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INTEGRATED MODEL FOR COORDINATED FORECASTING AND MANAGEMENT OF COUNTRIES' DECARBONIZATION

Abstract. *The article proposes an integrated model "Decarbonization – Collaborative Planning, Forecasting and Replenishment" (D-CPFR) for assessing, forecasting and coordinating decarbonization processes at the macroeconomic level. Unlike traditional approaches, the proposed method combines country clustering based on self-organizing maps (SOM), nonlinear forecasting using multilayer perceptron (MLP) and mechanisms for mutual management of decarbonization processes between countries.*

The key scientific result is the formalization of a cluster-oriented approach, within which clustering is used not only as a tool for analytical grouping of countries, but also as a mechanism for forming a common information and coordination space for economies with similar structural characteristics. This allows us to represent forecasting models as tools for adaptive scenario-oriented decision support systems.

It is substantiated that the use of nonlinear forecasting allows authors to take into account nonlinear relationships between economic, energy, institutional and social factors of countries' decarbonization potential, as well as reduce structural forecasting errors for countries with high transformational instability. This approach was used as a basement for implementation mechanisms for intra-cluster and inter-cluster interaction of economies. Hence, ensuring the coordination of investment decisions, technology transfer and management of climate strategies, as well as transparency of decision-making.

The practical significance of the model is the possibility of its application for the formation of adaptive climate policy, support for strategic planning of the energy transition, coordination of green investments and the development of international cooperation in the field of a country's decarbonization. The proposed approach can be used as an analytical basis for building digital platforms for managing decarbonization processes at the national and international levels.

Keywords: *green economy, machine learning, clustering, macroeconomic modeling, CO_2 emissions, neural networks, sustainability.*

ІНТЕГРОВАНА МОДЕЛЬ УЗГОДЖЕНОГО ПРОГНОЗУВАННЯ ТА УПРАВЛІННЯ ДЕКАРБОНІЗАЦІЄЮ КРАЇНАМИ

Анотація. *У статті розглянуто методологічні основи авторської інтегрованої моделі Decarbonization – Collaborative Planning, Forecasting and Replenishment (D-CPFR) для оцінювання та координації процесів декарбонізації на макроекономічному рівні. Модель поєднує кластеризацію країн на основі self-organizing maps та нелінійного прогнозування із застосуванням multilayer perceptron та механізми міжкластерної взаємодії. Обґрунтовано, що запропонований підхід дозволяє враховувати структурну неоднорідність економік, формувати адаптивні сценарії енергетичного переходу та підтримувати прийняття рішень у сфері кліматичної політики, зелених інвестицій і міжнародної координації декарбонізаційних стратегій країнами-учасниками.*

Ключові слова: *зелена економіка, машинне навчання, кластеризація, макроекономічне моделювання, викиди CO_2, нейронні мережі, сталий розвиток.*

Formulation of the problem. Modern processes of global decarbonization are characterized by high structural complexity, which is established in the nonlinearity of relationships between economic, energy, technological and institutional indicators, as well as in significant cross-country heterogeneity. Therefore, the use of traditional linear models for forecasting CO_2 emissions and assessing climate policy is insufficient, as they do not allow for proper consideration of structural differences between countries and the dynamic nature of transformation processes.

Modern research is increasingly focusing on the need to integrate digital technologies and co-governance mechanisms into sustainable development and decarbonization management systems between economies. In particular, the use of machine learning allows modeling complex nonlinear dependencies between decarbonization factors, while cluster analysis creates the prerequisites for taking into account the structural heterogeneity of economic systems.

In response to these challenges, there is a need to develop integrated models that combine forecasting, scenario planning and coordination mechanisms of management between countries. One of the promising directions is the adaptation of the concept of collaborative planning, forecasting and replenishment (CPFR), which is traditionally used in logistics and supply chain management, to the tasks of macroeconomic management of decarbonization processes.

