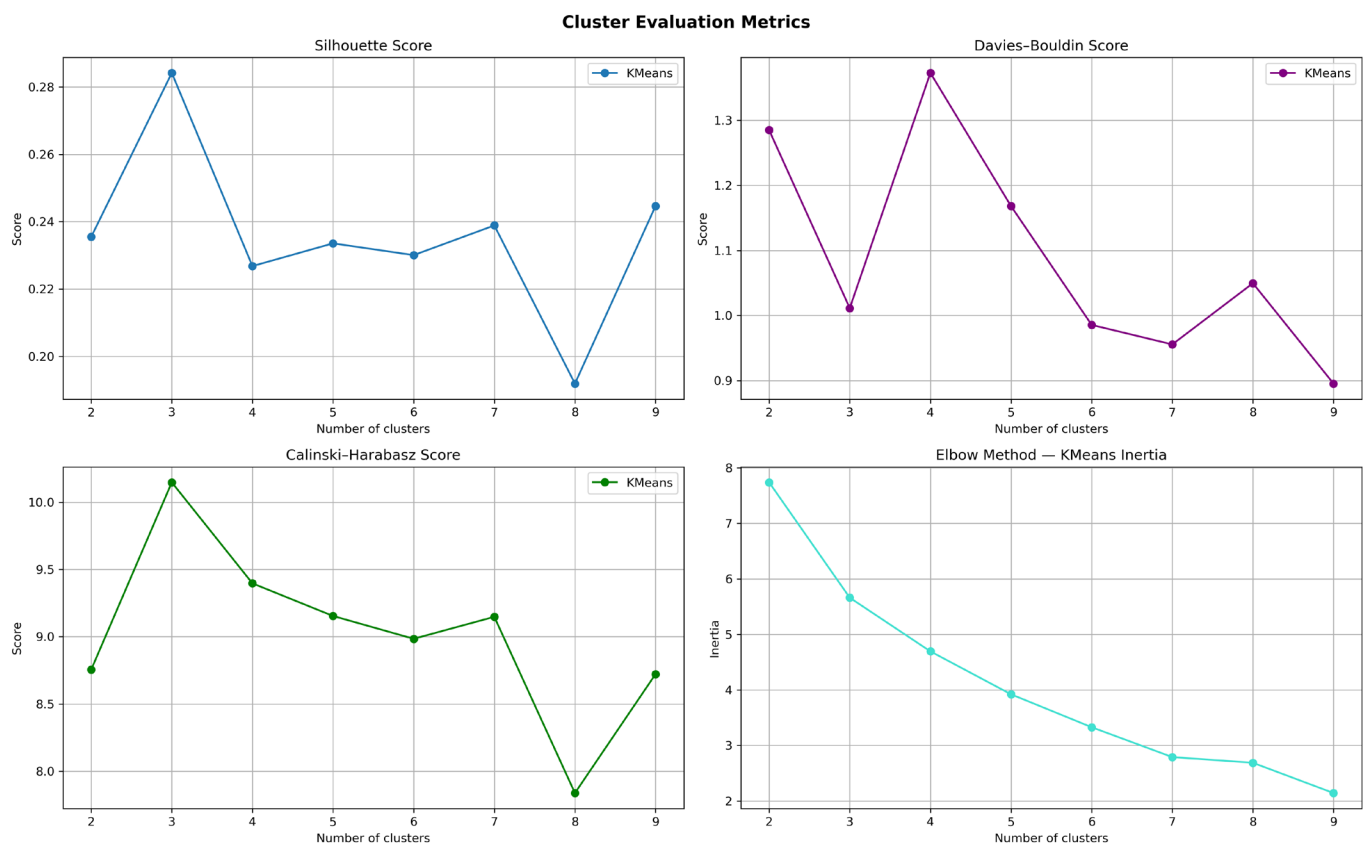


Figure 7. Determining the number of clusters.

At the same time, the Davies–Bouldin index reached relatively low values for larger numbers of clusters, with the minimum value recorded for $k = 9$ (0.8953), while the Calinski–Harabasz index also attained its maximum for $k = 3$ (10.1483), fact also highlighted in the results presented in Table 5.

Table 5. Cluster-number indications according to validation criteria.

Indicator	Recommended k
Silhouette	3
Davies–Bouldin	9
Calinski–Harabasz	3

The validation results do not point to a fully unambiguous clustering solution, which is expected in macro-comparative analyses of EU member states, where countries often display gradual rather than sharply separated differences in socioeconomic and innovation-related performance. The three-cluster solution was nevertheless selected because it is supported by two of the three validation indices: both the Silhouette coefficient and the Calinski–Harabasz index reach their highest values for $k = 3$. Although the Davies–Bouldin index records its lowest value for $k = 9$, such a solution would divide the EU-27 sample into a large number of small groups, reducing the stability, interpretability, and policy relevance of the resulting typology. In this context, the purpose of the clustering procedure is not to identify narrowly fragmented country groups, but to construct a parsimonious grey-clustering typology distinguishing between relatively high, intermediate, and low performance profiles.

Therefore, the selected three-cluster solution should be interpreted as an analytically useful classification framework rather than as evidence of sharply separated natural clusters. This interpretation is consistent with the grey systems perspective adopted in the paper, where cluster membership reflects degrees of affiliation to broader performance classes under conditions of partial information and multidimensional heterogeneity.

The fact that the three validation indices do not indicate the same optimal number of clusters should not be interpreted as an inconsistency, but rather as a consequence of their different evaluation logics. The Silhouette coefficient evaluates the average cohesion of observations within their assigned cluster relative to their separation from neighbouring clusters, whereas the Davies–Bouldin index focuses on the average similarity between each cluster and its most similar alternative cluster, with lower values indicating better separation [80,81]. The Calinski–Harabasz index, in turn, evaluates the ratio between-cluster dispersion and within-cluster dispersion [80]. As a result, these metrics may favour different levels of granularity, particularly in multidimensional socioeconomic datasets where country profiles are gradual rather than sharply separated. Similar situations are observed in applied clustering studies that jointly report Silhouette, Davies–Bouldin, and Calinski–Harabasz measures, showing that the preferred clustering solution depends not only on metric optimization, but also on the structure of the data and the analytical objective of the classification [82].

The selection of the optimal number of clusters was further supported through the Elbow method applied to the K-Means inertia values. As illustrated in Figure 7, the inertia decreases substantially between $k = 2$ and $k = 3$, after which the rate of improvement becomes noticeably smoother. This behaviour suggests the presence of an “elbow” around $k = 3$, indicating that additional clusters provide only limited gains in terms of within-cluster variance reduction. While more granular solutions may slightly improve some validation criteria, they also increase model complexity and reduce the usefulness of the classification for comparative policy interpretation.

The Elbow method results are consistent with the Silhouette and Calinski–Harabasz indices, both of which also attain their highest values for $k = 3$. Although the Davies–Bouldin index continues to slightly improve for larger values of k , the marginal benefits are relatively limited and come at the expense of reduced interpretability and increased model

complexity. Consequently, the three-cluster solution was considered the most balanced and methodologically appropriate configuration for the subsequent analysis.

The hierarchical clustering dendrogram obtained using Ward's linkage method provides additional support for the selection of the three-cluster solution. As illustrated in Figure 8, a clear separation between the groups can be observed at the selected cut-off distance of approximately 1.57, where the dendrogram partitions the countries into three relatively distinct clusters.

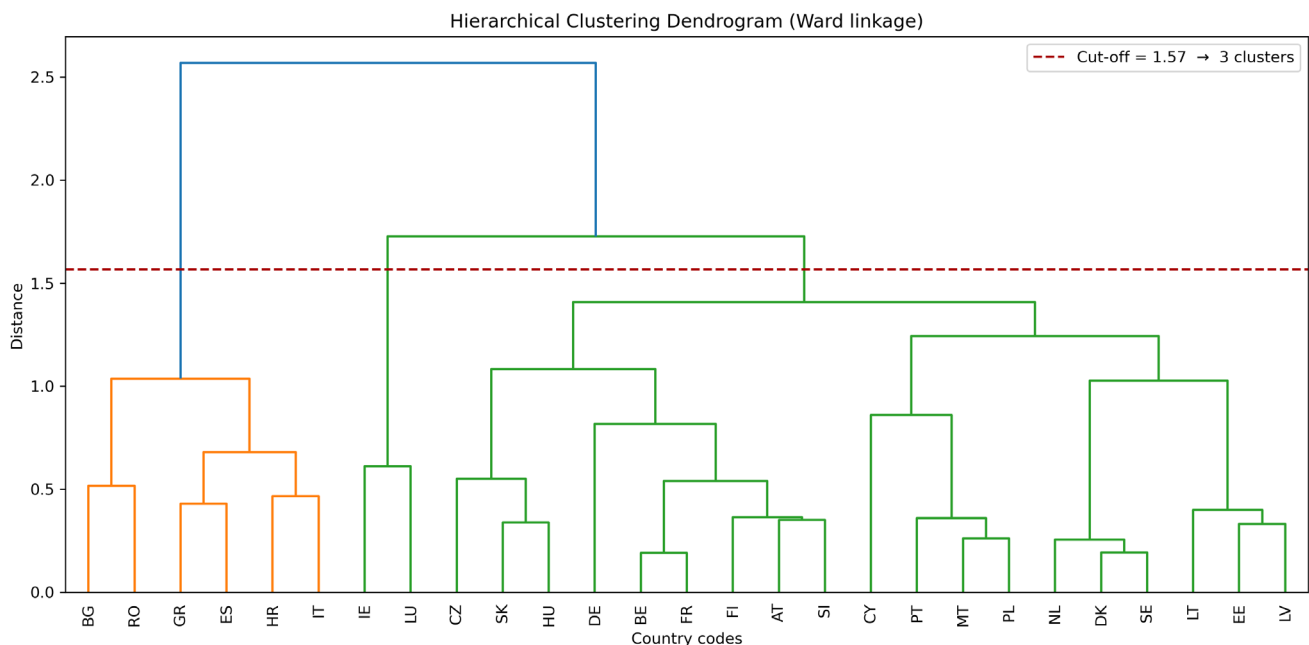


Figure 8. Dendrogram.

