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Mirjana Radovanović, Goran Šimić & Jámbor Attila

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Sustainable and secure energy development of the European Union: Artificial intelligence-based approach for policymaking

Mirjana Radovanović, Corvinus University of Budapest, Fővám tér 8, 1903 Budapest, HUNGARY, mirjana.radovanovic@uni-corvinus.hu,
CORRESPONDING AUTHOR Tel: +381 64 205 7261

Goran Šimić, Academy of Technical and Art Applied Studies, School of Electrical and Computer Engineering, Belgrade 11000, REPUBLIC OF SERBIA, goran.simic@viser.edu.rs

Jámbor Attila, Corvinus University of Budapest, Fővám tér 8, 1903 Budapest, HUNGARY, attila.jambor@uni-corvinus.hu

Abstract

Background

The European Union considers the decarbonization of Europe by 2050 a strategic objective. This necessitates finding the solutions that will support the intricate process of formulating energy policies and decisions with enduring implications for the economy, environment, and social welfare of European Union citizens and beyond. The primary objective of this study is to evaluate the suitability of an artificial intelligence (AI)-based approach in policymaking (control stage) with the aim of achieving a more optimal formulation of the common European energy policy and the policies of individual member states.

Results

Given the scope and volatility of the data, as well as the research objective, data processing was conducted using clustering—a technique within artificial intelligence (AI)—which is suitable for producing more precise, explainable, and provable (PEP) outcomes. In doing so, the study addresses one of the main obstacles to the broader use of AI in policymaking: the current lack of trust in AI-based solutions. The research was conducted in three stages. In the first stage, energy security indicators were determined based on 13 selected indicators using the aggregate approach. In the second stage, clustering was executed as an unsupervised machine learning method, utilizing the K-means algorithm as the designated learning model. In the third stage, a classifier model utilizing an artificial neural network was proposed. The research findings have revealed that countries exhibiting the highest levels of energy security, and consequently the most favorable conditions for sustainable growth, have different energy portfolios, unique economic frameworks, and differing energy prices.

Conclusions

The research findings are significant in the domains of energy and environmental policies, decision theory, and AI (with special emphasis on the EU AI Act). The research highlights the efficacy of an interdisciplinary approach and contributes to the studies about the use of AI in policymaking, with emphasis on the improvements that will lead to its greater power and precision—one of the milestones for efficient policymaking. Policymaking based on PEP AI outcomes can be seen as one of the most efficient methods for strategic planning and control of decarbonization of Europe; therefore, the paper also proposes recommendations in this context.

Keywords

Decarbonization; European Union; Artificial Intelligence; PEP AI outcomes; Clustering; Policymaking.

Background

The decarbonization of Europe is undoubtedly one of the European Union's most ambitious objectives since its establishment [1], primarily aimed at achieving a total reduction of CO_2 emissions by 2050 [2]. The aforementioned implies a multifaceted process of planning, implementation, and regulation across all sectors of the economy and society, with a particular focus on transformations in the industrial, transportation, and agricultural sectors, while preserving the environment and biodiversity [3]. Given that the extraction and combustion of fossil fuels generate the majority of greenhouse gases, the primary focus is on energy and energy-related matters. Moreover, the European Union aims to enhance its energy independence over the long term, minimize energy imports [4] and improve energy efficiency while increasing production from renewable sources. The aforementioned activities are exceedingly intricate and demanding, particularly during a period of complex geopolitical changes [5].

Considering the current state of the economy and the supply of energy sources, the European Union and its member states are transitioning to an economy that will result in a reduction of greenhouse gas emissions. Nevertheless, the continuous priority of ensuring energy stability and providing sufficient energy sources [6] has become increasingly important in the wake of the complex geopolitical shifts that commenced during the COVID-19 pandemic and escalated after 2022 [7]. Furthermore, the European Union must consider the competitiveness of its economy and the social status of its population; hence, energy prices represent another aspect critical for sustainable energy development.

Numerous factors influence and will continue to impact the energy growth of the European Union. Primarily, the European Union's foreign policy and its collaboration, or lack thereof, with specific countries and regions that have consistently provided energy supplies for decades have a significant impact [8]. The supply of natural gas, an environmentally acceptable energy source, is a significant issue due to the suspension of delivery from the Russian Federation [9]. The European Union stands unified on the matter of terminating coal extraction, although opinions diverge over the utilization of nuclear energy. Moreover, the energy acquired by the European Union from renewable sources is environmentally praiseworthy, yet it predominantly generates electricity. The challenge of substituting fossil (liquid) energy for industrial operations and transportation remains unresolved; however, the initial outcomes of replacing fossil fuels with renewable energy are promising [10]. Furthermore, the establishment of the European Union's energy infrastructure preceded the endorsement of decarbonization as a strategic objective [11]. Any alteration in this regard necessitates the development of new infrastructure facilities and corridors, which are substantial construction projects demanding considerable financial resources and an intricate legal procedure. Implementing the measures in neighboring non-European Union countries, each with its own particularities, further complicates the situation [12].

The management of the intricate process of decarbonizing Europe can be examined from multiple perspectives; however, it is essential to acknowledge that the relevant institutions of the European Union and its member states confront the significant challenge of formulating energy policies to facilitate this endeavor. It is crucial to emphasize that the process of decarbonization proceeds alongside the objectives of sustainable development, which presents a further challenge to policy-making [13].

Each management process necessitates an analysis of the system's condition that demands oversight and the implementation of specific modifications. A highly precise evaluation of the present circumstances and anticipated requirements is necessary, along with prior assessments, forecasts, and scenario analyses, which demand an interdisciplinary approach and the application of methods pertinent to decision-making, monitoring, and forecasting [14].

The effectiveness of implemented measures in the field of sustainable energy development is evaluated using a variety of methods and approaches. In light of the multifaceted nature of sustainable and secure energy development, the evaluation employs a variety of indicators that can point to specific characteristics and imply the need for a potential shift in approach.

A multitude of studies employ various methodologies to assess the attained level of sustainable energy development throughout the European Union. The findings of the 2020 study utilizing decomposition analysis indicate a deceleration in energy efficiency advancements, highlighting the necessity for implementing more ambitious measures, particularly in the heating domain, alongside an acknowledged need for enhanced monitoring [15].

Research indicates that a significant challenge is the insistence of European Union member states on their sovereignty as they endeavor to make decisions aligned with their interests, thereby aggravating integration and the formulation of a unified energy policy for the European Union [16]. The necessity for governance is evident, particularly concerning the nature of policy monitoring, as climate-related regulations are perceived as legally robust, accompanied by a stringent monitoring system. Such a framework causes problems in terms of implementation in member states and complicates the cooperation of certain countries with the European Commission. Consequently, modifications in this area are imperative [17]. There is evidence that, due to the aforementioned, public authorities are hesitant to demand the further introduction of stringent measures in the area of decarbonization [18].