This study proposes a D-CPFR model that integrates self-organizing map methods, multilayer perceptron, and collaborative decision-making mechanisms to form an adaptive decarbonization forecasting and coordination system. A feature of the approach is that clustering is considered not only as an analytical tool for segmenting countries, but also as a basis for forming network interaction between states with similar structural characteristics and decarbonization potential.

Analysis of recent research and publications. Modern research in the field of decarbonization is increasingly focused on the use of AI-driven approaches and machine learning methods to analyze complex nonlinear relationships between economic, energy and institutional factors. Yao P., Xiangyu W., Xiaoyun W. [1], Miroshnychenko I., Kravchenko T., Drobyna Y. [2], Peng Y. H., Khairudin N. B., Salleh D. B. [3], Zatonatska T., Soboliev O., Artyukhov A., Zatonatskiy D., Balan V., Wołowiec T., Woźniak D. [4], Zatonatska T., Soboliev O., Zatonatskiy D., Dluhopolska T., Rutkowski M., Rak N. [5], Liu P., Guo N., Liu Y. [6], Suprême H., de Montigny M., Sorto-Ventura K. R. [7], Usman M., Akbar A., Hedvicakova M. [8], Wei H., Wang Y. [9], Setiawan N., Soewarno N., Rahmiati A. [10], Zhi J., Shi D., Ouyang X. [11] and others.

In particular, researchers [1] analyze the mechanisms through which environmental regulation affects CO_2 emission intensity and demonstrate that these effects are transmitted through multiple structural and innovation-related channels. Their findings support the use of nonlinear and multi-factor modeling approaches for capturing the complexity of decarbonization processes.

The study [2] applies intelligent forecasting techniques to renewable energy generation and shows that machine learning approaches are capable of capturing nonlinear and time-dependent patterns in energy systems, particularly in developing-country contexts. A similar methodological direction is presented in [3], where interpretable machine learning models are used to analyze and predict corporate carbon disclosure behavior. The authors highlight that AI-based approaches provide improved explanatory and predictive capacity compared to traditional linear specifications when dealing with high-dimensional ESG-related data.

Studies [4–5] focus on the application of ESG principles in energy project evaluation and planning, emphasizing their role in improving investment decision quality and aligning energy sector development with sustainability objectives. The findings of [6] further indicate that corporate digital transformation is associated with reduced carbon emissions and improved ESG performance, highlighting the role of digital technologies as an enabling factor in structural decarbonization transitions.

The work [7] develops time-series-based modeling frameworks for energy system planning under conditions of increasing renewable energy penetration. The authors emphasize that modern energy systems are characterized by high volatility and structural uncertainty, which strengthens the need for adaptive and data-driven forecasting approaches.

Researchers [8] examine the macroeconomic effects of decarbonization and find that these impacts are heterogeneous across countries, depending on differences in economic structure, institutional quality, and investment capacity. This result supports the relevance of cluster-based approaches for modeling decarbonization pathways.

Studies [9] and [10] demonstrate that the effectiveness of decarbonization strategies is strongly influenced by the integration of green innovation and ESG-oriented practices into corporate decision-making processes. In addition, [11] shows that variation in environmental regulation stringency across regions can lead to divergent carbon emission trajectories, reinforcing the importance of regulatory heterogeneity in decarbonization modeling.

The literature review shows that decarbonization is characterized by high structural heterogeneity and nonlinearity of the relationships between indicators. However, most existing studies focus either on local forecasting models or on individual economic factors, while the integration of AI-driven forecasting, cluster analysis, and adaptive control systems remains underexplored. This justifies the feasibility of developing cluster-oriented AI-driven decarbonization models.

The purpose of this study is to provide a methodological description of the integrated D-CPFR model for assessing, forecasting, and coordinating decarbonization processes, taking into account cross-country heterogeneity, nonlinear dependencies, and collaborative governance mechanisms. In accordance with the stated goal, the research is aimed at:

task 1. Structural formalization of the relationships between the stages of clustering, namely forecasting and collaborative governance mechanisms;

task 2. Description of the main functional components of the D-CPFR model and their role in the processes of assessing, forecasting and coordinating decarbonization;

task 3. Presentation of the conceptual architecture of the model as a basis for the formation of coordinated climate strategies and adaptive management of decarbonization processes.