The structure of the dendrogram indicates a reasonable degree of homogeneity within clusters and increasing dissimilarity between clusters as the linkage distance grows. Moreover, the relatively large jump in linkage distance observed before the final merges suggests that combining the clusters further would reduce the interpretability and distinctiveness of the resulting groups. Therefore, the dendrogram analysis confirms the validity of the three-cluster configuration identified through the Silhouette, Davies–Bouldin, Calinski–Harabasz, and Elbow method analyses.

Consequently, all subsequent results are interpreted as broad performance typologies rather than as rigid country groupings, and the cluster labels are used to facilitate comparative interpretation of relative performance across scenarios.

4.2. Grey Clustering Functions

This subsection details how the normalized indicators are converted into membership degrees for the three identified groups (Figure 9). This establishes the decision boundaries, which serve to define the profile of each cluster for all analyzed indicators.

Cluster A is the one in which high performance was recorded. To create this cluster, a superior measure function is used, defined by the thresholds 0.60 and 0.70. From an analytical standpoint, any indicator exceeding the 0.70 threshold indicates full membership in this group, while values below 0.60 are considered insufficient for this cluster. Cluster B represents average performance. This category uses a standard form function, which groups states with intermediate results. The range with the highest stability, where membership is complete, lies between 0.40 and 0.60. Movement toward the other clusters is suggested by the upward (0.30–0.40) and downward (0.60–0.70) slopes. Cluster C, or the low-performance

cluster, is formed using a lower-order measure function, specific to countries that score low on the indicators. Maximum membership in this cluster is assigned to values below the 0.30 threshold, with the probability of membership decreasing as the value approaches 0.40 (Table 6).

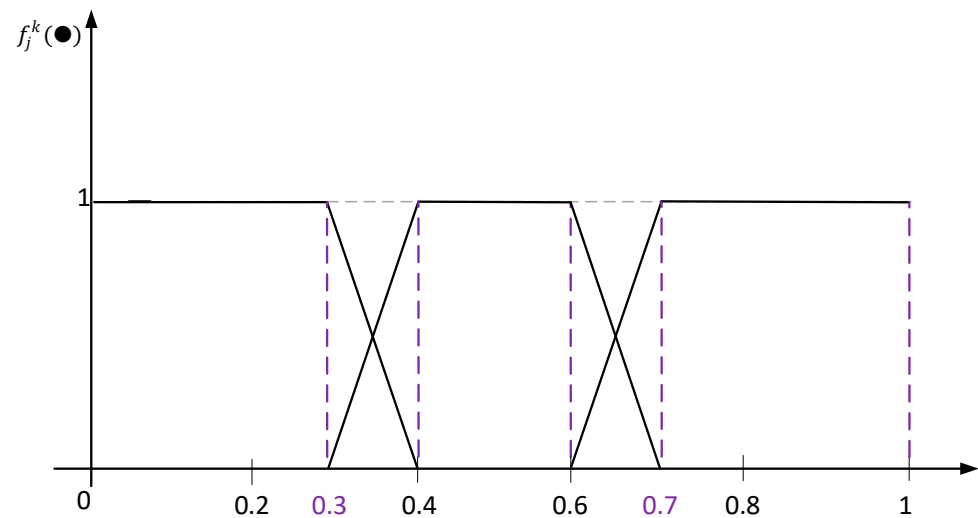


Figure 9. Grey clustering functions for clusters A, B and C.

Table 6. The membership threshold values for the identified grey classes.

Indicator	Cluster	$f_j^k(\bullet)$
I_1N-I_7N *	$k = A$	$f_j^A[0.60; 0.70; -; -]$
	$k = B$	$f_j^B[0.30; 0.40; 0.60; 0.70]$
	$k = C$	$f_j^C[-; -; 0.30; 0.40]$

* "N" stands for the normalized values of the indicators.

Further, it should be mentioned that the threshold values used for the grey membership functions were established based on the distribution and normalized scale of the analyzed indicators. Since all variables were normalized within the interval $[0, 1]$, the thresholds were selected to divide the data into three interpretable performance categories corresponding to low, medium, and high levels. The values 0.30 and 0.70 were chosen as reference boundaries for low and high performance, respectively, while the intermediate intervals (0.30–0.40 and 0.60–0.70) were introduced to create gradual transitions between neighbouring clusters. This approach avoids rigid classifications and allows observations located near the boundaries to partially belong to multiple clusters, reflecting the uncertainty and continuous nature of socioeconomic phenomena. The establishment of these values also ensures consistency and comparability across all normalized indicators included in the analysis.

4.3. Basic Year Scenarios Results

This section of the article presents the results obtained by grouping the member states of the European Union, taking into account the weight assigned to the two main dimensions of the analysis.

Scenario 1: The greatest importance is placed on strategic innovation capacity.

In this scenario, full weight is given to the three innovation indicators (I_1 , I_2 , I_3), so that the influence of sustainable results is reduced to zero. In other words, η_1 and η_2 have

been set to 0.3333 and η_3 has been set to 0.3334, due to the fact that we have an odd number of indicators. For the second dimension, η_4 – η_7 were all set to 0.

According to Table 7 and Figure 10, it can be seen that Cluster A, which has the highest performance, consists of eight countries, including Belgium, Denmark and Sweden, which are the countries with the greatest innovation potential. Cluster B contains the most countries, comprising 12 nations such as Germany, France and Finland, thus indicating a moderate to high capacity for innovation. Cluster C includes 7 countries, including Romania, Bulgaria and Italy, identifying the regions with the lowest investment in innovation in 2021.

Table 7. Country clusters for Scenario 1.

Cluster	Components
A	Belgium, Denmark, Ireland, Cyprus, Lithuania, Luxembourg, Netherlands, Sweden
B	Germany, Estonia, Greece, Spain, France, Latvia, Malta, Austria, Poland, Slovenia, Slovakia, Finland
C	Bulgaria, Czechia, Croatia, Italy, Hungary, Portugal, Romania

Member states

- Cluster A
- Cluster B
- Cluster C



Figure 10. Countries on the map for Scenario 1.

Scenario 2: Prioritizing innovation capacity with a low emphasis on sustainability.

In this scenario, the weighting is distributed as 75% for innovation capacity and 25% for sustainable development outcomes. For η_1 – η_3 the weight was set at 0.2500 and for η_4 – η_7 at 0.0625 for each indicator.

The purpose of this scenario was to test whether assigning a moderate weight to sustainable outcomes alters the results obtained in the previous scenario, where the ranking

was established exclusively based on investments in innovation. It is important to note that the results obtained are identical to those in Scenario 1 (Table 8), indicating that assigning a 25% weight to results is not sufficient to alter the composition of the performance groups.

Table 8. Country clusters for Scenario 2.

Cluster	Components
A	Belgium, Denmark, Ireland, Cyprus, Lithuania, Luxembourg, Netherlands, Sweden
B	Germany, Estonia, Greece, Spain, France, Latvia, Malta, Austria, Poland, Slovenia, Slovakia, Finland
C	Bulgaria, Czechia, Croatia, Italy, Hungary, Portugal, Romania

Scenario 3: Equal importance given to both dimensions.

This scenario assigns a 50% weight to each dimension, with the aim of providing an overview of the efficiency of the process of “transforming” innovation resources into sustainable outcomes. Thus, indicators η_1 and η_2 each received a score of 0.1666, while η_3 received 0.1668 and indicators η_4 through η_7 were each assigned a weight of 0.1250.

This time, Cluster A has expanded to 11 countries with the addition of the Czech Republic, Slovenia and Finland, demonstrating that these countries have the ability to convert inputs into tangible results as efficiently as possible. Cluster B has shrunk to 9 countries this time, all of which show average performance. Cluster C continues to consist of countries such as Romania, Bulgaria, Croatia, Italy, Hungary and Portugal, highlighting persistent difficulties in both dimensions analyzed (Figure 11 and Table 9).

