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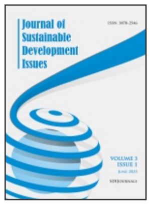

Explaining Economic and Environmental Outcomes Through Renewable Energy Quality: An Interpretable Machine Learning Approach Using XGBoost and SHAP

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ABSTRACT

This study analyzes the effects of renewable energy systems on macroeconomic and environmental results for seven countries from 2000-2023. Three new indices were formed to show not only the quantitative but the structural and qualitative parts of renewable energy systems: the Green Energy Growth Rate, Energy Diversity Index, and Risk Adjusted Green Score. These respectively show the growth rate of production, the sources of energy diversity, and the volatility-adjusted stability of renewable energy production. Renewable Energy Indicators of Economic Growth: A Novel Explainable Framework. We try to answer whether or not a green energy index accelerates economic development while trying to answer the question of whether or not the green score diminishes environmental pollution. Using the machine learning-based XGBoost regression model and SHapley Additive exPlanations methodology- powerful tools that offer relatively new approaches to the twin problems of renewable energy indicators toward economic growth, and environmental pollution- the paper quantifies both numerically and casually the contributions of renewable energy indicators to economic growth, FDI, gross savings, public finances, and particulate matter-related environmental damage. Country-specific response profiles to these energy indicators were grouped through K-Means clustering analysis. At a more intuitive level of understanding results, one notes that the Risk Adjusted Green Score (RAGS) has the greatest power in terms of influencing the reduction of environmental damage. Closest to the classical theoretical relation with the dependent variable is found to be the Green Energy Growth Rate (GEGR). The Energy Diversity Index (EDI) proves support and support-based balance, particularly within public finance indicators. Countries are clustered into three structural groups based on the 18-dimensional SHAP response profiles. This can offer much intuition into the heterogeneity of energy policy impacts and sustainability outcomes. The study has revealed the inadequacy of policies towards renewable energies, which are directed merely to the expansion of capacity in the context of the goals of sustainable development. It argues for the development of a policy design framework that incites dimensions of diversity and stability in a holistic manner that could more adequately undertake the requirements of both economic development and the protection of the environment.

Keywords: Renewable Energy Indicators, XGBoost Regression, SHAP Analysis, Sustainable Development

JEL Classification: Q42, Q01, Q56, C55, O44, F21

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1. INTRODUCTION

The energy transition is not a side issue in the environmental or engineering debate; it forms the central vector of future development over global development and economic resilience and ecological sustainability. As countries race to reconfigure their energy systems under mounting pressure regarding climate change and fossil fuel uncertainty, renewable energy has come to not only offer a technically feasible solution but to represent a new way of grappling with the questions of how the economy should grow and the direction in which society should develop. Throughout this change, most of the current talk has favored quantitative measures-established capacity, price per watt, or CO_2 cuts-as signs of development. These signs are vital for comparing progress in infrastructure and checking carbon impact, but they normally cover the inside forces that control the efficiency and strength of renewable energy systems. For indeed, the less aspect of what can make a renewable energy system successful is not just the big in its size but how it is set up—how it can change, fit in, and support both money and green goals over time. A growing body of research reveals that there is a very complex relationship between renewable energy and the paths of development at all levels, including the national trajectory. Over a lower scale, renewable energy use positively correlates with G.D.P. growth, especially in countries when fossil fuel dependencies are reduced and the green sectors are nurtured through targeted investments and innovation ecosystems. Such factors have lately come up in the E.U. Countries under the strategic linkage of renewable uptake with economic dynamism and financial development under the Green Deal initiative. In such areas, the shift from fossil o renewable is not only a carbon calculus but an economic recalibration which diversifies energy risk and spurs green employment and macroeconomic stability. The environmental dividends of renewable energy are concomitant. This is seen from the fact that solar, wind, and hydro sources have for long proved significantly effective in reducing the emission of greenhouse gases. Thereby, it goes without saying that local and international sustainability goals are met (Ren et al., 2020; Sharma et al., 2021; Bano et al., 2021). Such countries have less energy price volatility and lower healthcare expenditure due to pollution, and their overall international standing is enhanced because trade access, foreign direct investment, and geopolitical relations are now strongly influenced by environmental indicators (Borzuei et al., 2022; Simionescu et al., 2020). The benefits of renewable energy are not exactly evenly distributed, as was implicitly assumed by the optimistic formulation above. Rather, their realization waxes deep on existing infrastructural capacity within a given policy coherence and, indeed, the political economy of energy governance. While high-income nations may have the capacity to use capital-intensive renewables as a means of enhancing their global competitiveness, the low-income ones often find it difficult to mobilize the required investment for such a long gestation period with so many transitional risks to be integrated into their often-fragmented grids (Omri & Nguyen, 2014; Candra et al., 2023; Sudaryanto, 2019). This asymmetry in renewable energy adoption underscores the importance of designing policies that are not only ambitious but also structurally adaptive to varying national contexts. Empirical research reveals that the same renewable energy investment can yield divergent macroeconomic outcomes depending on a country's institutional readiness, industrial structure, and socio-political cohesion (Yusoff et al., 2023; Işık et al., 2017). In nations with well-established energy governance and robust grid infrastructure, renewables tend to amplify economic resilience. Conversely, in contexts where governance is fragmented or energy systems are centralized and brittle, the same transition may exacerbate inequalities or create new forms of energy insecurity (Candra et al., 2023; Saparulu et al., 2024). The issue is not only one of scale, but of system architecture. A renewable energy system's internal configuration-its growth trajectory, diversity of sources, and volatility-adjusted stability-forms a critical triad that determines its real-world efficacy. Simply expanding capacity without regard to source balance or operational stability may lead to energy surpluses without utility, fiscal burdens without returns, or emissions reductions without social legitimacy. What is needed is a framework that treats renewable energy systems as complex, adaptive infrastructures whose qualitative dimensions-such as equity, transparency, and decentralization-are just as important as megawatt totals (Chen & Yang, 2021; Dobravec et al., 2021; Razmjoo et al., 2021). Indeed, Khan and

Gunvant (2023) argue that policy capacity must transcend mere budget allocation or technical expertise; it must include institutional reflexivity, deliberative governance, and mechanisms for inclusive participation. Such elements are not ancillary but fundamental to the long-term viability of sustainable energy systems. Without these qualitative underpinnings, quantitative expansion may stall, misfire, or fail to achieve its intended developmental outcomes. This view is echoed in Šikšnelytė-Butkienė et al. (2019), who call for a multidimensional assessment of sustainability that includes social acceptance, ecological integrity, and policy effectiveness. Relying solely on economic efficiency or carbon reduction as performance metrics risks occluding the very societal processes that make energy transitions politically feasible and environmentally coherent. This is not just a theoretical concern; it has tangible implications for policy design, especially when deploying large-scale infrastructure in communities with complex social fabrics or contested land use. System resilience, then, cannot be divorced from system legitimacy. And legitimacy, in turn, is co-produced through participatory structures, localized planning, and institutional trust. The operational success of a wind farm or solar array hinges not only on technical specifications but also on how well it has been socially integrated—how it reflects the needs, values, and expectations of the communities it is meant to serve.