The main material presentation. Within the framework of the implementation of the above stated tasks, based on the conducted research, the functional dependence between the set of input parameters and the set of output solutions regarding the decarbonization potential of countries is presented in the form of a structural model (Fig.1). The proposed model integrates the methods of cluster analysis, nonlinear machine learning and multi-criteria optimization, which allows taking into account the structural heterogeneity of countries, the scenario nature of decarbonization processes and ensuring the formation of economically justified and socially sustainable solutions.

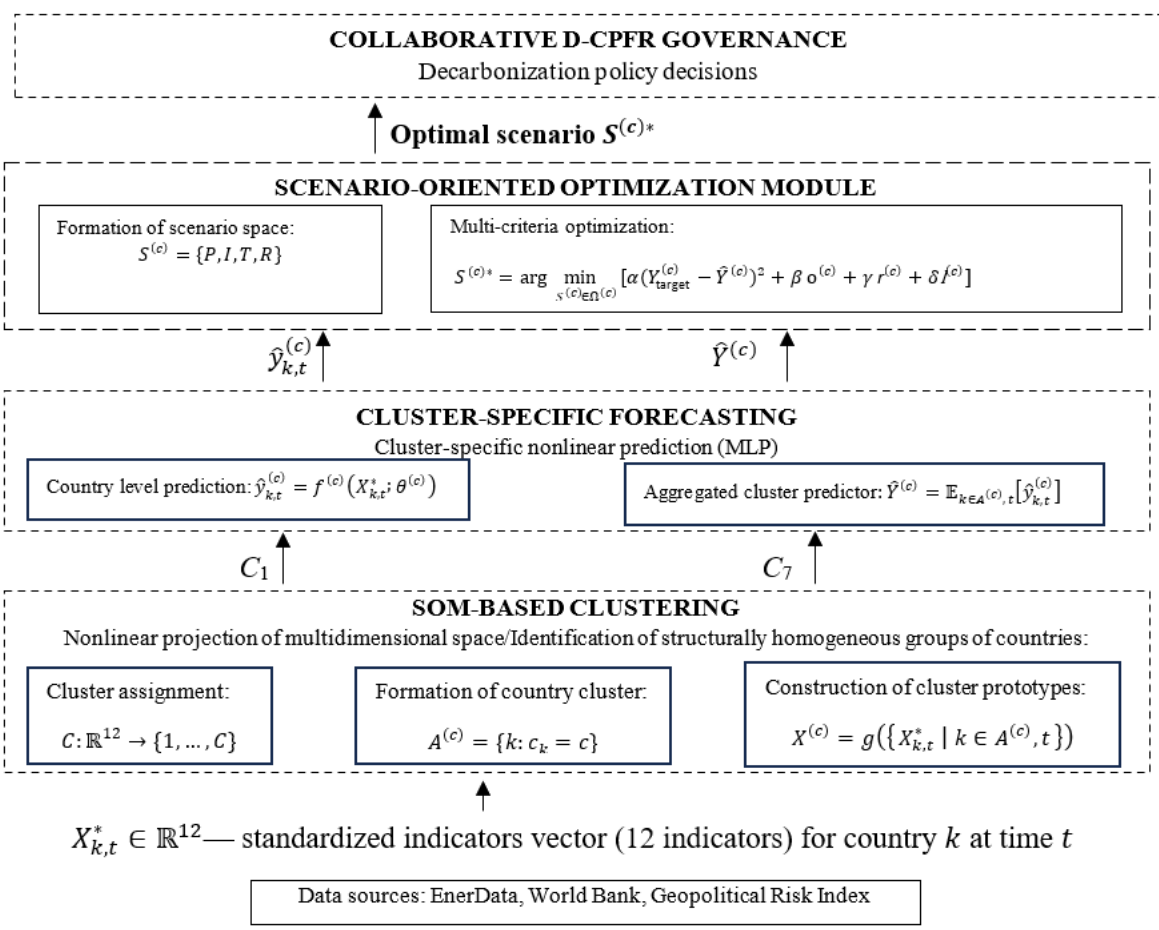

Fig.1. Structural architecture of the D-CPFR hybrid framework for decarbonization assessment and forecasting