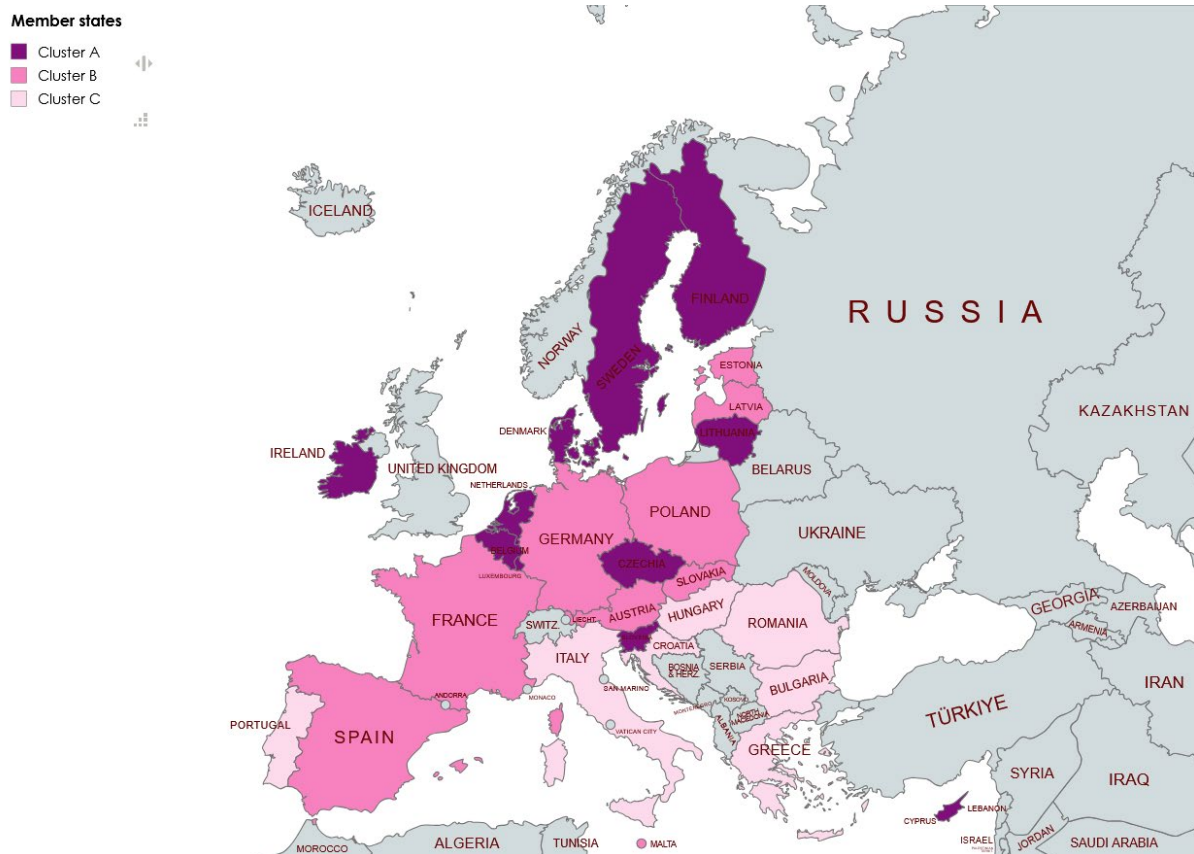


Figure 11. Countries on the map for Scenario 3.

indicators η_1 – η_3 were assigned a weight of 0 and η_4 – η_7 were each assigned a weight of 0.2500.

Table 10. Country clusters for Scenario 4.

Cluster	Components
A	Czechia, Denmark, Germany, Estonia, Ireland, Cyprus, Lithuania, Hungary, Netherlands, Slovenia, Slovakia, Finland, Sweden
B	Belgium, France, Croatia, Luxembourg, Malta, Austria, Poland, Portugal
C	Bulgaria, Greece, Spain, Italy, Latvia, Romania

Cluster A has now reached its maximum size of 15 countries, confirming the leading position of countries such as Austria and Poland in terms of sustainability. Cluster B consists of 6 countries, representing moderate stability in sustainable outcomes. Cluster C consists of a group of 6 countries, including Romania, Bulgaria and Italy, which face significant challenges in achieving sustainable development goals (Table 11 and Figure 13).

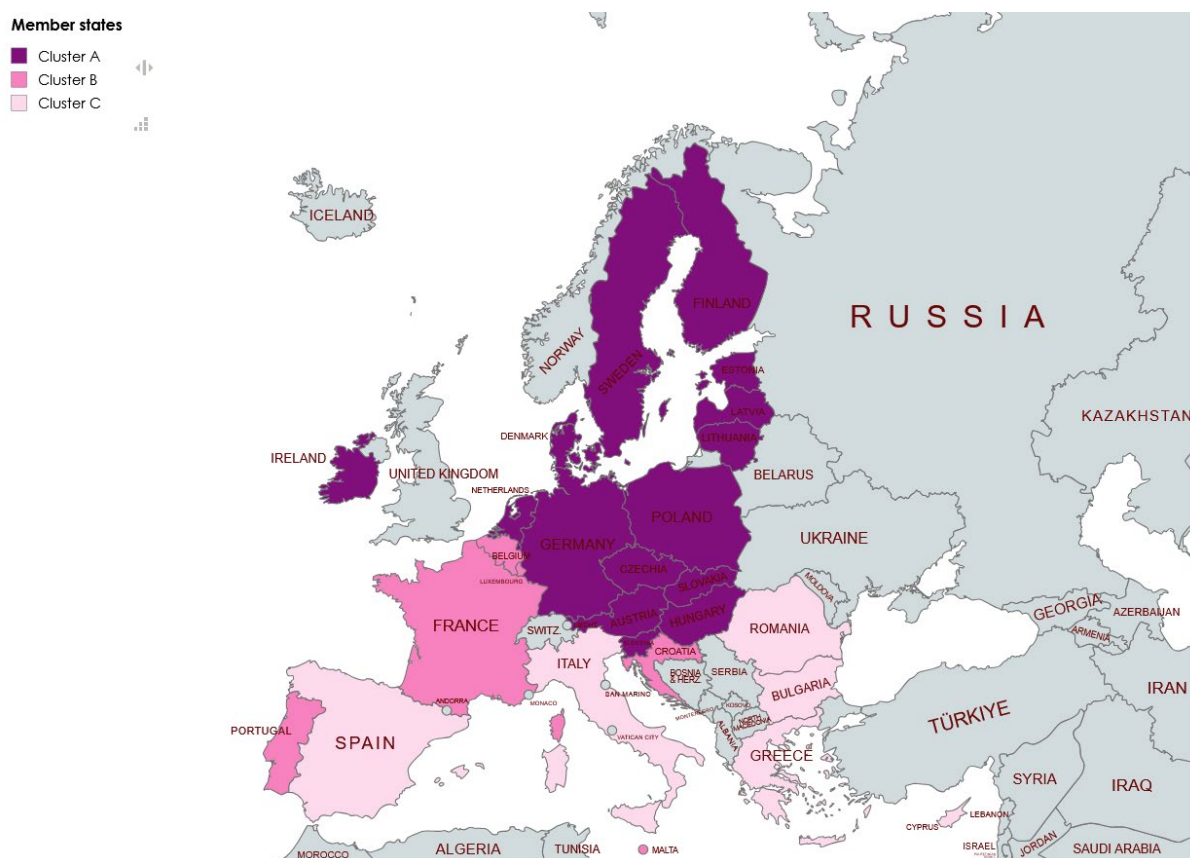


Figure 13. Countries on the map for Scenario 5.

Table 11. Country clusters for Scenario 5.

Cluster	Components
A	Czechia, Denmark, Germany, Estonia, Ireland, Latvia, Lithuania, Hungary, Netherlands, Austria, Poland, Slovenia, Slovakia, Finland, Sweden
B	Belgium, France, Croatia, Luxembourg, Malta, Portugal
C	Bulgaria, Greece, Spain, Italy, Cyprus, Romania

Threshold Sensitivity Analysis

The threshold sensitivity analysis results (summarized in Table 12) indicate that the country classifications are generally stable under small-to-moderate perturbations of the grey membership thresholds. Across the five scenarios and the three alternative threshold specifications, 353 of the 405 country-threshold comparisons reproduced the baseline classification, corresponding to an overall stability rate of 87.2%. Stability was highest in the extreme scenarios, where the classification was based exclusively on strategic innovation capacity or exclusively on sustainable development outcomes. In Scenario 1 and Scenario 5, a total of 75 of the 81 comparisons reproduced the baseline classification, corresponding to stability rates of 92.6% in both cases. The mixed scenarios showed somewhat higher sensitivity, particularly Scenario 3, where 65 of the 81 comparisons remained unchanged. This result is consistent with the balanced nature of Scenario 3, where both input-oriented and outcome-oriented dimensions jointly influence the grey clustering coefficients.

Table 12. Threshold sensitivity analysis across weighting scenarios.

Scenario	T1	T2	T3	Overall	Overall Stability
	(Unchanged Countries/Total Countries)				
S1	26/27	24/27	25/27	75/81	92.6%
S2	24/27	23/27	23/27	70/81	86.4%
S3	21/27	24/27	20/27	65/81	80.2%
S4	22/27	24/27	22/27	68/81	84.0%
S5	25/27	26/27	24/27	75/81	92.6%
Total	118/135	121/135	114/135	353/405	87.2%

The observed reclassifications affect a limited number of countries and occur mainly between adjacent classes, suggesting that threshold perturbations primarily influence boundary cases rather than altering the overall typological structure. Therefore, the sensitivity analysis supports the robustness of the broad high/intermediate/low classification, while also confirming that countries located close to class boundaries should be interpreted with appropriate caution.

This all-country threshold sensitivity analysis provides a broad robustness check of the grey membership specification. To complement it, the following discussion further distinguishes between countries with stable scenario profiles and countries that behave as boundary cases when the analytical weighting scheme changes.

4.4. Dynamic Scenarios Results

At this stage of the research, the analysis focuses on the evolution of member states over the 2022–2024 period, with Scenario 3 being consistently applied. This represents the scenario in which a perfect balance is maintained, with a 50–50% weighting between innovation capacity and sustainable development outcomes. The weights were distributed as follows: indicators η_1 and η_2 received 0.1666, η_3 received 0.1668, and the sustainability indicators (η_4 – η_7) each received 0.1250.

Scenario 3—2022: Strengthening the High-Performing Group.

For 2022, Cluster A has clearly expanded, now comprising a total of 12 member states. A notable development is that of Germany, which has managed to move from Cluster B (in 2021) to the group of top performers (in 2022). Cluster B now consists of 8 countries, including Spain, France and Austria, indicating stability in average performance for the European core. Cluster C remains constant with 7 members, still comprising countries such

as Romania, Bulgaria and Italy, which continue to face difficulties in achieving a balance between investment and sustainable results (Table 13 and Figure 14).