This paradigm—that renewable energy systems must be understood not only in terms of their physical output but also through their structural and relational characteristics—forms the conceptual core of this study. We posit that the quality of renewable energy systems, defined by the interplay of growth rate, source diversity, and volatility-adjusted stability, constitutes a more accurate predictor of national outcomes than capacity alone. This triadic quality structure does not merely complement traditional indicators; it challenges the epistemic foundations upon which current policy models rest. To interrogate this hypothesis, our approach bridges theory with empirically grounded techniques. Drawing upon machine learning, explainable AI, and statistical clustering, we construct and analyze three theory-driven indicators: Green Energy Growth Rate (GEGR), which quantifies the pace at which renewable energy expands; Energy Diversity Index (EDI), adapted from Shannon entropy, which captures the balance and variety of energy sources; and Risk Adjusted Green Score (RAGS), modeled on Sharpe-like ratios, which integrates growth and volatility into a single stability-adjusted metric. These indicators allow us to go beyond mere correlation, offering an interpretative lens through which to understand how structure influences function in national energy systems. These energy quality indicators are then linked to six national outcomes—five macroeconomic (GDP growth, FDI inflows, gross savings, public revenue, and government expenditure) and one environmental (particulate matter damage)—through XGBoost regression. Rather than treating these models as opaque black boxes, we apply SHAP (SHapley Additive exPlanations) values to elucidate the marginal contributions of each indicator to each outcome variable, offering a transparent, localized, and comparative understanding of energy–economy–environment interactions. But this study does not stop at prediction. The second stage introduces a clustering layer that groups countries based on the structural patterns revealed by their SHAP vectors. Each country is characterized by an 18-dimensional SHAP profile—three indicators multiplied across six outcomes—reflecting how that nation's macroeconomic and environmental performance responds to different energy system qualities. These profiles are then grouped using unsupervised KMeans clustering to reveal latent typologies of energy behavior. Crucially, these clusters are not aligned along traditional lines such as geography, income level, or emissions output. Instead, they reflect a novel taxonomy of systemic behavior: how nations respond, at a structural level, to the qualitative properties of renewable energy. Countries that appear dissimilar on the surface may share deep commonalities in how their economies and ecosystems react to specific energy configurations, while others with shared characteristics—such as GDP per capita—may diverge sharply in their energy sensitivity profiles. This insight carries profound implications. It disrupts the practice of policy transplantation—where strategies successful in one country are replicated wholesale in another—by insisting on a more nuanced structural diagnosis. It also reframes global energy diplomacy, suggesting that cooperation should be built not on static attributes, but on shared patterns of responsiveness. This structural perspective opens the door to a more intelligent and equitable approach to energy policy—one that treats similarity not as a matter of surface attributes but of internal behavior. Countries that cluster together based on their SHAP-derived energy response profiles can become peers in policy experimentation, knowledge exchange, and coordinated investment strategies. This form of alignment, grounded in how nations function rather than how they appear, offers a promising alternative to both geographic regionalism and income-group categorization. Moreover, the integration of SHAP into this analytical architecture addresses a critical tension in sustainability research: the trade-off between model performance and interpretability. Traditional econometric models, while statistically rigorous, are often too linear and too restrictive to capture the conditional, nonlinear interactions embedded in complex systems. On the other hand, machine learning models, while powerful in their predictive capacity, are frequently criticized for their opacity—the so-called "black box" problem. By employing SHAP, we sidestep this dichotomy. We retain the high-resolution pattern recognition of advanced algorithms while gaining access to the marginal logic of variable influence. This makes it possible not only to know what the system is doing, but to understand why it is doing it—knowledge that is indispensable for policymaking, stakeholder communication, and democratic accountability. What emerges from this dual-layered methodology is not just a predictive tool but an interpretive framework. It is a way of seeing: a mode of inquiry that respects the complexity of energy transitions without reducing them to oversimplified narratives. It allows us to move past the idea that more is always better—that bigger capacity, more investment, or faster growth will necessarily yield sustainability. Instead, it asks what kinds of systems endure, adapt, and integrate over time and under pressure. In this sense, the study contributes to three overlapping literatures: the structural analysis of energy systems, the application of interpretable machine learning in policy contexts, and the political economy of sustainability. It speaks to scholars interested in the systemic dimensions of renewable energy, as well as to practitioners seeking tools for grounded, context-sensitive policy intervention. Finally, this research insists that sustainability is not a fixed destination reached through technical compliance. It is a continuous process—fragile, political, and iterative—dependent on the ways in which societies organize, distribute, and govern their energy infrastructures. A sustainable energy future, then, will not be delivered solely through the expansion of capacity, but through the cultivation of systems that are as inclusive, resilient, and intelligent as the challenges they aim to address.

Here, in this light, the shift to green power has to be seen not just as a material change—swapping coal for sun, or gas for wind—but as a structural switch of the energy-economy-ecology link. This change needs not just new tech but new thoughts: a move from straight, amount-based models to dynamic, quality-focused frameworks that can consider diversity, risk, and looped effects. Such a change is very important because the time of the Sustainable Development Goals is increasing. While building renewable energy infrastructure is key to achieving the goals related to climate, much more is required by the SDGs than just reducing emissions. They require equity, resilience, participation, and institutional integration—all aspects that cannot simply be measured with capacity metrics. Without looking at these features, the expansion of renewable energy will be very technocratic and extractive—it will create more inequality, which is what it is trying to get rid of. Decentralization and local engagement were found to be the key success factors in energy policy in Dobravec et al. (2021) and Razmjoo et al. (2021) research. Meanwhile, operational flexibility in system design was proven to be required by such factors in the research of Chen and Yang (2021). The above views present a simple but strong understanding: energy systems are a part of social technical systems. On them depends on the task success and end in case of an actual engineering relationship, per implied value and imagined future. Thus, the study is not only a part of the techie fine-tuning input for the use of green energy. It is a push to reconsider the check, plan, and control of energy systems. Bringing into the spotlight quality, growth action, diversification, and volatility-adjusted resilience, this work tries to widen the review terms for energy shifts. Setting nations into groups based on these aspects it gives a kind that is not set in stone or telling, but alive and open to interpretation: a map not of where countries are, but of how they react. In summary, this paper argues that sustainability as not a by-product of scale but the outcome of structural design. Therefore, countries aspiring to lead in the global energy transition must pursue something beyond megawatts and carbon savings. They must pursue the deeper questions of what type of system is to be built, whom it serves, how it shall adapt, and most importantly, whether it can last. The subsequent sections detail the methodology used to operationalize these questions, followed by a comprehensive literature review that situates this study within the broader academic discourse. This is succeeded by an in-depth analysis of the data and empirical findings derived from the model. Finally, the paper concludes with a discussion of the results and their policy implications, offering insights into how this new perspective on energy system quality can inform sustainable energy transitions.