Source: developed by the author

The number and structure of indicators were deliberately balanced in such a way as to avoid excessive parameterization and ensure managerial and analytical interpretability of the results. The set of indicators meets the requirements of modern economic and energy management, as well as the principles of digitalization of analytical processes, which involve the use of compact but information-enhanced data by reducing the computational complexity of the model, increasing its resistance to multicollinearity and ensure effective integration into decision support systems.

The study uses data for 45 countries for the period 2014–2023, generated on the basis of international databases with open access [12-14]. The information base includes 13 (1 dependent and 12 are independent) standardized indicators that characterize the energy, economic, institutional and environmental aspects of countries and provide comprehensive coverage of key factors of decarbonization determination (Table 1).

Table 1

The description of 13 indicators and 45 countries used in the dataset.

Countries	Algeria, Argentina, Australia, Azerbaijan, Belgium, Brazil, Canada, Chile, China, Colombia, Czechia, Denmark, Egypt, France, Germany, India, Indonesia, Iran, Italy, Japan, Kazakhstan, Malaysia, Mexico, Netherlands, New Zealand, Nigeria, Norway, Poland, Portugal, Romania, Russia, Saudi Arabia, Singapore, South Africa, South Korea, Spain, Sweden, Thailand, Turkiye, Ukraine, United Arab Emirates, United Kingdom, United States, Uzbekistan, Vietnam	
Category	**Indicators (*X*) for *k* country**	**Time, *t***
Energy [12]	Energy intensity of GDP at consumption	2014–2023
	Oil products domestic consumption	
	Natural gas domestic consumption	
	Electricity domestic consumption	
	Share of renewables in electrification	
	Share of wind and solar in electrification	
	Electrification	
	Coal and lignite domestic consumption	
Demography [13]	Urban population growth (annual %)	
Economy [13]	GDP per capita growth (annual %)	
Risk [14]	Geopolitical Risk Index	
Globalization [14]	Globalization Index	
Environment [12]	Average CO_2 emission factor	

Source: developed by the author based on [12-14]

The selection of 13 indicators was carried out on the basis of interrelated criteria applied to formed the dataset and balanced in terms of economic significance, statistical reliability and methodological consistency with the cluster optimization model proposed in the study (Table 2).

Table 2

Applied criteria for the selection of indicators for the dataset.

Criterion	Description	Purpose for the model
Economic and energy relevance	The model includes indicators that directly influence the carbon intensity of the economy and decarbonization processes.	Ensures the economic interpretability and practical relevance of modeling results.
International comparability and data availability	Indicators were selected from unified international databases [12–14], ensuring methodological consistency and data availability for 45 countries during 2014–2023.	Provides comparability of observations across countries and time periods.
Statistical quality and suitability for modeling	The selection process considered the stability of time series, absence of critical gaps, and multicollinearity testing.	Supports the formation of a stable multidimensional feature space suitable for econometric and AI-based modeling.
Structural representativeness	The selected variables capture key dimensions of decarbonization potential, including energy balance, macroeconomic dynamics, institutional quality, and environmental performance.	Ensures a comprehensive assessment of decarbonization processes and reflects the systemic nature of the low-carbon transition.

Source: developed by the author

According to the model (Fig. 1), the original data are represented by a set of $N_{k,t}$, which are transformed into a standardized indicators space:

$$X^*_{k,t} = \varphi(N_{k,t}) \tag{1}$$

where $X^*_{k,t} \in \mathbb{R}^{12}$ — vector of standardized indicators for country k at time t.