Table 13. Country clusters for Scenario 3—2022.

Cluster	Components
A	Belgium, Czechia, Denmark, Germany, Ireland, Cyprus, Lithuania, Luxembourg, Netherlands, Slovenia, Finland, Sweden
B	Estonia, Spain, France, Latvia, Malta, Austria, Poland, Slovakia
C	Bulgaria, Greece, Croatia, Italy, Hungary, Portugal, Romania

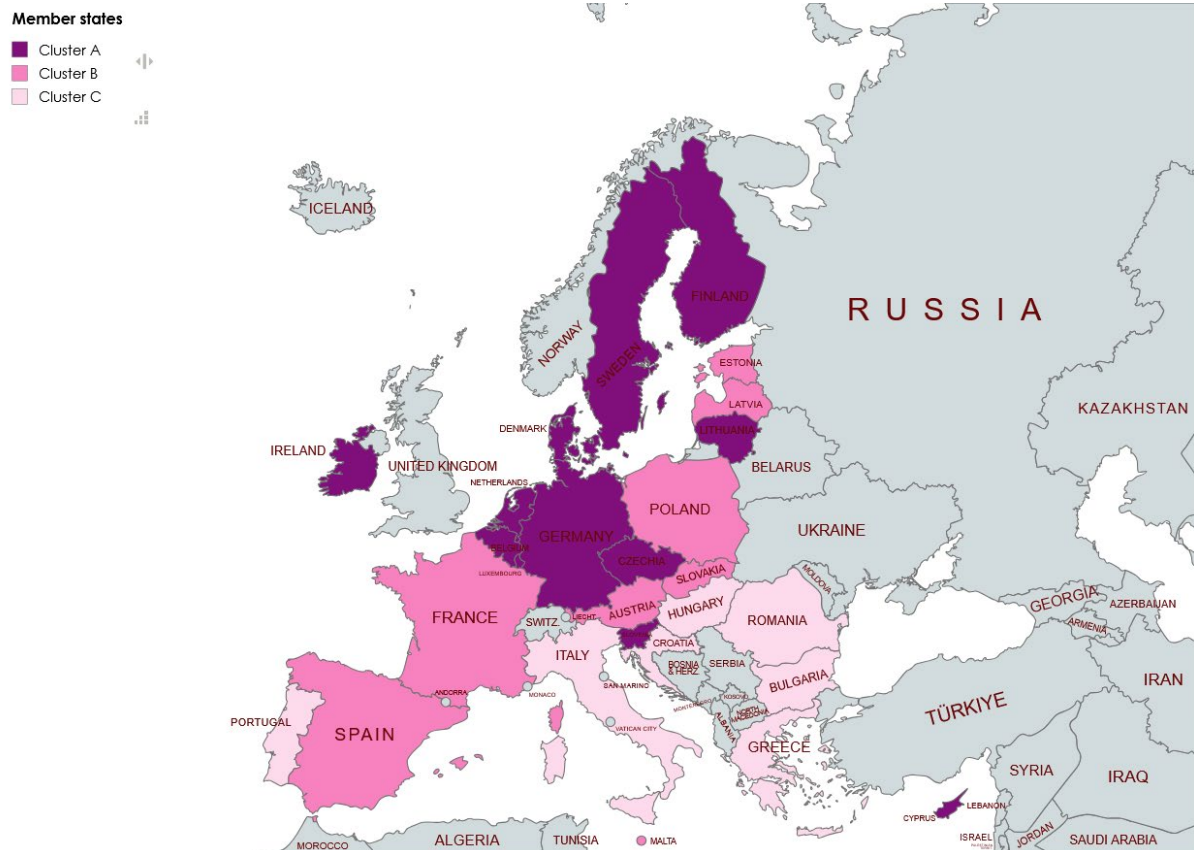


Figure 14. Countries on the map for Scenario 3—2022.

Scenario 3—2023: The Dynamics of Structural Change.

Cluster A has seen a slight decline, now comprising 11 countries. The changes within this cluster include France's rise into this elite group, while Germany and Slovenia return to Cluster B. Thus, Cluster B expands to 9 countries, with Croatia being one of the countries joining it, having managed to leave the low-performance group (Cluster C). Cluster C remains at 7 countries; however, even though Croatia has improved, Spain has dropped from Cluster B, signalling a deterioration in the balance between innovation and sustainability this calendar year (Table 14 and Figure 15).

Scenario 3—2024: Convergence Trends and New Challenges.

In this scenario, Cluster A consists of 10 countries, representing those that have performed well (e.g., Denmark, Sweden, the Netherlands, Belgium). It is worth noting that this year, Finland leaves the group of leaders, dropping into Cluster B. Cluster B thus becomes the largest group, with 11 member states. Bulgaria's positive progress stands

out, as it has moved from Cluster C to Cluster B, suggesting an improvement in the analyzed indicators. Cluster C has reached the minimum size of 6 countries (Greece, Spain, Italy, Hungary, Portugal and Romania), representing the group requiring the most urgent economic policy interventions (Table 15 and Figure 16).

Table 14. Country clusters for Scenario 3—2023.

Cluster	Components
A	Belgium, Czechia, Denmark, Ireland, France, Cyprus, Lithuania, Luxembourg, Netherlands, Finland, Sweden
B	Germany, Estonia, Croatia, Latvia, Malta, Austria, Poland, Slovenia, Slovakia
C	Bulgaria, Greece, Spain, Italy, Hungary, Portugal, Romania

Member states

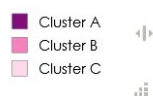


Figure 15. Countries on the map for Scenario 3—2023.

Table 15. Country clusters for Scenario 3—2024.

Cluster	Components
A	Belgium, Czechia, Denmark, Ireland, France, Cyprus, Lithuania, Luxembourg, Netherlands, Sweden
B	Bulgaria, Germany, Estonia, Croatia, Latvia, Malta, Austria, Poland, Slovenia, Slovakia, Finland
C	Greece, Spain, Italy, Hungary, Portugal, Romania

Table 16. The composition of the clusters in Scenarios 1–5.

Country	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
	Cluster				
Austria	B	B	B	B	A
Belgium	A	A	A	B	B
Bulgaria	C	C	C	C	C
Croatia	C	C	C	B	B
Cyprus	A	A	A	A	C
Czechia	C	C	A	A	A
Denmark	A	A	A	A	A
Estonia	B	B	B	A	A
Finland	B	B	A	A	A
France	B	B	B	B	B
Germany	B	B	B	A	A
Greece	B	B	C	C	C
Hungary	C	C	C	A	A
Ireland	A	A	A	A	A
Italy	C	C	C	C	C
Latvia	B	B	B	C	A
Lithuania	A	A	A	A	A
Luxembourg	A	A	A	B	B
Malta	B	B	B	B	B
Netherlands	A	A	A	A	A
Poland	B	B	B	B	A
Portugal	C	C	C	B	B
Romania	C	C	C	C	C
Slovakia	B	B	B	A	A
Slovenia	B	B	A	A	A
Spain	B	B	B	C	C
Sweden	A	A	A	A	A

The results in Table 17 show that 10 countries remain in the same cluster across all five scenarios: five in Cluster A, two in Cluster B, and three in Cluster C. The remaining countries show scenario-sensitive classifications, meaning that their position changes under at least one weighting configuration. These cases should be interpreted as boundary or weight-sensitive profiles rather than as unstable results. This overview also clarifies that Austria is part of a broader group of scenario-sensitive countries, while remaining a relevant illustrative case because its classification changes when full weight is assigned to sustainable-development outcome indicators.

In order to provide an interpretation of the results, the data were grouped into specific categories to observe where certain countries stand. This allows us to identify countries that need greater investment in research and those where there is a need to learn how to better manage existing resources.

Table 17. Scenario-stability patterns across Scenarios 1–5.

Stability Pattern Across Scenarios 1–5	Countries	Interpretation
Stable in Cluster A across all five scenarios	Denmark, Ireland, Lithuania, Netherlands, Sweden	Consistently favourable profile across all weighting assumptions
Stable in Cluster B across all five scenarios	France, Malta	Consistently intermediate profile across all weighting assumptions
Stable in Cluster C across all five scenarios	Bulgaria, Italy, Romania	Consistently vulnerable profile across all weighting assumptions
Scenario-sensitive classification	Austria, Belgium, Croatia, Cyprus, Czechia, Estonia, Finland, Germany, Greece, Hungary, Latvia, Luxembourg, Poland, Portugal, Slovakia, Slovenia, Spain	Countries whose classification changes under at least one weighting scenario, suggesting sensitivity to the relative emphasis assigned to innovation-capacity and sustainability-outcome indicators

5.1.1. Consistent Leaders: Excellence Across the Board

A relatively small group of countries has been identified that could be classified as a “functional ideal.” This category includes Denmark, Ireland, Lithuania, the Netherlands, and Sweden, the only countries that have consistently maintained their position, remaining in Cluster A regardless of the weighting used. This suggests that these countries have both high levels of investment in innovation capacity, such as research and education and favourable performance in terms of GDP, social inclusion, and low emissions. The results thus indicate the existence of a relatively strong association between the strategic dimension of innovation and sustainable development outcomes.