2. LITERATURE REVIEW

The link between renewable energy development and its ripple effects on economic growth and sustainability of the environment, and policy making has been of keen scholarly interest over the last decades. Most of the existing studies have explored these links from a quantitative relationship between renewable energy consumption and various macroeconomic indicators. They bear positive links with growth and stability in most of the cases reported. Moreover, the degree of portfolio diversity and system resilience are found to be instrumental in enhancing the effectiveness of renewable energy transitions. This implies moving beyond economic and environmental metrics to the metrics of governance structures, policy capacity, and participatory mechanisms to assess their influences on energy transformation and equity. Despite the general advances, most works are still fragmentary, with structural quality measures very scarcely integrated, rendering complicated energy–economy–environment interactions less interpretable. It is this gap that the present study seeks to fill by providing a review that synthesizes the principal thematic constructs in the existing knowledge and identifies the research motivation for the study at hand, which is based on the multidimensional and interpretable approach.

Table 1: Summary of Key Literature on Renewable Energy, Economic Growth, Environmental Impact, and Policy Dimensions

Theme	Author(s)	Year	Methodology	Key Findings
Renewable Energy and Economic Growth	Li et al.	2021	Panel Regression	Renewable energy consumption has a positive effect on financial development and economic growth.
Renewable Energy and Economic Growth	Simionescu et al.	2020	ARDL Model	Renewable energy use in EU countries is significantly and positively correlated with GDP.
Renewable Energy and Economic Growth	Şoavă et al.	2018	Panel Data Analysis	Long-term renewable energy consumption supports economic growth.
Renewable Energy and Economic Growth	Apergis & Payne	2011	VECM Causality Analysis	Bidirectional causality exists between RE and GDP in Central American countries.
Renewable Energy and Economic Growth	Işık et al.	2017	Linear and Non-linear Relationship Testing	The nexus between tourism, renewable energy, and growth is complex and varies by region.
Portfolio Diversity, System Stability, and Structural Quality	Cîrstea et al.	2018	Composite Sustainability Index	Norway and Sweden lead with high renewable energy sustainability scores.
Portfolio Diversity, System Stability, and Structural Quality	Kukharets et al.	2023	Threshold Regression Analysis	Countries surpassing 32% RE consumption exhibit GDP growth without increased energy import dependency.
Portfolio Diversity, System Stability, and Structural Quality	Güler et al.	2024	Panel Data Analysis	Investment, growth, and unemployment significantly influence renewable transition in OECD countries.
Portfolio Diversity, System Stability, and Structural Quality	Režný & Bureš	2019	Extended Neoclassical Growth Model	Different energy scenarios produce varying economic outcomes in the long term.
Portfolio Diversity, System Stability, and Structural	Formánek	2019	Semi-parametric Spatio-Temporal Analysis	Regional GDP is spatially and temporally affected by RE consumption levels.

Theme	Author(s)	Year	Methodology	Key Findings
Quality				
Environmental Impact and Emission Reductions	Ren et al.	2020	Dynamic Spatial Panel Model	Renewable energy and economic growth reduce CO_2 emissions in the EU.
Environmental Impact and Emission Reductions	Sharma et al.	2021	Panel Regression (8 Asian Countries)	RE consumption significantly reduces ecological footprint.
Environmental Impact and Emission Reductions	Bano et al.	2021	ARDL Bounds Testing	Tourism and RE consumption improve environmental quality in Pakistan.
Environmental Impact and Emission Reductions	Balsalobre-Lorente et al.	2018	ARDL with Natural Resource Variables	Electricity generation and natural resource use significantly influence CO_2 emissions.
Policy Capacity, Governance, and Participation	Šikšnelytė-Butkienė et al.	2019	Neutrosophic MULTIMOORA	Governance quality, social acceptance, and ecological footprint are key to sustainable energy.
Policy Capacity, Governance, and Participation	Dobravec et al.	2021	Qualitative, Multi-level Energy Planning	Local energy initiatives and multi-level governance are critical for RE transition.
Policy Capacity, Governance, and Participation	Razmjoo et al.	2021	Literature Synthesis + Policy Commentary	Communication between local and national levels is essential for sustainable energy policies.
Policy Capacity, Governance, and Participation	Chen & Yang	2021	Process Design (Chemical Integration of RE)	Flexible system design improves energy efficiency and integration outcomes.
Country Heterogeneity, Clustering, and Income Thresholds	Vyrostková et al.	2024	FMOLS (Fully Modified OLS)	Higher GDP per capita correlates with increased RE investment in Eurozone countries.
Country Heterogeneity, Clustering, and Income Thresholds	Sudaryanto	2019	Panel Regression (6 Asian Countries)	In some low-income countries, higher GDP levels may reduce RE consumption due to infrastructure gaps.
Country Heterogeneity, Clustering, and Income Thresholds	Yusoff et al.	2023	Macroeconomic Determinants Analysis	Economic growth, price trends, and policies shape RE development in Malaysia.
Country Heterogeneity, Clustering, and Income Thresholds	Omri & Nguyen	2014	Cross-national Panel Data Analysis	Income level and institutional factors determine RE consumption.
Country Heterogeneity, Clustering, and Income Thresholds	Cîrstea et al.	2018	Clustering + Composite Index	Scandinavian countries cluster together with high RE sustainability metrics.
Oil Prices, External Shocks, and Strategic Renewable Transitions	Tambari et al.	2023	Comparative Panel Analysis (African Countries)	Oil price increases incentivize RE investment in oil-importing countries.
Oil Prices, External Shocks, and Strategic Renewable Transitions	Borzuei et al.	2022	Time Series Analysis (Iran)	Energy prices and growth rates directly influence RE development.
Oil Prices, External Shocks, and Strategic Renewable Transitions	Saparulu et al.	2024	Panel Data Analysis	RE investment contributes to both economic sustainability and GHG reduction.
Oil Prices, External Shocks, and Strategic Renewable Transitions	Candra et al.	2023	Panel Regression	Renewable energy promotes environmental and economic sustainability jointly.