The conceptual architecture of the D-CPFR model presented in Figure 1 consists of 4 interconnected levels: level 1. SOM-based clustering; level 2. Cluster-specific forecasting; level 3. Scenario-oriented optimization; level 4. Collaborative D-CPFR governance.

At the first level, country clustering is implemented using Self-Organizing Maps, which provides a nonlinear projection of the multidimensional feature space and the formation of structurally homogeneous groups of countries [15]. Since cluster analysis requires a preliminary determination of the optimal number of clusters, an assessment of the quality of clustering was carried out for the studied database using internal metrics, in particular, Silhouette Score, Davies–Bouldin Index and Calinski–Harabasz Criterion. The use of these indicators allowed us to determine the most representative structure of the distribution of countries and to justify the formation of seven clusters (C = 7), which are characterized by similar parameters of decarbonization development [16]. Formalization of clustering is represented as [15]:

$$C: \mathbb{R}^{12} \to \{1, \dots, C\} \tag{2}$$

where each country is assigned a cluster c, and the set of cluster countries is defined as:

$$A^{(c)} = \{k: c_k = c\} \tag{3}$$

Within each cluster, an aggregated prototype is formed that reflects the generalized characteristics of the corresponding group of countries:

$$X^{(c)} = g(\{X^*_{k,t} \mid k \in A^{(c)}, t\})$$

The second level of the model involves the implementation of cluster-specific forecasting based on a multilayer perceptron (MLP). For each cluster, a separate nonlinear forecast function is constructed:

$$\hat{y}^{(c)}_{k,t} = f^{(c)}(X^*_{k,t}; \theta^{(c)}) \tag{4}$$

where $\hat{y}^{(c)}_{k,t}$ — is the predicted level of CO_2 emissions for country k, a $\theta^{(c)}$ — the parameters of the neural network model of cluster c.

In this case, the aggregated forecast for the cluster is defined as:

$$\hat{Y}^{(c)} = E_{k \in A^{(c)}, t}\left[\hat{y}^{(c)}_{k,t}\right] \tag{5}$$

The third level of the model is represented by a scenario-oriented optimization module. Within each cluster, a set of scenarios is formed:

$$S^{(c)} = \{P, I, T, R\} \tag{6}$$

where P — political parameters; I — investment factors; T — technological development; R — regulatory environment.

The optimal scenario is determined through multi-criteria optimization:

$$S^{(c)*} = \arg\min_{S^{(c)} \in \Omega^{(c)}} \left[\alpha(Y^{(c)}_{target} - \hat{Y}^{(c)})^2 + \beta o^{(c)} + \gamma r^{(c)} + \delta l^{(c)}\right] \tag{7}$$

where $Y^{(c)}_{\text{target}}$ target CO_2 emission level for cluster c; $\Omega^{(c)}$— feasible set of scenarios for cluster c, defined by economic, institutional, and technological constraints; $o^{(c)}$ — economic cost associated with implementing scenario $S^{(c)}$; $r^{(c)}$ — risk component (geopolitical, financial, technological uncertainty); $l^{(c)}$ — social impact component (inequality, energy access, institutional stability); $\alpha, \beta, \gamma, \delta \geq 0$ — weighting coefficients reflecting the relative importance of environmental, economic, risk and social objectives.

Thus, the model (Fig.1) integrates environmental, economic, social and risk components into a single decision-making system.

The final level of the model implements mechanisms of mutual governance, where countries in clusters are considered as interacting agents of a common decarbonization management system. In this context, clusters act as a medium for:

- coordination of climate policy;
- coordination of investment decisions;
- exchange of technologies;
- formation of mutual decarbonization scenarios.

It is also important to note that based on the formed cluster structure within the D-CPFR model, it is suggested to distinguish two interrelated scenarios of its application: intra-cluster and inter-cluster.