5.1.2. Resource Rich but Efficiency Constrained Economies

It is interesting to examine the performance of countries such as Belgium and Luxembourg. In Scenarios 1, 2, and 3, where innovation accounted for at least 50%, these countries remain in Group A. However, once the analysis focuses on results, in Scenarios 4 and 5, they end up in Group B, thus losing their leading position. This classification change suggests that, although these countries demonstrate a high capacity for innovation, their performance regarding indicators such as greenhouse gas emissions or the risk of poverty was not, according to the analysis, as high relative to the resources invested. Belgium and Luxembourg can be classified as high-input countries that possess resources but appear less favourably positioned when sustainability-outcome indicators are emphasized, compared to countries that have consistently remained in Cluster A, regardless of the scenario analyzed.

5.1.3. The Existence of “Output” but Without Resources

In contrast to Belgium and Luxembourg, at the other end of the spectrum, several countries appear to be achieving results even with fewer resources. This category includes: the Czech Republic, Estonia, Germany, Hungary, Slovakia, and Slovenia, which initially, in the first scenarios where innovation plays a more significant role, are placed in lower groups, such as Group B and Group C, but manage to move into Group A when scenarios focused on sustainable outcomes are given greater weight. The most representative examples are the Czech Republic and Slovenia, which in research move from Cluster C or Cluster B to Cluster A under sustainability-oriented weighting. This phenomenon reinforces the idea that these countries appear to have the capacity to prioritize sustainable development outcomes, even when their gross expenditure on research and development (GERD) or highly skilled human capital did not seem high.

5.1.4. The Existence of a “Fragile” Vulnerability

Unlike the cases observed so far, there are also countries whose classification depends decisively on a single set of indicators. Cyprus and Latvia are examples of this. According to the results, Cyprus is a strong leader in innovation, ranking in Group A in Scenarios 1–4, but in Scenario 5 it suddenly drops to Group C. This behaviour indicates a major imbalance, suggesting an economy that innovates but is less favourably positioned with respect to the analyzed sustainability-outcome indicators. Compared to Cyprus, Latvia exhibits the opposite behaviour, being in Cluster C in Scenario 4 but jumping directly to Cluster A in Scenario 5; in the remaining scenarios, it remains consistently in Cluster B. This suggests high performance on certain sustainability characteristics but a fragile innovation base.

5.1.5. Systemic Lag: The Core of Cluster C

Unfortunately, this category includes Bulgaria, Italy and Romania, which remain consistently trapped in Cluster C throughout all five scenarios. The stagnation of these countries indicates a twofold structural problem: on the one hand, a lack of strategic investment in innovation and on the other, an inability to produce sustainable results. For these countries, increasing the weight of a single dimension does not help, as their performance remains low on both fronts.

5.2. Dynamic Comparison for the Results Obtained in Scenario 3

The dynamic comparison was conducted using Scenario 3 as a balanced benchmark, in which strategic innovation capacity and sustainable development outcomes each receive 50% of the total weight. The purpose of this analysis is not to model a causal transition from innovation inputs to sustainability outcomes, but to examine how country classifications evolve over time when the weighting assumptions are held constant. This approach makes it possible to distinguish temporal changes in the underlying Eurostat indicators from classification changes caused by alternative weighting schemes (Table 18—in this table the colors of each cell correspond to the colors of the clusters obtained in Scenario 3 in each year of the analysis).

Table 18. Cluster composition for the 2021–2024 period in Scenario 3.

Country	Scenario 3			
	2021	2022	2023	2024
	Cluster			
Austria	B	B	B	B
Belgium	A	A	A	A
Bulgaria	C	C	C	B
Croatia	C	C	B	B
Cyprus	A	A	A	A
Czechia	A	A	A	A
Denmark	A	A	A	A
Estonia	B	B	B	B
Finland	A	A	A	B
France	B	B	A	A
Germany	B	A	B	B
Greece	C	C	C	C

Table 18. Cont.

Country	Scenario 3			
	2021	2022	2023	2024
	Cluster			
Hungary	C	C	C	C
Ireland	A	A	A	A
Italy	C	C	C	C
Latvia	B	B	B	B
Lithuania	A	A	A	A
Luxembourg	A	A	A	A
Malta	B	B	B	B
Netherlands	A	A	A	A
Poland	B	B	B	B
Portugal	C	C	C	C
Romania	C	C	C	C
Slovakia	B	B	B	B
Slovenia	A	A	B	B
Spain	B	B	C	C
Sweden	A	A	A	A

5.2.1. The Core of Stability in Cluster A: The Systematic Leaders

As in the previous case, it is important to begin by identifying the “systematic leaders”, those countries that never fall out of the high-performing group (Figure 17—in this figure the color of the countries correspond to the color used above for depicting cluster A).

This category includes: Belgium, the Czech Republic, Denmark, Ireland, Cyprus, Lithuania, Luxembourg, the Netherlands and Sweden. The dominant trait of these countries is the remarkable structural resilience they demonstrate, as evidenced by the results. Regardless of annual economic fluctuations, they have the ability to maintain an optimal correlation between investment in research and development and indicators of social and environmental well-being. It is important to note that this cluster includes countries from Central and Eastern Europe (the Czech Republic and Lithuania).

5.2.2. Improving Performance: Successes Achieved Along the Way

Dynamic analysis can highlight paths to success, where countries have managed to improve their relative performance. For example, France’s rise is noteworthy. France started in the 2021–2022 period as part of Cluster B (Figure 18—in this figure, the only countries colored are the ones belonging to cluster B), managing in 2023 to move to Cluster A (Figure 17), where it remained in 2024 as well. This trend suggests an improvement in public policies that have helped to better utilize innovation resources for sustainable results. Another example is the path taken by Bulgaria and Croatia. These two represent the clearest examples of positive convergence. Croatia was part of Cluster C during 2021–2022, managing to move to Cluster B in 2023. However, even more impressive is the case of Bulgaria, which only managed to leave Cluster C (Figure 19—in this figure the only countries colored are the ones belonging to cluster C) in 2024, moving up to Cluster B. These shifts indicate that the critical vulnerabilities previously recorded have been overcome.

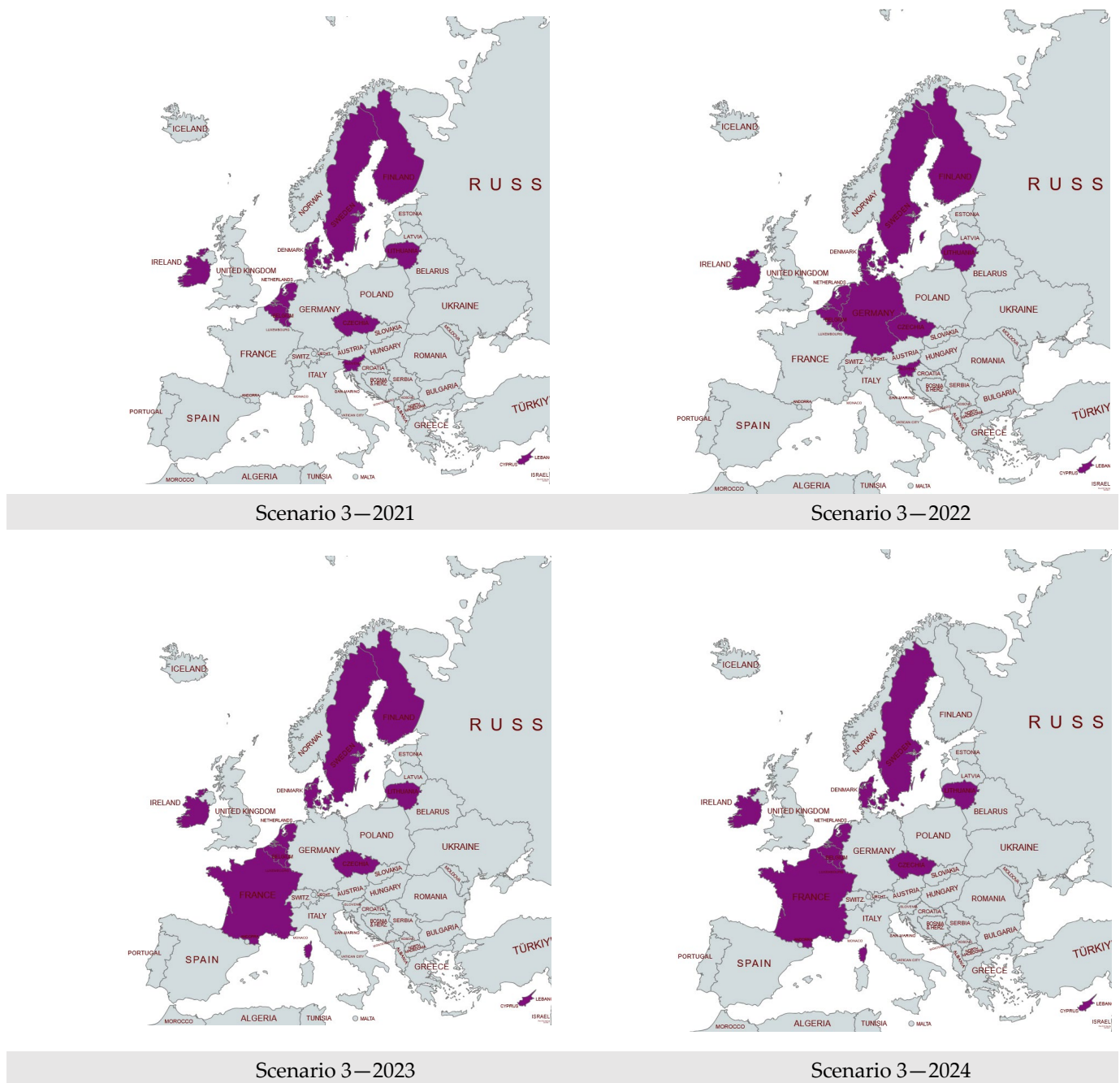


Figure 17. Comparison between the results obtained for cluster A in 2021–2024.