The 2019 Green Deal is defined as an umbrella document for the long-term growth of the European Union and is obligatory for all member states [19]. It represents a continuation of the European Union's decade-long initiatives aimed at constantly enhancing environmental quality and reducing climate change impacts. Considering the intricacy of the present circumstances and the significant uncertainty across all domains, it is imperative to closely examine the efficiency of the measures adopted thus far and to forecast future trends, as the current measures are mostly not robust [20].

The evaluation of the efficiency of the implemented measures can be conducted using several methods; nevertheless, given the intricacy of the issue, cluster analysis is deemed the preferred method. Specifically, cluster analysis is a factor analysis of data where the variables have not been pre-categorized into subsets, based on the predictors [21]. This approach enables the derivation of sets of mutually similar systems, as such similarity highlights particular specificities crucial for understanding the observed system – in this case, regarding the sustainable and energy-secure development of the European Union. Pointing to the most significant characteristics is a fundamental premise for quality management in this domain, as energy policies are intricate, and their (positive or negative) repercussions endure for decades.

Cluster analysis is used in studies requiring the examination of extensive data sets and variables that lack evident correlation. This is particularly relevant for sustainable energy development, as it is characterized by a multitude of indicators whose correlations may be ambiguous, undefined, variable, or interpreted differently. The 2020 study employing cluster analysis indicates that European Union member states demonstrate inertia about changes in energy consumption, with the existing energy infrastructure recognized as the principal cause thereof [22]. The same year saw the publication of a study on the correlation between energy consumption and social factors, suggesting the need for additional efforts to formulate socially acceptable policies for energy production from renewable sources [23]. Scandinavian countries predominantly use renewable energy for transportation, whereas other countries primarily use it for heating [24].

The cluster analysis of European Union energy security, which is a critical component of sustainable energy development, is a separate area of research. The analysis of energy security trends in European Union countries, covering a period from 1978 to 2014, distinctly revealed a group of countries exhibiting initially low energy security, which has progressively improved over time, serving as a potential model for other countries [25]. Research on energy consumption in the European Union from 1990 to 2021 indicates an upward trend of natural gas consumption, stagnation in nuclear energy, and the continued significance of crude oil in the energy mix over this period [26]. The latest 2024 study, utilizing eight indicators, categorized countries into six groups based on particular similarities in decarbonization and climate mitigation policies. Belgium, the Netherlands, and Poland recorded the largest gaps between individual indicators of sustainable energy transition, indicating the greatest variability in levels of implementation of the required measures. Bulgaria and the Republic of Serbia recorded the smallest gap in terms of energy transition, that is, the highest degree of similarity [27].

Cluster analysis has demonstrated efficacy in forecasting under circumstances of significant uncertainty, which can be applied to the sustainable energy future of the European Union [28] and the 2022 study indicated the necessity of developing special energy and climate strategies for specifically defined clusters [29]. In doing so, it is important to remember that countries with higher political stability typically implement energy policies that yield better long-term outcomes [30]. Although studies on the evaluation and quantification of energy security do exist, it remains essential to assess their reliability [31, 32], with particular attention to indicators related to energy prices [33], while also taking into account changes in EU environmental policies [34] and developments in EU candidate countries [35].

Methods

Thirteen indicators of energy security were used in the research:

1. CO_2 emissions per capita
2. Electricity prices for household consumers
3. Electricity prices for non-household consumers
4. Energy efficiency
5. Energy import dependency by products
6. Energy intensity
7. Population unable to keep home adequately warm by poverty status
8. Imports of electricity and derived heat by partner country
9. Imports of natural gas by partner country
10. Imports of oil and petroleum products by partner country
11. Net greenhouse gas emissions
12. Primary energy consumption
13. Share of energy from renewable sources

An analysis was conducted on data for indicators over a 10-year period (2013–2022). The majority of the indicators, specifically 10 of them, have a detrimental effect on energy security. Only three indicators have a positive impact on energy security, specifically: *Energy intensity, Primary energy consumption*, and *Share of energy from renewable sources*. All other indicators exert a negative impact. The selection of indicators was based on the author's previous and similar studies [36, 37, 38, 39].

To mitigate potential subjective influences, improve clarity, and derive the energy security value for an individual EU country in a given year, an expression was employed, illustrating the normalized values of indicators for a specific year and the corresponding impact (positive or negative) on energy security. The equation for calculating a country's energy security in a given year is as follows (Equation 1):

$$ES_{ik} = \sum_{j=1}^{N} s_j * F_{jk} \qquad \text{(Eq.1)}$$

, where ES_{ik} is the energy security of the country indexed by *i* in year *k*, N is the number of indicators included in the research (in the specific case

N=13), s_j is the impact of the indicator indexed by *j* on ES_i , with s_j value derived from the set {-1,1}; finally, F_{jk} is the value of the indicator indexed by *i* in year *k*.

The gathered data illustrate significant disparities in the energy security factor values across various countries; hence, normalization was conducted as part of the data preparation for subsequent processing. The *min-max* method was employed for normalization, yielding values inside the interval [0,1], as expressed by the following equation:

$$F_{i,k,norm} = \frac{F_{i,\ k,\ real} - F_{k,min}}{F_{k,max} - F_{k,min}} \quad \text{(Eq.2)}$$

, where $F_{i,k,norm}$ is the normalized value of factor *F* for country indexed by *i* in year *k* , $F_{i,\ k,\ real}$ is the actual value of factor *F* for country indexed by *i* in year *k*, while $F_{k,max}$ and $F_{k,min}$ are the maximum and minimum values of factor *F* across all countries, considered for year *k*.

Clustering

Given the complexity (multidimensionality) of the data (13 indicators across 27 countries over 10 years), clustering was selected as an unsupervised machine learning method to categorize countries based on ES_{ik} value similarity, using the K-means algorithm as the specific learning model. Six experiments were conducted, varying the number of clusters from three to eight. The K-means algorithm initially generates *n* centroids randomly for *n* clusters. Typically depicted as points in a plane, centroids are hypothetical data from which the distances of actual data are computed relative to each centroid, thereby facilitating the initial grouping. In each new iteration, centroids are recalculated, and data is reclassified. Thus, the algorithm is reiterated until system stability is attained (shown by the absence of centroid changes or data reclassification).