The intra-cluster scenario is focused on countries with similar structural characteristics of decarbonization development, in particular the level of energy dependence, technological development and institutional stability. In this case, the D-CPFR model functions as a mechanism for coordinating transformations in a relatively homogeneous environment, where interaction is based on the commonality of problems, goals and management approaches. This creates the prerequisites for harmonizing climate policy, coordinating investments and forming common decarbonization scenarios. At the same time, a fundamentally important element of the model is the dynamic nature of clustering. The use of self-organizing maps allows not only to group countries according to similar characteristics, but also to track changes in their positions in clusters and movements between clusters over time. This approach makes it possible to analyze the dynamics of decarbonization development and assess the effectiveness of implemented policies and reforms. Of particular importance is the fact that SOM clustering allows you to identify leading countries and countries lagging behind in decarbonization processes. As was determined in previous studies [17], individual clusters are characterized by the presence of countries with a high level of decarbonization efficiency, which can be denoted as "leaders" for other participants "followers" in the cluster structure. Accordingly, the country's approach to the positions of leading clusters or its transition to more developed clusters can be interpreted as a sign of improving decarbonization potential, increasing the effectiveness of climate policy and adapting the economy to low-carbon transformation.

Contrary, the inter-cluster scenario describes the interaction between structurally heterogeneous groups of countries. Such interaction creates the prerequisites for the transfer of technologies, investments, management practices and institutional experience between clusters with different levels of decarbonization development. In this context, countries with high decarbonization indicators can act as a source of technological and organizational solutions for countries with higher carbon intensity of the economy.

Thus, the D-CPFR model performs not only the analytical function of data clustering, but also forms the basis for assessing the trajectories of decarbonization development, analyzing the progress of countries in dynamics and building mutual management mechanisms. This allows authors to interpret the D-CPFR model not only as a forecasting tool, but also as a multi-level system for coordinating decarbonization processes, within which clustering provides tracking of structural changes, identification of transformation leaders and support for adaptive management of climate strategies for countries.

Conclusions. The article considers the authors' proposed comprehensive approach to assessing and forecasting the decarbonization potential of countries, which combines cluster analysis, machine learning and joint management methods within the framework of the decarbonization concept – mutual planning, forecasting and replenishment. The developed methodology takes into account nonlinear relationships between economic, energy, institutional and social determinants of decarbonization, as well as significant inter-country heterogeneity, which is critically important for the correct modeling of climate trajectories.

The scientific novelty is the extension of the classical CPFR concept to the level of macroeconomic management of decarbonization processes and its combination with clustering based on SOM and cluster-specific nonlinear forecasting models based on MLP. The model provides a transition from traditional models to adaptive structures capable of taking into account the structural heterogeneity of economic systems. The formalization of a scenario-based decision-making mechanism through multi-criteria optimization that integrates climate objectives, economic costs, risks and social consequences is implemented in the structural model.

The practical significance of the proposed method is the possibility of applying the results to the formulation of climate and energy policies at the national and international levels, planning investments in green transformation and developing energy transition scenarios. The integration of ESG principles extends the functionality of the model, taking into account the social consequences of decarbonization and ensuring compliance with the Sustainable Development Goals. This approach is particularly important for countries with economies in transition, where institutional instability and structural volatility require adaptive analytical tools.

Future research prospects include empirical validation of the model on expanded panel data, integration of financial and technological indicators, and development of digital platforms to support joint management of decarbonization. A separate direction is the study of mechanisms of inter-cluster coordination and assessment of their impact on the effectiveness of global climate policy.