5.2.3. Vulnerability and Regression: Performance Alerts

It should be emphasized that high performance is not a permanent state and can be constantly affected by internal imbalances. Regression can be observed in the cases of Finland and Slovenia, both of which started at the beginning of the range in Cluster A. However, Slovenia regressed to Cluster B in 2023, followed by Finland in 2024. This downward trend suggests that the benefits of those massive investments no longer have the capacity to offset potential declines in development indicators. Spain, in turn, moved from Cluster B to Cluster C in 2022, starting in 2023, indicating both a loss of competitiveness and an inability to maintain a balance between innovation and sustainability in the face of economic shocks. It is also worth noting the behaviour of Germany, which started in 2021 as part of Cluster B, migrated to Cluster A in 2022 and returned to Cluster B in 2023–2024, reflecting a high sensitivity to the current geopolitical and energy context.

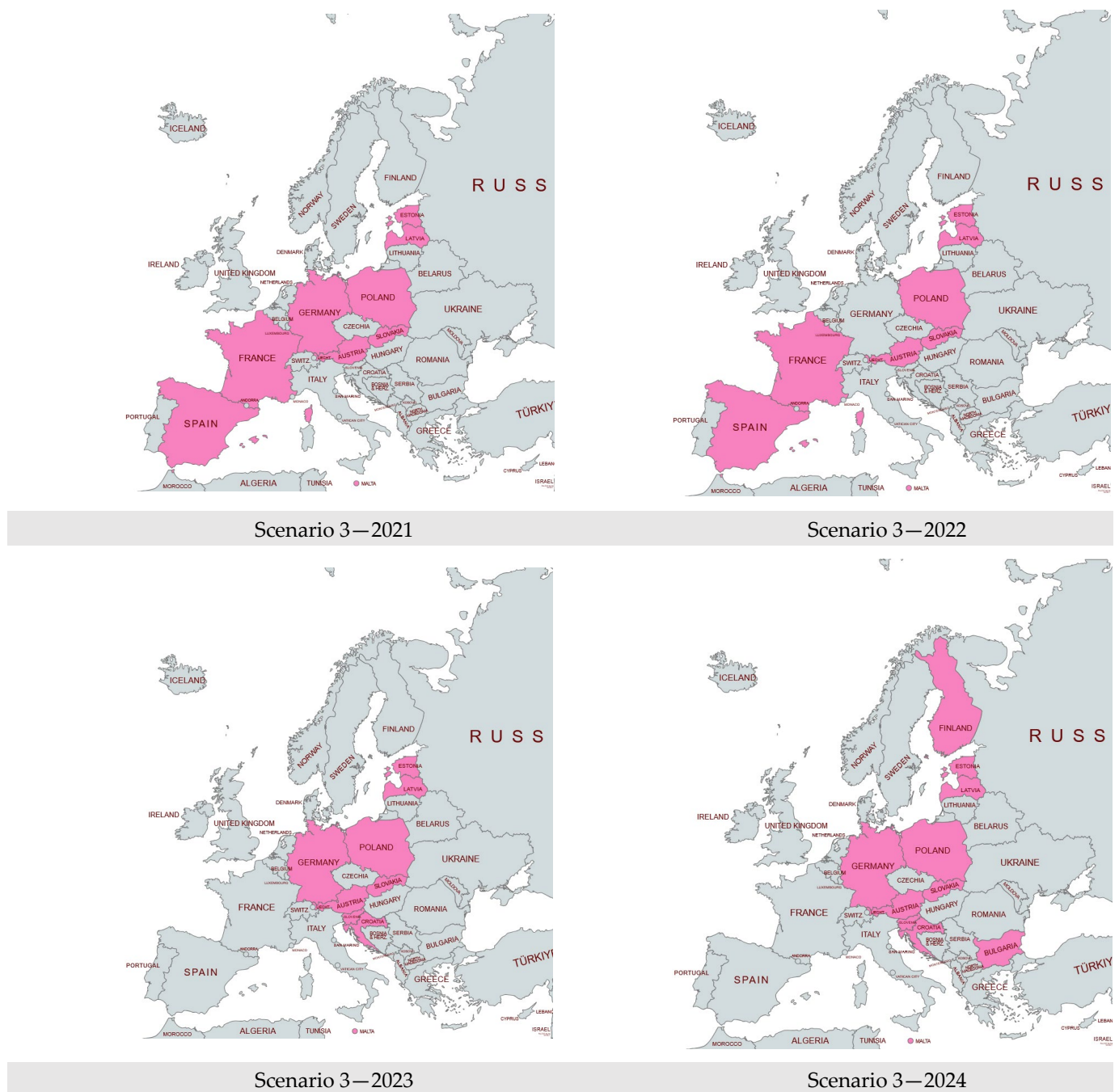


Figure 18. Comparison between the results obtained for cluster B in 2021–2024.

5.2.4. The Stagnant Core of Cluster C: Significant Challenges

As might be expected, a group of countries remains stuck in the low-performance zone, regardless of short-term fluctuations (Figure 19). This segment includes Greece, Hungary, Italy, Portugal and Romania. For these countries, the 2021–2024 period represented a period of structural stagnation under Scenario 3. They lacked the capacity to initiate changes in direction strong enough to successfully leave Cluster C. This situation, of remaining consistently within this cluster, indicates the need for reforms far more profound than the mere allocation of funds, with an emphasis on improving the efficiency of mechanisms for absorption and economic transformation.

The dynamic analysis has shown that, although the European Union is moving toward convergence, the quality and pace of this convergence are highly uneven. Given the

situations identified, while countries such as France and Bulgaria demonstrate a positive capacity for adaptation, Romania and Italy remain in a zone of persistent risk, requiring much more targeted convergence policies.

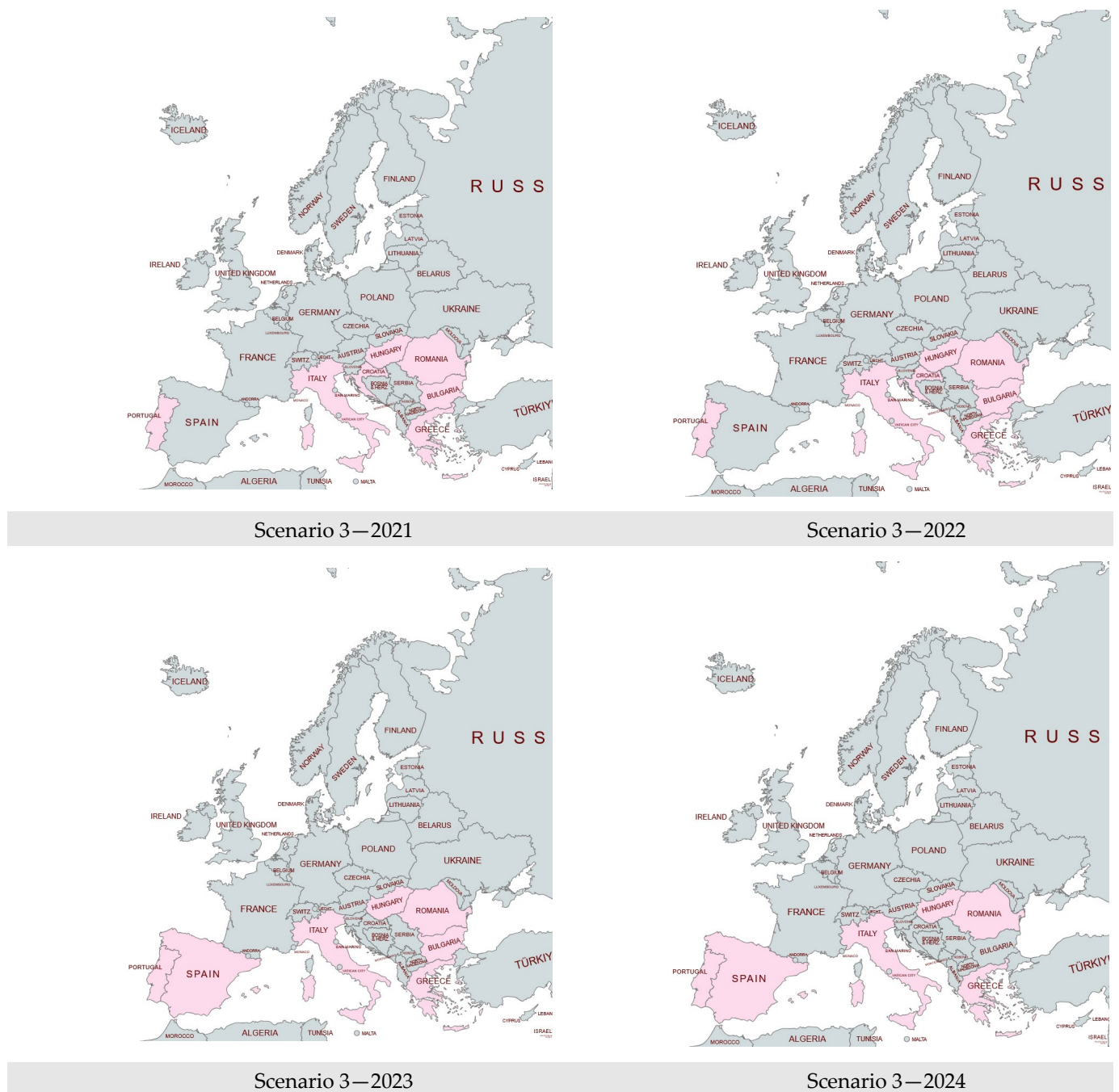


Figure 19. Comparison between the results obtained for cluster C in 2021–2024.