Developing the classifier model

The clustering results are subsequently used in the development of the classifier model. Assuming the factors are independent, equally relevant, and comprehensive across all countries and years, the approach selected is to employ an artificial neural network (hereinafter ANN) for data classification. Unlike clustering, which uses data based on the annual value of the ES factor, artificial neural network (ANN) training requires the original data. A three-layer ANN model was developed for research, comprising 14 neurons in the input layer, 32 neurons in the hidden layer, and eight neurons in the output layer (Figure 1). In this way, it is possible to feed the ANN with data on 13 factors (13 neurons) and one neuron in the input layer for the year under consideration. Each class is represented by a single neuron in the output layer (totaling eight neurons). The quantity of neurons in the hidden layer is determined by experimentation (augmentation and reduction) during the model evaluation phase to minimize prediction error.

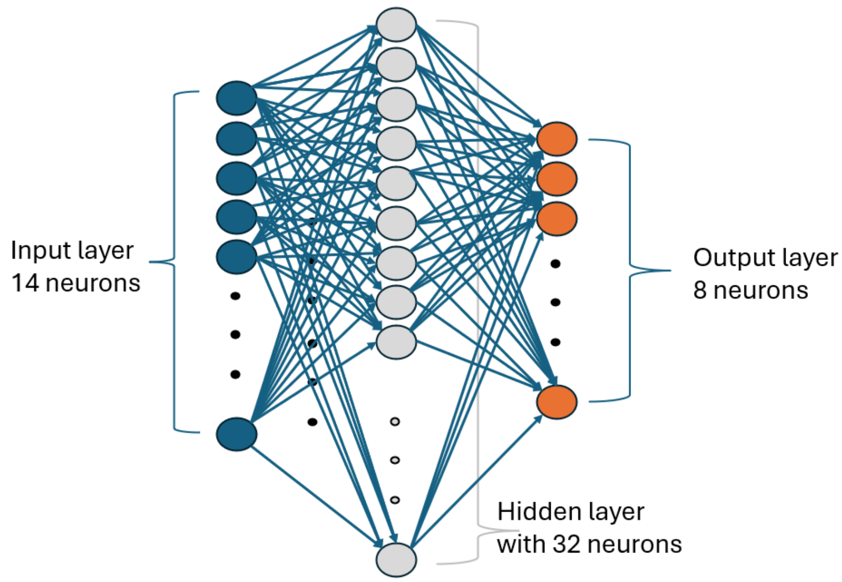

Figure 1 Three-layer ANN model

Results

Through an exploratory analysis of clustering outcomes, the groupings derived from six experiments were compared, leading to the conclusion that clustering into eight groups was the most optimal choice. The following illustration shows the grouping of 27 EU countries into eight clusters (Figure 2). Clusters are indexed in the range [0,7] and highlighted for clarity. The largest cluster (Cluster 0) comprises nine countries (data highlighted in yellow), followed by Cluster 3 with six countries (data highlighted in green), Cluster 5 with four countries (data highlighted in white), Cluster 4 with three countries (data highlighted in blue), and Cluster 7 with two countries (data highlighted in gray). Three countries are basically isolated cases—each representing a distinct cluster: Malta—Cluster 1, Sweden—Cluster 2, and Cyprus—Cluster 6.

EU countries	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Cluster
Czech_Republic	-2.2	-2.0	-2.2	-2.1	-2.2	-2.2	-2.1	-2.3	-2.4	-2.5	0
Estonia	-2.5	-2.3	-2.1	-2.3	-2.2	-2.2	-1.6	-1.3	-1.9	-2.0	0
Croatia	-2.1	-2.0	-2.2	-2.2	-2.3	-2.2	-2.2	-2.3	-2.1	-2.5	0
Latvia	-2.0	-2.0	-2.4	-2.3	-2.0	-2.0	-2.0	-2.1	-2.4	-2.7	0
Hungary	-2.0	-2.1	-2.0	-1.9	-1.9	-2.0	-2.3	-2.1	-2.2	-2.2	0
Poland	-1.7	-1.8	-2.0	-2.1	-1.9	-1.9	-1.9	-2.3	-2.0	-1.9	0
Republic_of_Slovenia	-2.1	-2.2	-2.5	-2.4	-2.4	-2.4	-2.2	-2.3	-2.0	-2.3	0
Slovakia	-2.4	-2.4	-2.5	-2.6	-1.9	-2.0	-2.4	-2.5	-2.2	-2.4	0
Finland	-1.7	-1.3	-1.3	-2.1	-1.7	-2.2	-2.1	-2.1	-1.8	-1.7	0
Malta	-4.4	-4.1	-3.6	-3.4	-3.4	-3.1	-3.3	-3.5	-2.9	-2.3	1
Sweden	-0.1	-0.2	0.0	-0.3	-0.3	-0.6	-0.2	-0.1	-0.3	-0.1	2
Belgium	-3.3	-3.5	-4.0	-3.6	-3.4	-3.9	-3.6	-3.5	-3.4	-3.5	3
Republic_of_Ireland	-3.4	-3.5	-3.8	-3.4	-3.2	-3.3	-3.4	-3.7	-3.9	-3.6	3
Greece	-3.2	-3.5	-3.6	-3.4	-3.2	-3.1	-3.1	-3.3	-4.1	-4.7	3
Spain	-3.4	-3.7	-3.9	-3.8	-3.7	-3.9	-3.0	-3.0	-3.5	-3.5	3
Italy	-3.7	-3.8	-3.8	-3.6	-3.6	-3.7	-3.7	-3.4	-4.0	-4.3	3
Netherlands	-3.4	-3.4	-3.6	-3.5	-3.1	-3.3	-3.3	-3.5	-3.5	-3.8	3
Denmark	-0.9	-0.9	-0.8	-1.0	-0.9	-1.3	-1.2	-1.3	-1.8	-2.3	4
France	-1.1	-1.1	-1.0	-1.3	-1.3	-1.2	-1.5	-1.7	-1.6	-2.3	4
Romania	-0.9	-0.9	-0.9	-0.9	-0.9	-1.0	-1.2	-1.5	-1.6	-2.5	4
Bulgaria	-2.6	-2.8	-3.0	-2.9	-2.9	-2.9	-2.9	-3.0	-3.6	-3.7	5
Germany	-2.8	-2.9	-2.8	-2.7	-2.7	-2.5	-2.7	-3.4	-3.1	-3.1	5
Lithuania	-2.2	-2.4	-2.5	-2.4	-2.3	-2.5	-2.9	-3.1	-3.3	-3.3	5
Austria	-2.3	-2.4	-2.4	-2.4	-2.6	-2.7	-2.9	-2.9	-2.6	-2.8	5
Cyprus	-4.8	-4.7	-4.5	-4.1	-4.4	-4.8	-4.6	-4.0	-4.0	-4.0	6
Luxemburg	-3.3	-3.3	-3.2	-3.1	-2.9	-3.1	-3.2	-3.2	-3.1	-2.6	7
Portugal	-3.1	-3.0	-3.0	-2.9	-3.0	-2.5	-2.8	-2.6	-2.5	-2.8	7

Figure 2 Clustering of European Union countries based on energy security values

The following diagrams illustrate the data provided in the table above.