The existing body of literature on renewable energy has continuously emphasized positive impacts on economic growth, macroeconomic stability, and environmental sustainability in different countries. Diversification of the portfolio and system stability has over the years emerged as a matter of good resilience and sustainability of the energy infrastructure and enables the country to better withstand economic as well as environmental pressure. Some more empirical evidence shows that the adoption of renewable energy is instrumental in reducing greenhouse gas emissions and improving air quality; that is, it are basic preconditions of the global sustainability agendas (Ren et al., 2020; Sharma et al., 2021). These benefits, however, are contingent upon specific country-level factors or variables, such as the maturity of the infrastructure, the quality of governance, and capacity in policies. This is in light of the fact that such factors play a crucial role in not only the effectiveness but also the equity of investment in renewable energy (Dobravec et al., 2021). Thus, advanced clustering analyses do not imply the existence of pronounced heterogeneity in national responses to the integration of renewable energy; it simply underscores, once more, the imperative need for context-sensitive and socially inclusive policy frameworks if truly sustainable transitions are to be achieved (Vyrostková et al., 2024; Sudaryanto, 2019). Secondly, and most importantly, macroeconomic externalities, particularly volatile oil prices, do play a very significant role in the formulation of a renewable energy strategy, especially in economies that are highly fossil fuel-dependent (Tambari et al., 2023). This forms the basis for undertaking the current in-depth research initiative that critically gaps qualitative dimensions grounding sustainability in energy systems. Earlier studies have based their assessment more on capacity-based quantitative measures that do not adequately relate the complicated interaction effecting structural stability, diversification balance, and risk-adjusted performance. What little there is is hardly legible in terms of the energy–economy–environment interactions that are truly multivalent, with many analyses conducted on the basis of oversimplified econometric modelling or "black-box" machine learning methods.

Our study has developed a three-dimensional sustainability-based framework which combines growth dynamics, energy source diversity, and volatility-adjusted stability in composite indicators. Making black box results of artificial intelligence techniques transparent and interpretable, this paper provides an insight into how these dimensions interact toward macroeconomic and environmental outcomes. Countries are also newly clustered based on their structural response profiles—not mere traditional economic or geographic classifications—to enable the detection of specific policy typologies that can better accommodate the diverse sustainability tracks of different countries. This research goes beyond the conventional assessment of renewable energies by methodological innovation as well as by theoretical clarity. It provides policymakers and researchers with a strong analytical view to understand and control energy shifts in a way that fully includes economic growth, environmental care, and social fairness— foundations of sustainable development. So our input is not just to the academic talk but also to the real ruling of energy systems in a time that asks for quick and all-around sustainability.

3. MODEL SPECIFICATION AND DATA

3.1 Model Specification

This section presents the data sources, analytical framework, and methodological tools that were applied to study the multiple links from renewable energy system quality to macroeconomic and environmental outcomes at the country level. In this study, we used comprehensive data on renewable energy consumption and major economic and environmental indicators. High-capacity machine learning methods with interpretable models are then applied to uncover complex, nonlinear interactions. The study then explains how growth rate, portfolio diversity, and risk-adjusted stability are synthesized into composite indicators and how the SHapley Additive exPlanations (SHAP) values are applied. It further explains how unsupervised clustering algorithms help to classify countries based on their structural response similarities, thus offering an informed perspective on the different energy transition journeys.

3.2. Data

Our primary dataset comprises annual renewable energy production volumes for seven countries, encompassing solar, wind, hydroelectric, and other renewable energy sources measured in megawatt-hours (MWh). These raw production figures capture detailed year-to-year variations and the compositional differences across energy sources. Building upon this data, we constructed three composite indicators representing renewable energy system quality: growth rate (Green Energy Growth Rate), source diversity (Energy Diversity Index), and volatility-adjusted stability (Risk Adjusted Green Score). These indicators allow for a multi-aspect analysis of system performance, showing not just the quantitative changes in energy production but also the structural balance and stability of the energy portfolio. What follows gives a detailed account of computation methods for these composite indicators, machine learning models applied, and interpretability techniques used. Besides the newly constructed indicators, the study brings key economic and environmental variables into the picture of understanding the impact of the renewable energy system. Table 2 gives the full set of variables used in the analysis and their detailed descriptions.

Table 2. Variables Used in the Study and Their Descriptions

Variable Name (Abbreviation)	Description	Unit / Type	Source
GEGR	Annual growth rate of renewable energy consumption	Percentage (%)	Calculated from energy mix data
EDI	Shannon entropy-based measure of energy source diversity	Index (0-1)	Calculated from energy mix data
RAGS	Ratio of energy growth to volatility, indicating stability	Ratio (unitless)	Calculated from energy mix data
GDP	Annual percentage growth of Gross Domestic Product	Percentage (%)	World Bank
FDI	Net inflows of FDI as a percentage of GDP	Percentage (%)	UNCTAD
GS	National gross savings as a percentage of GDP	Percentage (%)	World Bank
REV	Government revenue as a percentage of GDP	Percentage (%)	IMF Government Finance Statistics
EXP	Government expenditure as a percentage of GDP	Percentage (%)	IMF Government Finance Statistics
PM	Estimated environmental damage from particulate matter	Index / $\mu g/m^3$	World Health Organization (WHO)

*The first three variables (GEGR, EDI, RAGS) were calculated by the author using raw energy and volatility data based on standard methods in the energy economics literature.

All data preparation and analysis were done using the Python programming language in the environment of Jupyter Notebook. Data cleaning, processing, and analysis steps were executed in a series of commands using libraries such as pandas and numpy. The time series properties of the variables were checked, and the stationarity of the variables was confirmed with the Augmented Dickey-Fuller test prior to analysis. The correlation analysis and tests of multicollinearity of variables were run in Python with the numpy and seaborn libraries. Then the dataset was put into a method-compatible way to apply analytics, ready for machine learning models and statistical analyses. This phase provided a key step in the check for result soundness and validity. During the modeling phase, the XGBoost Regressor algorithm was implemented in the Python environment. To improve the model performance, I ran the hyperparameter optimization systematically using the Grid Search method. The table below shows the main hyperparameters of the XGBoost algorithm and how they affect model performance.