5.3. Illustrative Weight-Perturbation Analysis for a Boundary Case: Austria

Austria was selected for an illustrative weight-perturbation analysis because it represents a scenario-sensitive boundary case. As shown in Table 19 (as extracted from Table 16, where the colors of the cells corresponds to the colors of the clusters of Austria in each scenario, as previously determined), Austria is classified in Cluster B under Scenarios 1–4, but moves to Cluster A under Scenario 5. This change does not imply a real-world transition, but reflects the fact that Austria’s classification improves when the analytical framework gives full weight to sustainable-development outcome indicators. The purpose of the simu-

lation is therefore limited and specific: to assess whether Austria's Scenario 5 classification remains stable when the non-zero weights in that scenario are randomly perturbed.

Table 19. Summary of the results obtained for Austria in Scenarios 1–5.

Country	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
	Cluster				
Austria	B	B	B	B	A

Having this situation in mind, for cluster stability we have slightly altered the values for the η_1 – η_7 associated with Scenario 5. The purpose was to determine to which extent the classification of Austria in cluster A with respect to the conditions of Scenario 5 remains constant when the weights η_1 – η_7 change. As a brief description for Scenario 5, it should be mentioned that in this scenario the η_1 – η_3 were zero, while the η_4 – η_7 were 0.25.

In order to conduct this analysis, a Python 3.14.0 script has been developed that performs 200,000 simulations under the following conditions: the η_4 – η_7 weights (which were not zero) have been altered by changing them in a random manner by up to $\pm 1\%$ (Case 1), $\pm 3\%$ (Case 2), $\pm 5\%$ (Case 3), and, respectively, $\pm 7\%$ (Case 4), with the condition that the sum of the η_4 – η_7 remains the same, namely 1.

Furthermore, in order to determine to which extent the values for the grey clustering coefficient corresponding to object *Austria* in Cluster A (noted $\sigma_{Austria}^A$) are further from the values obtained for *Austria* in Cluster B or C (noted $\sigma_{Austria}^B$ and respectively $\sigma_{Austria}^C$), an indicator noted as $\Delta_{A(Austria)}$ has been created, whose values are determined as:

$$\Delta_{A(Austria)} = \sigma_{Austria}^A - \max(\sigma_{Austria}^B, \sigma_{Austria}^C)$$

If positive, this indicator extracts the superiority of the grey clustering coefficient for *Austria* in Cluster A ($\sigma_{Austria}^A$) compared to the values of the grey clustering coefficient in Cluster B or C. If negative, it symbolizes first that Austria has no longer been attributed to Cluster A (but to one of the Clusters B and C) and highlights by how much the grey clustering coefficient (for Cluster B or C) has been superior to the one obtained for Cluster A.

The results of the simulations are synthetized in Table 20. From these results, it can easily be noticed that in none of the cases has Austria been attributed to Cluster C, which was expected, given the results we have had in Scenarios 1–4.

Table 20. Cluster stability simulation results.

Cluster	Case 1	Case 2	Case 3	Case 4
	(Variation by up to $\pm 1\%$)	(Variation by up to $\pm 3\%$)	(Variation by up to $\pm 5\%$)	(Variation by up to $\pm 7\%$)
	No of Situations (Percentage)			
A	200,000 (100%)	199,999 (99.99%)	194,691 (97.35%)	181,739 (90.87%)
B	0 (0%)	1 (0.01%)	5309 (2.65%)	18,261 (9.13%)
C	0 (0%)	0 (0%)	0 (0%)	0 (0%)

Regarding the results obtained for Case 1 when the weights were altered by up to $\pm 1\%$, it can be noted that Austria remained in Cluster A, showing cluster stability at small alterations of the considered weights. Considering the results obtained for $\Delta_{A(Austria)}$ in Case 1, as expected, all the values are positive given the fact that Austria is placed in all the situations in Cluster A, while the values of $\Delta_{A(Austria)}$ range between 0.0149 and 0.0301.

Table 21 provides the characteristics of 10 of the 200,000 simulated situations, which have been randomly extracted and included in this paper. It should be mentioned that in

this paper we have reported the values using 4 digits, while in our simulations we have worked with 17 digits.

Table 21. Case 1—10 randomly selected simulations.

η_4	η_5	η_6	η_7	$\sigma_{Austria}^A$	$\sigma_{Austria}^B$	$\sigma_{Austria}^C$	Cluster	$\Delta_{A(Austria)}$
0.2510	0.2420	0.2551	0.2519	0.4511	0.4309	0.1180	A	0.0202
0.2453	0.2535	0.2493	0.2520	0.4546	0.4301	0.1153	A	0.0245
0.2424	0.2538	0.2509	0.2528	0.4565	0.4295	0.1139	A	0.0270
0.2562	0.2473	0.2514	0.2451	0.4518	0.4278	0.1204	A	0.0240
0.2565	0.2469	0.2476	0.2490	0.4475	0.4319	0.1206	A	0.0156
0.2453	0.2519	0.2484	0.2544	0.4525	0.4322	0.1153	A	0.0203
0.2540	0.2477	0.2462	0.2521	0.4469	0.4338	0.1194	A	0.0131
0.2508	0.2490	0.2496	0.2507	0.4512	0.4309	0.1179	A	0.0203
0.2449	0.2532	0.2502	0.2517	0.4553	0.4296	0.1151	A	0.0258
0.2534	0.2496	0.2454	0.2516	0.4476	0.4333	0.1191	A	0.0143

Considering the results obtained for $\Delta_{A(Austria)}$ in Case 1, as expected, all the values are positive given the fact that Austria is placed in all the situations in Cluster A, while the values of $\Delta_{A(Austria)}$ range between 0.0149 and 0.0301.

An almost similar situation is encountered for Case 2, where only 1 of the 200,000 simulations has placed Austria in cluster B and not in Cluster A. Regarding the remainder of the 199,999 simulations, it should be noted that the highest value of the $\Delta_{A(Austria)}$ is equal to 0.0453. Table 22 provides 10 randomly selected simulations from the 200,000 runs in Case 2.

Table 22. Case 2—10 randomly selected simulations.

η_4	η_5	η_6	η_7	$\sigma_{Austria}^A$	$\sigma_{Austria}^B$	$\sigma_{Austria}^C$	Cluster	$\Delta_{A(Austria)}$
0.2495	0.2495	0.2485	0.2525	0.4507	0.4321	0.1172	A	0.0186
0.2533	0.2505	0.2470	0.2492	0.4499	0.4310	0.1191	A	0.0189
0.2412	0.2480	0.2550	0.2558	0.4559	0.4307	0.1134	A	0.0252
0.2485	0.2540	0.2526	0.2448	0.4584	0.4248	0.1168	A	0.0336
0.2509	0.2468	0.2472	0.2552	0.4470	0.4350	0.1179	A	0.0120
0.2516	0.2495	0.2494	0.2495	0.4515	0.4302	0.1182	A	0.0213
0.2518	0.2462	0.2549	0.2471	0.4543	0.4273	0.1183	A	0.0270
0.2514	0.2517	0.2521	0.2448	0.4560	0.4259	0.1182	A	0.0301
0.2503	0.2490	0.2549	0.2457	0.4566	0.4257	0.1177	A	0.0309
0.2533	0.2509	0.2503	0.2454	0.4536	0.4274	0.1191	A	0.0262

Additionally, from the database with the simulations, the only situation in which Case 2 Austria has been attributed to Cluster B instead of A has been extracted—please consider the information in Table 23. It has to be noted, even in this case, that in Python the results have been reported using 17 digits, while in Table 23 the results have been included using only 4 digits. Considering the value of the decision margin indicator, $\Delta_{A(Austria)}$, for the highlighted situation, it can be noted that its value is very close to 0, being reported as -9.13×10^{10} , showing only a small favour for cluster B compared to cluster A. Given

these considerations, it can be said that even for a deviation of $\pm 3\%$, perfect stability is encountered.

Table 23. Case 2—The situation in which Austria has been attributed to cluster B.

η_4	η_5	η_6	η_7	$\sigma_{Austria}^A$	$\sigma_{Austria}^B$	$\sigma_{Austria}^C$	Cluster	$\Delta_{A(Austria)}$
0.2567	0.2429	0.2428	0.2575	0.4396	0.4397	0.1207	B	-9.13×10^{10}

For Case 3, where the variation is by up to $\pm 5\%$, the number of cases in which Austria is included in cluster B increased to 2.65% of the total simulations. Table 24 depicts 10 of the obtained simulations, presenting a mix of outcomes, both Cluster A and Cluster B. Considering the overall margins for the decision indicator, $\Delta_{A(Austria)}$, it can be noted that it took values between -0.0151 and 0.0606 , with a higher decision margin in the case in which Cluster A was determined than in the case in which Cluster B was the selected cluster, showing, once more, the superiority of the solutions indicating Cluster A as the solution for Scenario 5.

Table 24. Case 3—10 selected simulations featuring both outcomes.