Cluster 0 (labeled *Moderate and stable*) is presented in the following figure (Figure 3). This cluster comprises nine EU countries exhibiting the highest levels of energy security (ES) stability. The mean value of the ES index is the highest, totaling -2.116. Two countries (Finland and Estonia) exhibit significant disparities when compared to other countries. Nevertheless, compared to the other clusters, this cluster exhibits the least variance (0.071), and its standard deviation is likewise minimal at 0.267 (only Cluster 7, which comprises two countries, has a lesser standard deviation).

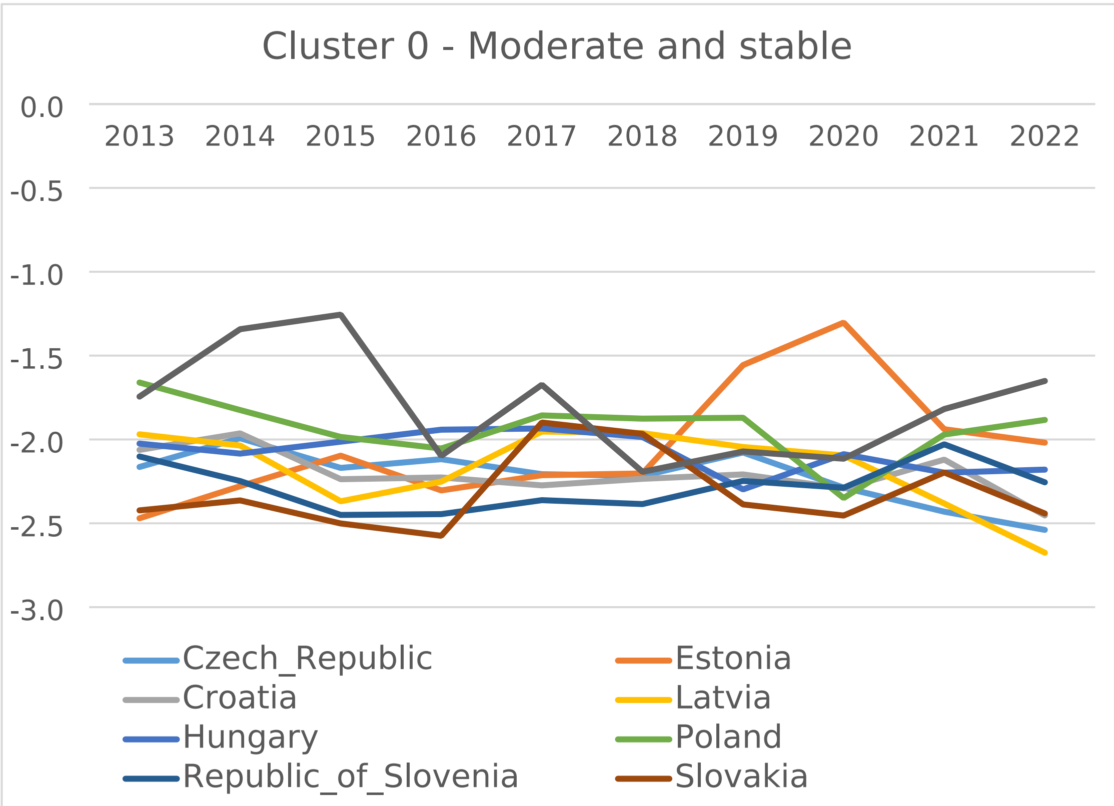

Figure 3 Clustering of European Union countries based on energy security values:
Cluster 0

The following figure (Figure 4) illustrates Cluster 3 (labeled *Low and slightly descending*), comprising six EU countries that demonstrated significant stability in ES over the first five years of observation; nevertheless, post-2020, the majority of countries in this cluster experienced a slight decline in ES. This decline affected the rather insignificant ES index, currently at -3.552. This cluster comprises fewer countries than Cluster 0; nonetheless, the variance (0.097) and standard deviation (0.312) values of the sample set are greater, signifying reduced cohesiveness within the group.

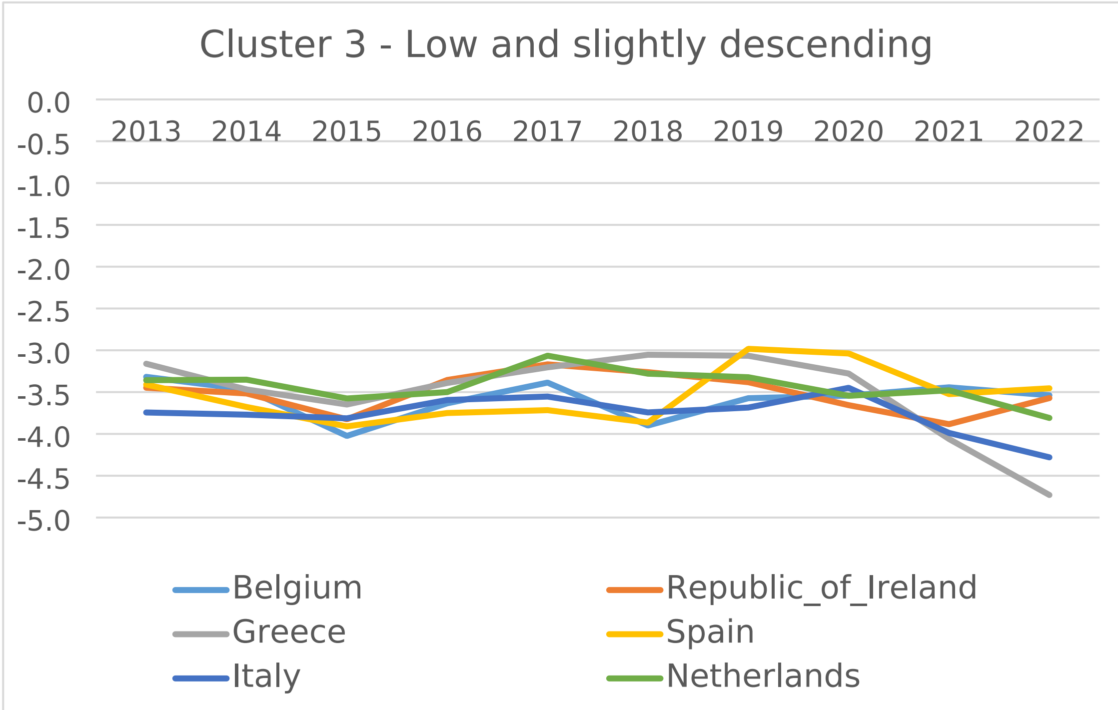

Figure 4 Clustering of European Union countries based on energy security values:
Cluster 3