Table 3: Key Technical Features and Hyperparameters of XGBoost Regressor

Parameter	Description	Typical Values / Range	Impact on Model Performance
learning_rate	Step size shrinkage used to prevent overfitting	0.01, 0.05, 0.1	Controls how quickly the model adapts; smaller values lead to slower but potentially more accurate convergence
max_depth	Maximum depth of each decision tree	3, 5, 7	Controls model complexity; deeper trees can capture more interactions but risk overfitting
n_estimators	Number of boosting rounds	100, 300, 500	More rounds can improve performance but increase training time and overfitting risk
subsample	Fraction of training samples used for each tree	0.6, 0.8, 1.0	Introduces randomness to prevent overfitting
colsample_bytree	Fraction of features sampled for each tree	0.6, 0.8, 1.0	Controls feature sampling to reduce correlation and overfitting
early_stopping_rounds	Number of rounds without improvement to stop training	10	Stops training if no improvement to validation metric, preventing overfitting

4. METHODOLOGY

A mostly mathematical description of the method (method or model) to be used in a theoretical or empirical analysis. Appropriate application based on the chosen method computer implementation using a software package.

This part gives a simple overview of the main analytical methods and technical steps used in the study. First, the composite renewable energy quality indicators from actual production data are defined, accompanied by their calculation methods. These were followed by first undertaking basic data checks, stationarity and correlation assessments to ascertain the suitability of the dataset for modeling. SHapley Additive exPlanations (SHAP) values were used to interpret model outputs for a feature-by-feature analysis of the contribution of each to target variables. That is, unsupervised KMeans clustering was run on SHAP values to find structural response patterns of the countries' energy systems. From simple to high dimensionality and interpretability, this methodological framework allows for in-depth analysis of the economic and environmental impacts of renewable energy systems.

4.1. Renewable Energy Indicators: Definitions and Construction

The analysis starts by constructing key indicators that characterize the quality of renewable energy systems based on raw production data from various energy sources. These composite indicators not only measure the quantity but also capture the structural and dynamic aspects of renewable energy production at the national level.

The first indicator, the Green Energy Growth Rate (GEGR)**,** represents the annual percentage change in a country's renewable energy production capacity. It quantifies how rapidly a country expands its total green energy output each year. Mathematically, it is defined as:

$$GEGR_{i,t} = \frac{RE_{i,t} - RE_{i,t-1}}{RE_{i,t-1}} X100 \tag{1}$$

where denotes the renewable energy production of country iii in year ttt, measured in units such as megawatt-hours (MWh), and t−1 refers to the previous year. This annual growth rate is computed for each year within the period 2000 to 2023, and an average growth rate over this entire period is calculated to summarize the typical expansion velocity of renewable energy capacity:

$$GEGR_{i,t} = \frac{1}{T-1} \sum_{t=2001}^{2023} GEGR_{i,t} \tag{2}$$

The second indicator, the Energy Diversity Index (EDI)**,** measures the diversity and balance of renewable energy sources within a country's energy portfolio. It is based on the Shannon Entropy formula:

$$EDI_i = \sum_{j=1}^{k} p_{ij} \,.\, ln_{pij} \tag{3}$$

Here, represents the proportion of renewable energy source j in the total renewable energy production of country i, and k is the number of renewable energy source types considered (such as hydro, solar, wind, biomass, geothermal). The EDI value ranges between 0 and ln(k), where a value of zero indicates complete reliance on a single energy source, and the maximum value corresponds to an equal distribution of energy production among all sources. Thus, higher EDI values reflect a more diversified and balanced renewable energy mix.

The third indicator is the Risk-Adjusted Green Score (RAGS)**,** designed to capture the stability of renewable energy growth by considering the volatility of the growth rates. It is calculated as a Sharpe-like ratio:

$$RAGS_i = \frac{\mathrm{GEGR}_i}{\sigma GEGR_i} \tag{4}$$

where GEGRi, is the average green energy growth rate for country i, and is the standard deviation (volatility) of the growth rate across the observed period.

Higher positive values of RAGS indicate that a country achieves strong and consistent growth in renewable energy capacity, while lower or negative values suggest unstable or fluctuating growth patterns. This multidimensional framework, grounded in fundamental production data, enables a comprehensive quantitative and qualitative assessment of renewable energy systems' performance. These indicators serve as critical inputs for the machine learning models and interpretability analyses discussed in the subsequent sections. The construction and use of these composite indicators build upon established methods in the renewable energy literature, as exemplified by studies such as Cîrstea et al. (2018), Kukharets et al. (2023), and Li et al. (2021), who emphasize the importance of growth, diversity, and stability metrics in assessing energy systems.

4.2. XGBosst Regressor

In this study, the XGBoost Regressor algorithm was employed as the primary predictive model due to its effectiveness in modeling complex and nonlinear relationships (Chen & Guestrin, 2016). XGBoost is a gradient boosting method that sequentially builds weak learners, typically decision trees. At each iteration, the model adds a new tree to minimize the residual errors from previous predictions.

The optimization of the model is based on minimizing a specified loss function. The general update formula is:

$$\hat{\tilde{y}}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(\chi_i) \tag{5}$$

where $\hat{\tilde{y}}_i^{(t)}$ is the prediction for the target variable at iteration t, and f_t is the newly added decision tree at iteration t.

The loss function is typically defined as the mean squared error or a similar error metric:

$$L^{(t)} = \sum_{i=1}^{n} l\big(y_i y^{(t-1)} + f_t(x_i)\big) + \Omega f_t \tag{6}$$

Here, is the loss function, $\hat{y}_i^{(t)}$ is the true value, and $\Omega(f_t)$is a regularization term that penalizes model complexity. This structure of XGBoost enhances model accuracy while also helping to prevent overfitting. Consequently, it effectively models the complex relationships between renewable energy indicators and macroeconomic and environmental variables. Machine learning models are especially powerful at capturing nonlinear and complex interactions; however, they are often considered "black boxes" due to limited transparency in their decision-making processes. Therefore, to increase interpretability of model outputs and to analyze the contributions of variables to target predictions in detail, SHapley Additive exPlanations (SHAP) methodology was utilized (Lundberg & Lee, 2017).

4.3. SHapley Additive exPlanations (SHAP)

SHapley Additive exPlanations (SHAP) are a method derived from game theory that calculates the contribution of each feature (variable) to the output of a machine learning model. These contributions, called Shapley values, fairly distribute the total model output among the features based on a cooperative game theory principle.