References

1. Yao, P., Xiangyu, W., & Xiaoyun, W. (2026). Unpacking the black box: Multiple mechanisms of environmental regulation on carbon emission intensity. *Sustainable Futures, 9*, 101822. https://doi.org/10.1016/j.sftr.2026.101822

2. Miroshnychenko, I., Kravchenko, T., & Drobyna, Y. (2021). Forecasting electricity generation from renewable sources in developing countries (on the example of Ukraine). *Neuro-Fuzzy Modeling Techniques in Economics, 10*, 164–198. https://doi.org/10.33111/nfmte.2021.164

3. Peng, Y. H., Khairudin, N. B., & Salleh, D. B. (2026). Predicting corporate carbon disclosure in China: Evidence from interpretable machine learning. *Sustainability, 18*(4), 4022. https://doi.org/10.3390/su18084022

4. Zatonatska, T., Soboliev, O., Artyukhov, A., Zatonatskiy, D., Balan, V., Wołowiec, T., & Woźniak, D. (2025). Sustainable energy investments: ESG-centric evaluation and planning of energy projects. *Energies, 18*(8), Article 1942. https://doi.org/10.3390/en18081942

5. Zatonatska, T., Soboliev, O., Zatonatskiy, D., Dluhopolska, T., Rutkowski, M., & Rak, N. (2024). A comprehensive analysis of the best practices in applying environmental, social, and governance criteria within the energy sector. *Energies, 17*(12), 2950. https://doi.org/10.3390/en17122950

6. Liu, P., Guo, N., & Liu, Y. (2026). Corporate digital transformation, carbon emissions, and ESG performance. *Empirical Economics*. Advance online publication. https://doi.org/10.1007/s00181-026-02918-1

7. Suprême, H., de Montigny, M., Sorto-Ventura, K. R., et al. (2026). An annual quasi-static time-series simulation framework for enhanced transmission system expansion planning. *arXiv*. https://doi.org/10.48550/arXiv.2605.00231

8. Usman, M., Akbar, A., & Hedvicakova, M. (2026). The economic impact of decarbonization. *Discover Sustainability, 7*(1). https://doi.org/10.1007/s43621-026-03318-2

9. Wei, H., & Wang, Y. (2026). Environmental regulation, corporate ESG environmental performance and the mediating role of green innovation: Evidence from China. *Business Ethics, the Environment & Responsibility*. Advance online publication. https://doi.org/10.1111/beer.70116

10. Setiawan, N., Soewarno, N., Rahmiati, A., et al. (2026). The impact of green innovation on business performance in the Indonesian automotive industry: The moderating role of environmental regulation. *Measuring Business Excellence*. Advance online publication. https://doi.org/10.1108/MBE-10-2025-0230

11. Zhi, J., Shi, D., & Ouyang, X. (2026). Towards carbon neutrality: The effects of environmental regulatory distance on corporate carbon emissions. *Cogent Economics & Finance, 14*(1). https://doi.org/10.1080/23322039.2026.2654239

12. EnerData. (2024). *World Energy & Climate Statistics – Yearbook 2024* [Dataset]. https://yearbook.enerdata.net/total-energy/world-consumption-statistics.html (accessed: 11.05.2026).

13. World Bank. (2024). *World Development Indicators* [Dataset]. https://datacatalog.worldbank.org/search/dataset/0037712 (accessed: 11.05.2026).

14. Geopolitical Risk Index. (2025). *Geopolitical Risk Index* [Dataset]. https://www.geopriskindex.com/results-final-risk-index/ (accessed: 11.05.2026).

15. Kohonen, T. (2013). Essentials of the self-organizing map. Neural Networks, 37, 52–65. https://doi.org/10.1016/j.neunet.2012.09.018

16. Zhytkevych, O. (2025). Review and selection of clustering algorithms for datasets in the context of countries' decarbonization. Economy of Ukraine, 68(11), 43–55. https://doi.org/10.15407/economyukr.2025.11.043

17. Zhytkevych, O., Matviychuk, A., & Kmytiuk, T. (2023). Modeling nations' decarbonisation potential. In F. Ortiz-Rodríguez, S. Tiwari, P. Usoro Usip, & R. Palma (Eds.), Communications in Computer and Information Science (Vol. 1888, pp. 60–77). Springer. https://doi.org/10.1007/978-3-031-43940-7_6

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