The following figure (Figure 5) illustrates Cluster 4 (labeled *High and descending*) comprising three countries. Despite the mean value of the ES index for these countries being the highest at -1.293, all countries exhibit a consistent trend of permanent decline, particularly evident post-2017. Alongside trends, the variance (0.119) and standard deviation (0.446) values of the sample set are suitable for clustering, considering that the group comprises only three EU countries.

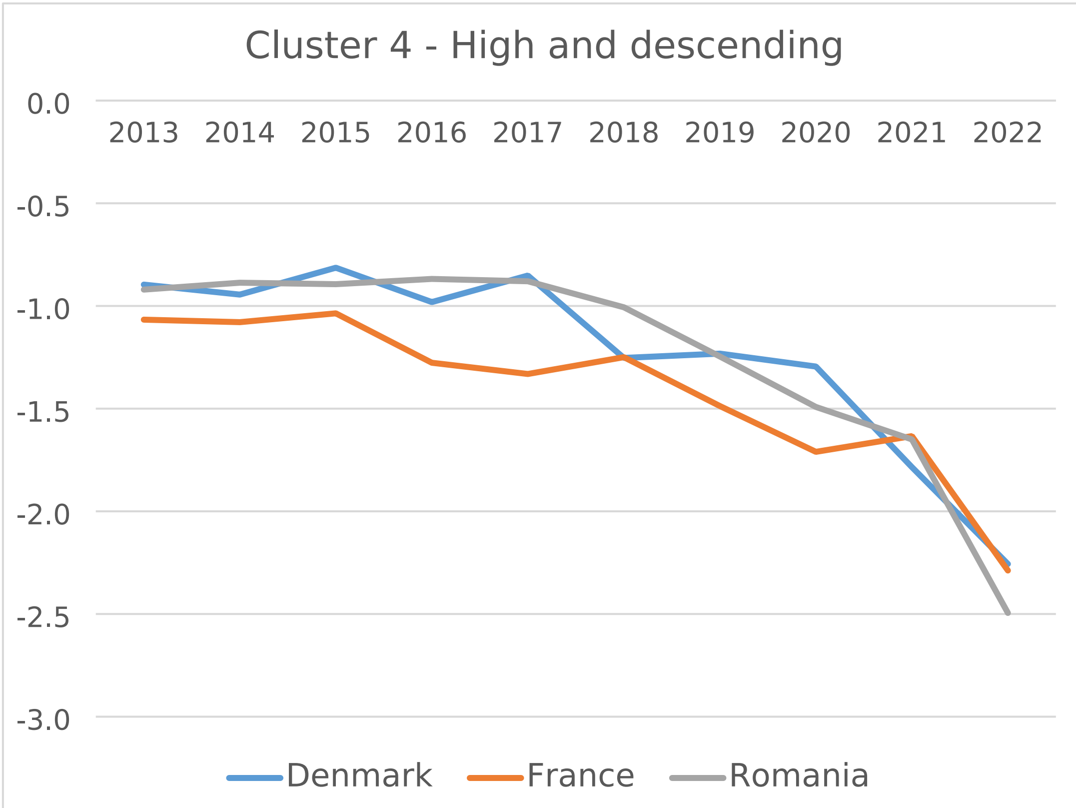

Figure 5 Clustering of European Union countries based on energy security values: Cluster 4

Cluster 5 (labeled *Moderate and descending*) comprises four EU countries (Figure 6), which also show a tendency for a persistent decline in ES, albeit less dramatically than in the preceding (blue) group. The mean value of the ES index for Cluster 5 countries is -2.797. Given that the data pertains to four countries, a standard deviation of 0.339 and a variance of 0.116 were deemed suitable for their classification into the same cluster.

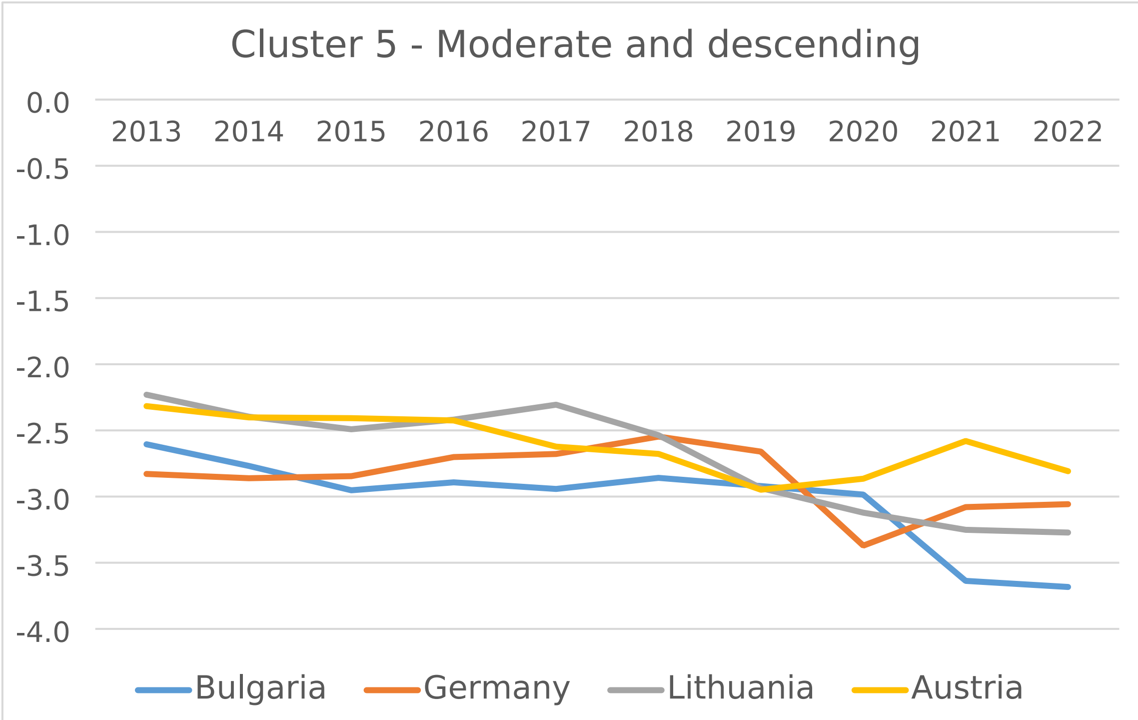

Figure 6 Clustering of European Union countries based on energy security values: Cluster 5