Mathematically, for a model *f* and a data point *x*, the SHAP value ϕ_i of feature i is computed over all subsets of features S⊆F\{i}S (where *F* is the full feature set) as follows:

$$\emptyset_i = \sum_{\mathbf{S}\subseteq\mathbf{F}\setminus\{\mathbf{i}\}} \frac{|S|!(|F|-|S|-1)!}{|F|!}\left[f_{S\cup(i)}(xsu(i)) - f_{s(xs)}\right] \quad (7)$$

Here, $f_s\,(x_s)$ denotes the model's prediction when only the features in the subset *S* are used, while $f_{S\cup(i)(xsu(i))}$ represents the prediction when feature iii is added to that subset. SHAP analysis thus offers a mathematically consistent and transparent way to decompose the model's output, showing how each feature contributes to shaping the predictions, whether those effects are positive or negative, and revealing the relative importance of each variable. In this study, SHAP was applied to the XGBoost model to provide a detailed understanding of how renewable energy indicators impact macroeconomic and environmental target variables. This approach makes complex model structures interpretable and yields results that are more accessible and meaningful for policymakers.

4.4. K-Means Clustering Analysis

Clustering analysis is an unsupervised learning technique aimed at grouping data points based on their similarities. In this study, the K-Means algorithm was used to classify countries based on the structural responses of their renewable energy systems derived from model outputs. K-Means partitions the dataset into a predetermined number of clusters, K, and assigns each data point to the cluster with the nearest centroid.

Mathematically, given a dataset X={x1,x2,...,xn} and the number of clusters *K*, the objective is to find the cluster assignments S={S1,S2,...,SK} that minimize the sum of squared distances within clusters, expressed as:

Argument of the minimum over *S* of the sum from k=1 to *K* of the sum over x_i in cluster S_k of the squared Euclidean distance between xi and the cluster centroid μ_{k1}, that is:

$$\min_S \sum_{k=1}^{K} \sum_{xi\in Sk} \|x_i - \mu_k\|2 \quad (8)$$

where μk is the mean vector of all points in cluster S_k.

The KMeans algorithm, originally proposed by MacQueen (1967), is a widely used unsupervised clustering technique that partitions data into a predetermined number of clusters by minimizing within-cluster variance.

The technique sequentially designates every datum to the closest prototype and revises the prototype as the average of designated points until it gets to a halt. This is very simple and quick to compute, hence commonly used for practical purposes in the investigation of data, particularly when working with many dimensions. The tudy develops a two-dimensional representation of the response of each country's renewable energy system based on SHAP values of the predictive model. These SHAP vectors will be clustered by the KMeans algorithm in order to group countries that have similar structural behaviors in their energy systems. This classification will help in setting up energy policies sensitive to these unique characteristics. KMeans has key strengths: easy implementation, scalability to large datasets, and the interpretability provided by rather compact summaries of group traits that are offered by cluster centroids (Steinley, 2006).

5. EMPIRICAL RESULTS AND DISCUSSION

This section presents the findings derived from the dataset and the applied methodologies. The impacts of renewable energy indicators on macroeconomic and environmental variables are examined in detail using the XGBoost regression model and SHAP values. Additionally, clustering analysis performed on SHAP outputs categorizes countries according to their structural responses to renewable energy systems. The findings offer insights into the direction and magnitude of variable effects, as well as the characteristic features of country groups. Model performance, variable importance, and clustering outcomes are discussed sequentially below.

5.1. Unit Root Test and Autocorrelation Test Results

Table 4. ADF Test Results

Variable	Form	Model	ADF Statistic	p-value	Lag (AIC)
GEGR	Level	Constant	-10.4354	0.0000	2
GEGR	Level	Constant + Trend	-10.6733	0.0000	2
ΔGEGR	First Difference	Constant	-8.3529	0.0000	8
ΔGEGR	First Difference	Constant + Trend	-8.3268	0.0000	8
EDI	Level	Constant	-6.7038	0.0000	6
EDI	Level	Constant + Trend	-7.2717	0.0000	6
ΔEDI	First Difference	Constant	-6.6364	0.0000	13
ΔEDI	First Difference	Constant + Trend	-6.6105	0.0000	13
RAGS	Level	Constant	-2.4271	0.1342	0
RAGS	Level	Constant + Trend	-2.5420	0.3073	0
ΔRAGS	First Difference	Constant	-12.2116	0.0000	0
ΔRAGS	First Difference	Constant + Trend	-12.1708	0.0000	0
GDP	Level	Constant	-3.5881	0.0060	3
GDP	Level	Constant + Trend	-3.7316	0.0204	3
ΔGDP	First Difference	Constant	-7.9176	0.0000	5
ΔGDP	First Difference	Constant + Trend	-7.8887	0.0000	5
FDI	Level	Constant	-8.9375	0.0000	0
FDI	Level	Constant + Trend	-9.4512	0.0000	0
ΔFDI	First Difference	Constant	-7.4615	0.0000	7
ΔFDI	First Difference	Constant + Trend	-7.4375	0.0000	7
GS	Level	Constant	-2.2644	0.1837	0
GS	Level	Constant + Trend	-2.2654	0.4532	0
ΔGS	First Difference	Constant	-12.3249	0.0000	0
ΔGS	First Difference	Constant + Trend	-12.2835	0.0000	0
REV	Level	Constant	-1.6540	0.4550	0
REV	Level	Constant + Trend	-1.6064	0.7899	0
ΔREV	First Difference	Constant	-13.5650	0.0000	0
ΔREV	First Difference	Constant + Trend	-13.5438	0.0000	0
EXP	Level	Constant	-2.0273	0.2747	0
EXP	Level	Constant + Trend	-2.0060	0.5982	0
ΔEXP	First Difference	Constant	-9.9177	0.0000	1
ΔEXP	First Difference	Constant + Trend	-9.8889	0.0000	1
PM	Level	Constant	-2.4695	0.1231	0
PM	Level	Constant + Trend	-2.8342	0.1847	0
ΔPM	First Difference	Constant	-12.4347	0.0000	0
ΔPM	First Difference	Constant + Trend	-12.3980	0.0000	0

All variables passed the ADF test in their differenced forms, exhibiting stationarity under both constant and constant-plus-trend models. The p-values were consistently zero, indicating a strong rejection of the unit root hypothesis. Lag selection based on the AIC criterion varied across the variables, reflecting optimal model adequacy.