η_4	η_5	η_6	η_7	$\sigma_{Austria}^A$	$\sigma_{Austria}^B$	$\sigma_{Austria}^C$	Cluster	$\Delta_{A(Austria)}$
0.2506	0.2434	0.2432	0.2628	0.4403	0.4419	0.1178	B	-0.0016
0.2558	0.2407	0.2489	0.2546	0.4438	0.4360	0.1202	A	0.0079
0.2506	0.2507	0.2472	0.2515	0.4503	0.4319	0.1178	A	0.0183
0.2504	0.2485	0.2464	0.2547	0.4477	0.4346	0.1177	A	0.0131
0.2617	0.2439	0.2478	0.2466	0.4454	0.4317	0.1230	A	0.0137
0.2426	0.2603	0.2430	0.2540	0.4539	0.4321	0.1140	A	0.0218
0.2565	0.2514	0.2545	0.2377	0.4581	0.4213	0.1205	A	0.0368
0.2469	0.2558	0.2556	0.2417	0.4628	0.4212	0.1161	A	0.0416
0.2485	0.2566	0.2537	0.2412	0.4616	0.4216	0.1168	A	0.0399
0.2597	0.2455	0.2364	0.2584	0.4352	0.4427	0.1221	B	-0.0074

Furthermore, for Case 4 (Table 25), where the values of the η_4 – η_7 have been further altered by up to $\pm 7\%$, as expected, the number of situations in which Austria has been classified in Cluster B increased—reaching 9.13% of the total simulated situations. As for the decision margins in this case, they range between -0.0302 and 0.0758 , highlighting, even in this case, that the results are in favour of associating Austria with Cluster A.

Overall, the simulation results indicate that Austria's Scenario 5 classification is stable under small and moderate perturbations of the non-zero weights. However, this result should be interpreted as an illustrative boundary-case test rather than as a comprehensive robustness validation of the entire clustering framework. The broader robustness evidence is provided by the all-country threshold sensitivity analysis across Scenarios 1–5, while the Austria simulation offers additional insight into the behaviour of one scenario-sensitive country located close to a classification boundary—Table 20.

5.4. Policy Recommendations

To support more balanced innovation and sustainability profiles among Member States, public policy recommendations are formulated in a differentiated manner, taking into account the typologies and performance profiles identified through the grey clustering model. Since the alignment gaps and vulnerabilities identified at the macroeconomic level

differ qualitatively from one group of countries to another, strategic interventions should also be tailored accordingly.

Table 25. Case 4—10 selected simulations featuring both outcomes.

η_4	η_5	η_6	η_7	$\sigma_{Austria}^A$	$\sigma_{Austria}^B$	$\sigma_{Austria}^C$	Cluster	$\Delta_{A(Austria)}$
0.2557	0.2522	0.2449	0.2472	0.4492	0.4306	0.1202	A	0.0186
0.2577	0.2601	0.2340	0.2483	0.4447	0.4342	0.1211	A	0.0104
0.2533	0.2556	0.2570	0.2341	0.4641	0.4169	0.1190	A	0.0472
0.2470	0.2407	0.2565	0.2557	0.4515	0.4324	0.1161	A	0.0191
0.2517	0.2425	0.2665	0.2393	0.4629	0.4188	0.1183	A	0.0441
0.2512	0.2464	0.2512	0.2512	0.4508	0.4312	0.1181	A	0.0196
0.2568	0.2466	0.2368	0.2598	0.4366	0.4427	0.1207	B	−0.0061
0.2429	0.2683	0.2440	0.2449	0.4613	0.4246	0.1141	A	0.0367
0.2387	0.2547	0.2614	0.2452	0.4677	0.4201	0.1122	A	0.0476
0.2419	0.2614	0.2415	0.2552	0.4532	0.4331	0.1137	A	0.0201

Specific Policies for “Systemic Laggards” (Structural Correlation of Cluster C).

This group, comprising countries such as Romania, Bulgaria, and Greece, faces a twofold structural failure: first, chronic underfunding of innovation capacity; and second, a systemic inability to generate sustainable results with social and environmental impact. For these economies, the following could be considered: stimulating research efforts (by increasing national budgets allocated to government spending on R&D); reforming human capital and education (by aligning tertiary education curricula with labour market demands); directly reducing social vulnerabilities (by implementing active labour market policies focused on professional retraining); or promoting ecological modernization (by redirecting European Union funds toward clean technologies and industrial energy efficiency).

Specific Policies for “Input-Rich, Output-Poor” (Efficiency Asymmetries).

Economies such as those of Belgium and Luxembourg demonstrate remarkable strategic innovation capacity, but lose their leading position when the analysis focuses strictly on social and environmental sustainability outcomes. Recommendations for this category: auditing the effectiveness of the green transition (by introducing strict mechanisms to monitor how research funds are directed toward innovation) or addressing social inequalities (by revising inclusion policies).

Specific policies for countries in transition and those with high volatility.

This category includes the economies of countries such as Germany, Finland, and Slovenia, which exhibited significant mobility between clusters during the period analyzed (2021–2024), indicating that their economic models are highly sensitive to external shocks. The recommended strategy for this group is decoupling critical dependencies (by protecting the industrial and innovation core through massive investments in energy security and domestic renewable resources) or increasing the flexibility of the knowledge-based labour market (by implementing advanced lifelong learning strategies).

5.5. Theoretical Implications, International Perspectives and Limitations

Throughout the research, a series of seemingly contradictory results emerged, leading to the formulation of linear economic hypotheses. The most obvious paradox is represented by the category of advanced economies characterized by “abundant resources, poor

outcomes" (e.g., Belgium, Luxembourg). Logically, a high level of public investment in R&D and a massive stock of tertiary human capital should automatically lead to high ecological efficiency and a reduction in social risks. However, our model demonstrates the opposite in these nations when the focus shifts toward sustainability. This result suggests the existence of institutional inefficiencies within the (NIS), where technological innovation fails to translate into eco-efficiency or social inclusion.

Furthermore, the study demonstrates that innovation capacity and sustainable development are not linked by a linear causal relationship; in fact, they form an asymmetric system that is strongly conditioned by each country's institutional absorption capacity. This means that the European Union's cohesion policies cannot generate real convergence if they rely solely on the allocation of funds for research infrastructure, without structural reform of the labour market and social protection mechanisms.

To extend these findings beyond the European Union, the country typologies identified must be contextualized within a broader international framework. The structural paradox of countries that, despite having resources, fail to achieve results is not merely a European regional anomaly; these countries actually reflect similar patterns of institutional decoupling documented in broader empirical studies from OECD countries and North America [83]. In fact, the international literature on macroeconomic efficiency highlights that innovation systems with high inputs often suffer from institutional saturation in which massive financial investments in research and development fail due to a lack of cross-sectoral synergies [84]. The results of our grey clustering analysis confirm that, in a highly integrated regulatory environment such as the European Union, simply accumulating resources is not enough. Without simultaneous institutional reforms that address labour market rigidities and social vulnerabilities, economies risk suffering.

These findings are also consistent with recent contributions in the literature on sustainability and public policy, which highlight that sustainable convergence processes are closely linked not only to the availability of technological or financial resources, but also to institutional capacity, the quality of governance, and long-term socioeconomic resilience [85,86]. In this regard, recent studies show that sustainable development is influenced by the interaction between innovation capacity, institutional coordination, and the ability of states to cope with structural transitions in contexts characterized by uncertainty. The findings of this research support this perspective, demonstrating that high levels of innovation-oriented investment do not automatically lead to sustainable outcomes, especially in the absence of effective institutional absorption mechanisms or balanced social policies.

Even though the methodology used offers flexibility, it must be acknowledged that the research has certain limitations. First, when clustering functions are defined, they are influenced by expert judgement, thereby introducing a degree of subjectivity in setting the membership thresholds. Although the threshold sensitivity analysis indicates generally stable results under small-to-moderate perturbations, wider changes in the grey membership thresholds may produce additional reclassification among countries located near class boundaries. Furthermore, although the threshold sensitivity analysis was conducted across all countries and scenarios, the weight-perturbation simulation was applied only to an illustrative boundary case. Future research could extend this simulation strategy to all countries, alternative normalization procedures, and alternative numbers of clusters. Second, the quality of the results is influenced by both the availability and the accuracy of the data extracted from Eurostat databases for the period analyzed.

6. Concluding Remarks

The primary objective of this study was to examine the extent to which strategic innovation capacity and sustainable development outcomes are aligned across European

Union member states. By applying grey clustering, the study provides a framework for classifying countries into performance typologies under conditions of partial information, multidimensional heterogeneity, and alternative weighting assumptions.

The contribution of the paper lies in showing how country classifications vary when the analytical emphasis shifts between innovation-capacity indicators and sustainable-development outcome indicators. Rather than producing a single ranking, the proposed framework highlights patterns of alignment, misalignment, and classification sensitivity across EU member states. The results should therefore be interpreted as evidence of relative positioning under alternative composite-index assumptions, not as proof of a causal transition from innovation inputs to sustainability outcomes.

The analysis revealed several distinct performance profiles. Countries such as Denmark, Ireland, Lithuania, the Netherlands and Sweden were classified as “consistent leaders,” having demonstrated consistent excellence and remaining in Cluster A regardless of the weighting scenarios applied. An analysis of the 2021–2024 period highlighted successful or progressive trajectories for countries such as France, Bulgaria and Croatia, which managed to improve their initial position within the European hierarchy. At the other end of the spectrum, countries such as Romania, Italy and Greece faced structural stagnation in Cluster C, forming the core that requires the most urgent public policy interventions to address certain weaknesses, thereby enabling them to align with the rest of the European Union member states.

For future research directions, we aim to expand the set of indicators by adding additional variables that would serve to reflect, for example, the digital dimension or climate resilience. Furthermore, “fuzzy” or hybrid techniques could be employed to reduce reliance on human judgement in defining inflection points, thereby enabling a comparison with the present analysis. Furthermore, from a regional perspective, this framework can be applied at the NUTS-2 (Nomenclature of Territorial Units for Statistics-2) or NUTS-3 level to identify intra-national disparities.

It can thus be concluded that, although the European Union is constantly evolving and making significant strides toward convergence, the pace and quality of this convergence remain uneven across Member States, thereby requiring a more tailored approach for those countries that are consistently in the high-risk zone.

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