Cluster 7, labeled *Moderate and slightly ascending* (Figure 7), comprises only two countries (Luxembourg and Portugal). This is the only cluster exhibiting a positive ES trend, with a regression line coefficient of 0.0506. The mean value of the ES index is -2.965. Despite observable variations in ES between these two countries in the period 2017–2022, the variance of 0.065 and standard deviation of 0.255 signify the cohesiveness within the cluster.

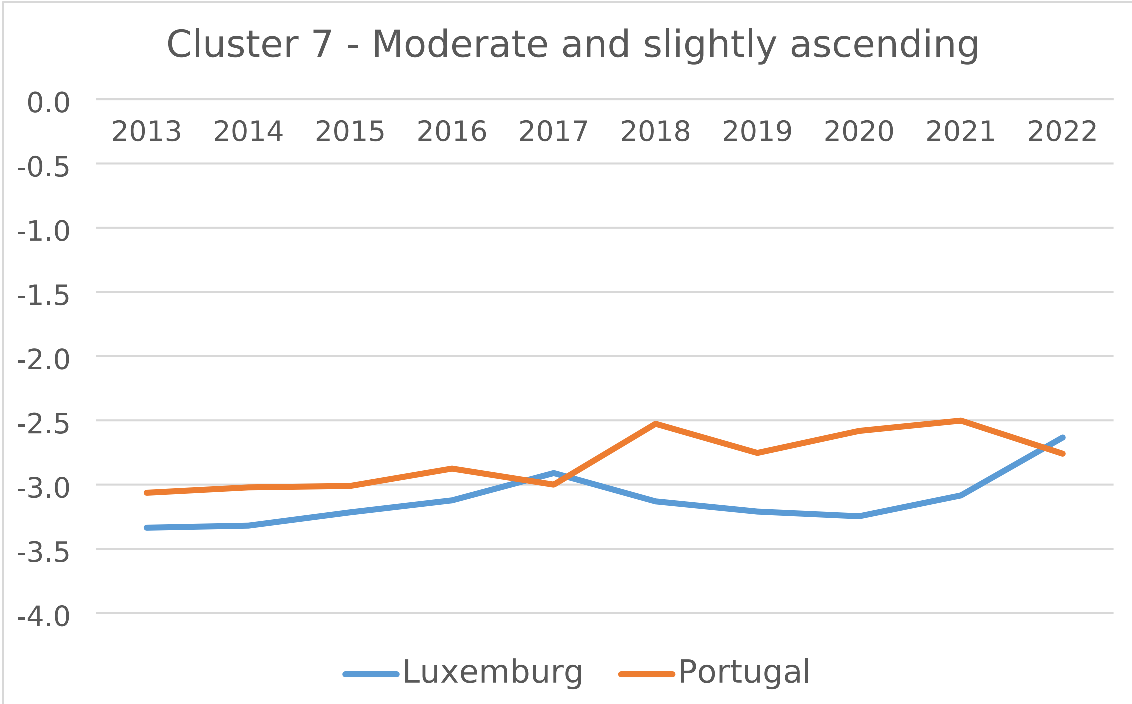

Figure 7 Clustering of European Union countries based on energy security values:
Cluster 7

The last illustration (Figure 8) includes specific cases of three countries. Malta, Cyprus, and Sweden each represent a separate cluster in the clustering process (1, 6, 2). Despite Malta and Cyprus exhibiting a favorable trend, the mean values of their ES indicators are significantly lower than those of the Cluster 7 countries, with Malta at -3.386 and Cyprus at -4.406. The growth coefficient for these two countries is higher compared to Cluster 7 (for Malta, the coefficient of the regression line is 0.1704, and for Cyprus, it is 0.0774).

Sweden represents another isolated case. Its ES is the largest and most stable in the entire observed period: the mean value of the ES indicator is -0.218, which is tenfold greater than that of other clusters. The regression line coefficient of -0.0048, variance of 0.022, and standard deviation of 0.149 suggest negligible fluctuations in the ES indicator over the observed decade.

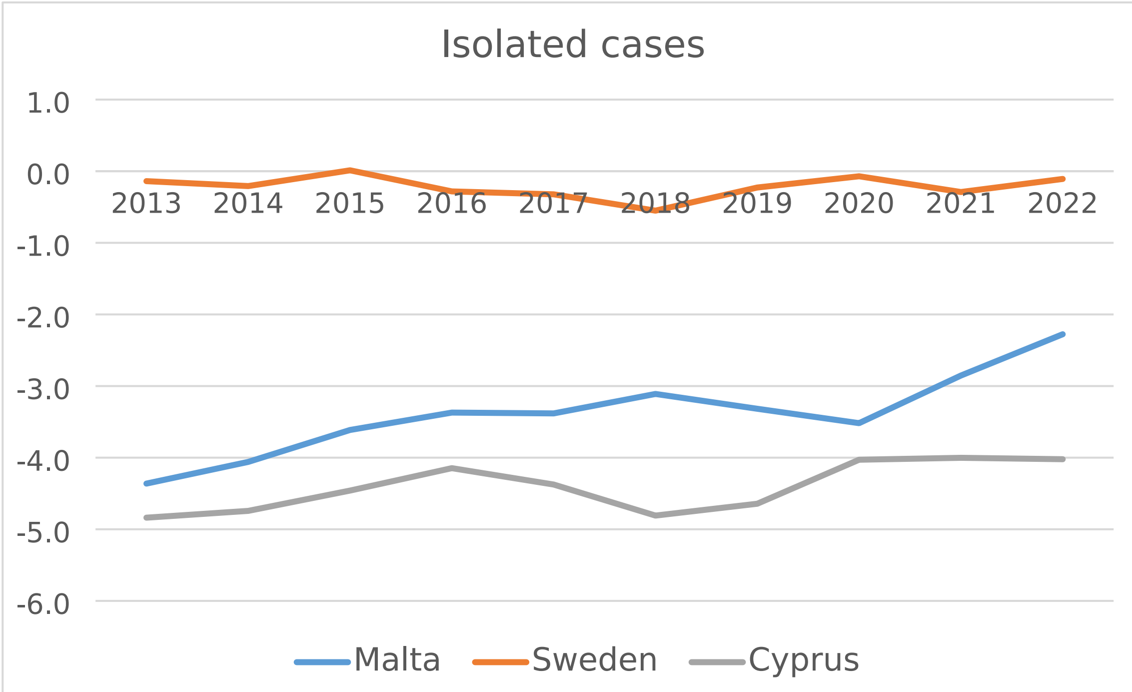

Figure 8 Clustering of European Union countries based on energy security values:
Isolated cases

For classification purposes, the eight classes are defined and labeled based on the eight clusters described above. Due to their peculiarity, the isolated cases are excluded from further considerations.