Figure 1. Correlation Matrix

The correlation matrix of differenced variables reveals several notable relationships. For instance, government expenditure (EXP) and government revenue (REV) exhibit a strong positive correlation (0.68), indicating a close relationship between these fiscal variables. Conversely, the Risk Adjusted Green Score (RAGS) and Particulate Matter Damage (PM) have a strong negative correlation (-0.68), suggesting that higher stability and growth in green energy sources are associated with reduced environmental damage. Additionally, Gross Savings (GS) demonstrates a moderate positive correlation with both GDP growth (GDP, 0.28) and PM (0.42), signifying potential interconnectedness between economic growth, savings rates, and environmental outcomes. Overall, this matrix underscores varying degrees of associations, reflecting complex interactions between economic performance, fiscal indicators, and environmental metrics within the analyzed dataset.

5.2. XGBoost Model Results

Results obtained from the XGBoost regressor feature importance indicate that for most target variables, including GDP Growth, Gross Savings, Revenue as a percentage of GDP, Expense as a percentage of GDP, and Particulate Damage, the RiskAdjustedGreenScore proves to be the most important predictor, with importance scores of 0.75 or over. For Foreign Direct Investment (FDI), that would be GreenEnergyGrowthRate, the first feature and with a score around 0.20. These results underline the importance of the conditions of stability of the renewable energy system with respect to most broad macroeconomic and environmental effects.

Table 5. XGBoost Regressor Feature Importance

Target Variable	Most Influential Feature
GDP	RAGS (≈ 0.76)
FDI	GEGR (≈ 0.20)
GS	RAGS (≈ 0.96)
REV	RAGS (≈ 1.00)
EXP	RAGS (≈ 0.99)
PM	RAGS (≈ 0.99)

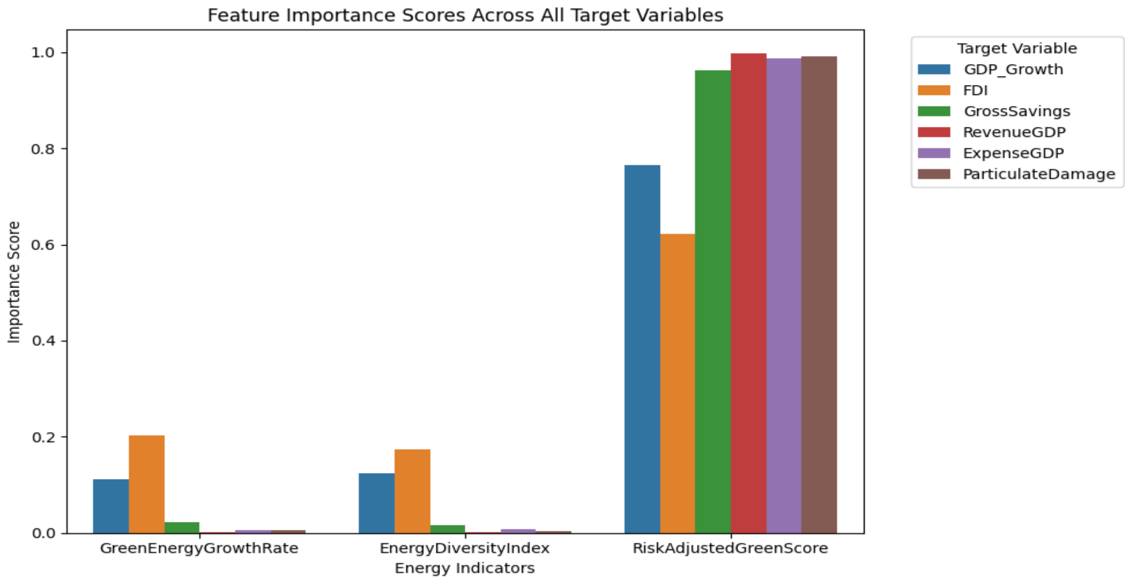

Figure 2. XGBoost Regressor Feature Importance Scores

Figure 2 shows the relative priority of three indicators for renewable energy across six goals. The RiskAdjustedGreenScore stands out by a large margin as the most important feature for GDP Growth, Gross Savings, Revenue as a percentage of GDP, Expense as a percentage of GDP, and Particulate Damage. On the other hand, Green Energy Growth Rate and Energy Diversity Index have very low importance ratings, though the former moderately influences FDI. These findings further validate that in molding financial and environmental results; stable adjusted renewable energy growth plays a very important part.

Table 6. XGBoost Regressor Performance Metrics

Target Variable	R^2	RMSE	MAE	MAPE (%)
GDP	0.1166	3.1091	1.9380	5.01
FDI	0.1206	2.5548	1.5771	3.13
GS	0.8902	0.0930	0.0685	2.30
REV	0.9107	0.1281	0.0844	2.80
EXP	0.9289	0.1070	0.0678	2.07
PM	0.9870	0.1425	0.1040	5.30

The performance metrics of the XGBoost regressor describe varying levels of explanatory power across the target variables. The model explains a substantial proportion of variance for grosssav, rev, gdp, exp, and partic with R^2 values greater than 0.89. Correspondingly, these variables show low error metrics (RMSE, MAE, and MAPE), hence relatively accurate predictions. However, r-squared values for the gdpgrowth and fdi are much lower at around 0.12, indicating that the model fit is quite low for these targets. This stark discrepancy may embody the true essence of the word "difficult" that has been ascribed to the term "complex" in describing the nature of the variables gdpGrowth and fdi, laden with all forms of external influences.

5.3. SHAP Analysis Results

SHAP analysis is one of the powerful techniques that can make machine learning model predictions interpretable by quantifying the contribution of each feature to individual predictions. In this study, we applied SHAP to understand the prediction decisions for XGBoost models across multiple target variables like GDP Growth, Foreign Direct Investment, and others. Our main focus was to check the relative contributions of the three key indicators for renewable energy—Green Energy Growth Rate, Energy Diversity Index, and Risk-Adjusted Green Score—to each target variable. The main research question that guided this analysis was: "What is the macroeconomic and environmental outcome of the most important component in renewable energy?" Having computed the average SHAP values as the mean impact of each energy indicator on each target variable, we then went further to establish for each target variable the most influential energy indicator and its corresponding average SHAP score. This provides a transparent, quantitative look into the varying roles different dimensions of renewable energy holdings play in economic and environmental dynamics.