After the clustering, the row data are used again for ANN training. The data structure is transformed to be suitable for this purpose. The layout of the ANN training data post-conversion is illustrated in the subsequent figure (Figure 9). The first row displays the abbreviated designations of the ES factors. The first 13 columns comprise the values of individual factors. The penultimate column comprises the years from which the data originates, whereas the last column contains the class to which the respective record (row) belongs.

CO2	EPHH	EPNHH	EE	ENIMP	ENINT	POWP	IMPEL	IMPGAS	IMPOIL	NETEM	ENCONS	RENEN	YEAR	CLASS
9.3	0.1641	0.0918	48.63	77.777	167.61	5.8	17243	19155	56422.9	84.7	48.6	5.088	2013	3
8.7	0.1678	0.0879	45.24	80.102	155.42	5.4	21791	16845.8	58143.8	80.9	45.2	5.845	2014	3
9	0.1842	0.092	45.66	84.145	153.6	5.2	23714	18766.1	59217.1	84.1	45.7	3.921	2015	3
8.8	0.1815	0.0879	48.45	75.891	160.97	4.8	14648	18232.8	58182.4	83	48.5	6.029	2016	3
8.7	0.179	0.0721	48.49	75.258	160.35	5.8	14189.4	17868.1	62879.7	83.1	48.5	6.637	2017	3
8.7	0.1976	0.0812	46.47	82.968	157.7	5.2	21635.9	19802.9	64717.1	83.8	46.5	6.709	2018	3
8.6	0.1954	0.0802	48.41	77.591	154.94	3.9	12734.4	23228.7	62916.4	83.2	48.4	6.817	2019	3
7.9	0.1798	0.081	43.88	78.044	147.17	4.1	13721.9	21659.4	52847.5	75.8	43.9	11.035	2020	3
8.2	0.2015	0.1035	48.74	70.824	153.22	3.5	15193.6	21280	57555.5	78.4	48.7	10.264	2021	3
7.7	0.3791	0.2012	45.23	73.95	138.48	5.1	16349.6	24174.3	55288.3	74.3	45.2	10.354	2022	3
6.3	0.0735	0.0716	16.51	38.313	438.49	44.9	3351	2698	8353	58.2	16.5	5.886	2013	5
6.1	0.0746	0.0747	17.26	35.171	454.1	40.5	4319	2683	8110	60.3	17.3	5.742	2014	5
6.6	0.0798	0.0772	17.96	36.446	459.04	39.2	4251	3010	8972	64.8	18	6.492	2015	5
6.3	0.0781	0.0778	17.67	38.472	436.15	39.2	4568	3094	9053	59.5	17.7	7.203	2016	5

Figure 9 Input data for ANN training

For ANN training, 80% of collected and classified data on ES factors in EU countries was used. The remaining 20% of the data was used for testing and evaluating the model. The ANN model underwent training for 80 epochs, resulting in an accuracy of 0.98 (test accuracy: 0.9814814925193787). The evaluation demonstrated that the number of 80 epochs is appropriate for the specified ANN model and the corresponding dataset used for training and evaluation.

In the exploitation phase, ANN classifier processes a time series of row data containing 13 features related to the country under consideration. As its primary output, the classifier determines the energy security class to which the country belongs. To obtain the argumentation, the ANN classifier provides a precise and exploratory view on the ES data in relation to the characteristics of the class assigned to the country. Figure 10 illustrates two examples of the ANN classifier's exploratory output. In the first example (Figure 10a), the examined country, labeled *Country-X.2*, is classified into the *Moderate and stable* energy security class. In the second example (Figure 10b), the country labeled *Country-X.4* is classified under the *Low and slightly descending* energy security class. The values of the ES indicators are displayed on the y-axis. This exploratory view enables a detailed comparison between the ES indicator values of the country under consideration and the typical values of the class to which it is assigned. The data for the analyzed country are represented by a solid black line.

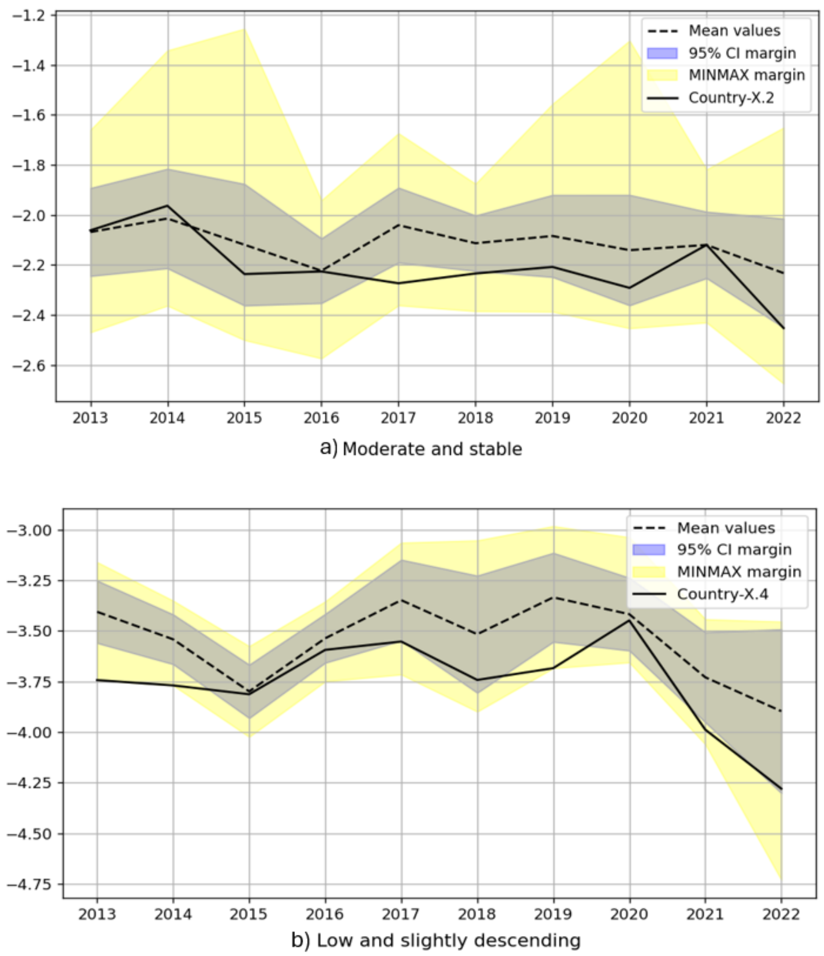

Figure 10 Two samples of ANN classifier - exploratory view

Two color-coded zones represent the margins of the assigned class. The darker margin corresponds to the 95% confidence interval, while the lighter margin reflects the min–max range. The presented visualization enables rapid and effective verification of changes in ES indicators over time—specifically, the extent to which such changes align with general trends of the assigned class, as well as the divergence of the observed country's indicator trends from those of the class as a whole. The mean values of energy security for the class are indicated by a dashed line. For deeper exploration, the ANN classifier enables the user to select a specific year and, by displaying the decomposed expression (Equation 1), analyze the contribution of individual factors to the resulting classification outcome.

From a policymaking perspective, the ANN classifier serves as a technique applicable not only to EU member states but also to EU candidate countries. In this way, policies of candidate countries can be optimized during the EU accession process, enabling timely adjustments in terms of both budgeting and legislative frameworks. This is particularly important given that changes affecting energy security are often profound and produce long-term consequences—not only for economic performance and social well-being but also in terms of geopolitical dynamics.

Discussion

For all countries under consideration, the calculated values of the energy security indicator are negative. This is primarily due to the fact that ten out of the thirteen indicators have a negative effect on energy security. Even Sweden, which exhibits the highest and most stable level of energy security, has negative values—although they are very close to zero. Within the data preparation phase, it was possible to shift all values to the positive range. However, such rescaling would not have had any impact on the clustering process.

Clustering based on the proposed energy security calculation model demonstrated that it is possible to group countries according to their mutual similarity in the values and trends of thirteen indicators over a ten-year period. Only three extreme cases were excluded from the training phase of the classification model. The first is Sweden, whose energy security—both in terms of value and stability—is significantly higher than that of all other countries. The other two cases are Malta and Cyprus. Their levels of energy security are markedly lower, and the dynamics of their indicator values deviate substantially from the patterns observed in other countries. This discrepancy is, to some extent, justified by their geographic and structural specificities: both are small island nations in Southern Europe, characterized by a lack of energy resources, geographic isolation from the mainland, and a high dependency not only on energy imports but also on imports of most other resources.

Given the multidimensional nature of the data included in the research, ANN was selected as the classification model. Following the elimination of isolated cases, the selection of an appropriate number of neurons in the hidden layer, and the specification of a suitable number of training epochs, the ANN classifier yielded satisfactory evaluation results. However, the model's accuracy could likely be improved if it were trained on monthly instead of annual time series data. In such a case, a recurrent neural network architecture with LSTM (Long Short-Term Memory) cells could be employed as the classification model instead of a feedforward ANN.

Conclusions

The decarbonization of Europe is undoubtedly the most ambitious objective the European Union has established since its inception, considering its scope, anticipated transformations, duration, and estimated budget. However, it must be implemented in a way that does not compromise energy security or the stability of energy supply. Despite the multitude of geopolitical challenges and volatility in import structures and prices, the European Union remains dedicated to decarbonizing the European continent by 2050. Given the aforementioned commitment, it is imperative to explore strategies for managing this highly intricate, multidimensional process that is affected by a multitude of diverse factors.

The primary objective of this study is to examine 13 indicators that determine a country's energy security (deemed essential for comprehensive sustainable development), which the authors regard as most significant and influential. Of the 13 selected indicators, as many as 10 adversely affect energy security, which closely aligns with actual conditions.

Following the establishment of the aggregated energy security indicator, clustering commenced, resulting in the identification of eight groups of countries exhibiting certain commonalities. Research has shown that this quantity of clusters is the most optimal. The largest number of countries (nine) comprise the country cluster demonstrating the steadiest energy security values in all respects: The Czech Republic, Croatia, Estonia, Latvia, Hungary, Poland, Slovenia, Slovakia, and Sweden. All countries (with the exception of Sweden) were formerly part of the Eastern Bloc and relied on energy supplies from the Russian Federation for decades. Denmark, France, and Romania reported the poorest outcomes and a persistent drop in energy security values. Only Luxembourg and Portugal recorded an increase in energy security.

The classifier model, developed through the clustering process, generates outcomes that are precise, explainable, and provable (PEP). The ANN classifier determines the energy security level of an observed country by assigning it to one of five predefined classes: *Moderate and stable*, *Low and slightly descending*, *High and descending*, or *Moderate and descending*. Each class is thoroughly explained, including detailed insight into every individual case—namely, each country assigned to that class. The provability of classification results is ensured by comparing the observed country’s energy security indicators with the class-specific mean values, trends, and variation margins.

Research focused on changes in energy security is of particular interest not only to the European Union as a whole but also to its individual member states and neighboring countries. Moreover, the state of energy security within the EU has a considerable impact on the Union’s economic performance and overall competitiveness. In light of the complex geopolitical shifts unfolding globally in the aftermath of the COVID-19 pandemic—and particularly after the outbreak of armed conflicts in Ukraine and the Middle East—research on methodologies for assessing energy security has gained heightened significance. The competitiveness of the EU economy is declining; the supply of natural gas (as an environmentally friendly energy source) is constrained due to sanctions imposed by the EU on the Russian Federation, and although renewable energy production is on the rise, it is not progressing rapidly enough to compensate for the Russian gas. Moreover, energy generated through these sources tends to be more expensive, which in turn increases production costs for EU-based industries. At the same time, energy prices for households continue to rise, and some EU countries are experiencing high and increasing levels of energy poverty. All of these factors underscore the need for further research focused on developing methodologies capable of assessing and forecasting a trend in a wide range of indicators that influence energy security. Given uncertainty across many domains, there is growing scope for exploring the potential of artificial intelligence in this field—provided that such approaches can deliver PEP AI outcomes that are acceptable to both decision-makers and the general public.

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Consent for publication

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Competing interests

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Authors' contributions

MR and GŠ prepared a draft of the study. GŠ completed data processing. AJ participated in literature review. All authors read and approved the final manuscript.

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