Table 7 – Average SHAP Values

Target	GEGR	ΔEDI	ΔRAGS
EXP	0.0052	0.0073	0.0152
FDI	0.1622	0.1549	0.0428
GDP	0.2594	0.1832	0.0748
GS	0.0068	0.0085	0.1212
PM	0.0112	0.0125	0.6111
REV	0.0041	0.0037	0.0517

Average SHAP values tell us that the RiskAdjustedGreenScore influences ExpenseGDP, Gross Savings, and Particulate Damage— most particularly on environmental damage. The other elements have more visible effects on GDP Growth and FDI. Therefore, the results obtained above confirm that there are diverse effects of the indicators of renewable energy for the macroeconomic and environmental objectives.

Table 8 – Most Influential Energy Indicator

Target	Most Influential Energy Feature	Mean SHAP Score
EXP	ΔRAGS	0.0152
FDI	GEGR	0.1622
GDP	GEGR	0.2594
GS	ΔRAGS	0.1212
PM	ΔRAGS	0.6111
REV	ΔRAGS	0.0517

It shows the most influential renewable energy indicator for each target variable based on the highest mean SHAP scores. Mostly driving the variation in ExpenseGDP, Gross Savings, Particulate Damage, and RevenueGDP is the RiskAdjustedGreenScore, indicating its critical role in both economic and environmental contexts. On the other hand, GreenEnergyGrowthRate is the leading factor for FDI and GDP Growth, thus indicating its importance in economic expansion. The above findings further distinctify the dimensions of renewable energy with their different levels of macroeconomic and environmental results.

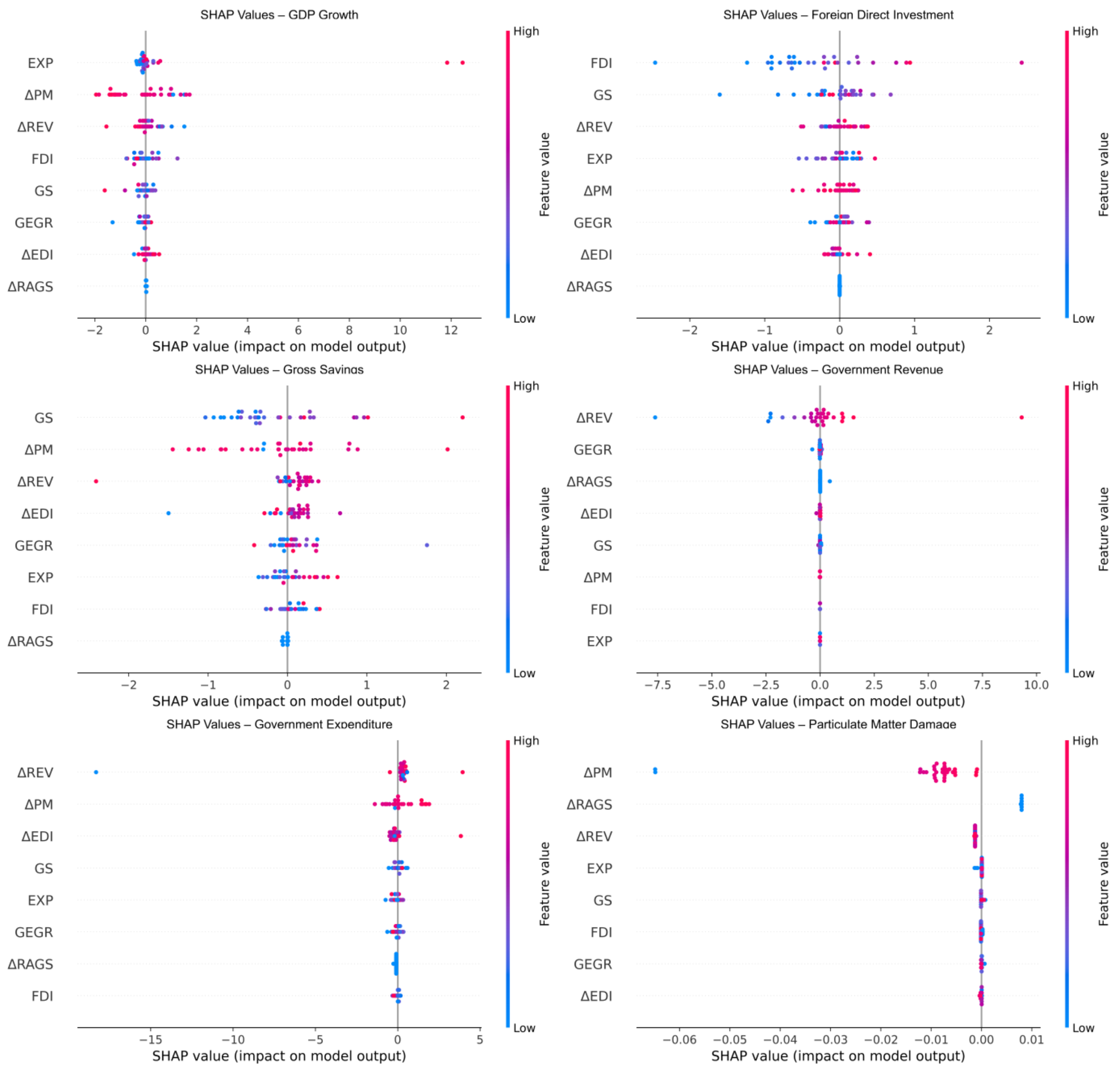

Figure 3. SHAP Values Showing Feature Contributions Across Target Variables

The SHAP value plots show the varied and particular impacts of the indicators of renewable energy on selected macroeconomic and environmental outcomes. The Risk-Adjusted Green Score proves pretty strong against the different dimensions, particularly in explaining variation in particulate damage and expenditure as a percentage of GDP. Such strong effects are not shown in Green Energy Growth Rate and Energy Diversity Index, which support their roles in economic dynamics. Higher values for these indices mostly show better performances in economic dimensions and have a somewhat linear relationship with the environmental dimensions. These results draw attention to the different roles and relative importance of the dimensions of growth, diversity, and stability of the renewable energy system in the diverse paths of development of the country.

5.4. Clustering Analysis of Country-Level Responses to Renewable Energy Indicators

The aim of the study is to model macroeconomic and environmental responses based on three key indicators of renewable energy: growth rate, diversity, and stability of its production. It is herewith assumed that SHAP values have enabled us to quantitatively capture how these features of energy are manifested. The profiles of response, which are 18 dimensional (that is, three indicators by six target variables) are clustered by the KMeans algorithm. This clustering will then make it possible to take a more aggregate as well as between-country contrast, enabling more nuanced policy findings.

Table 9. Description of K-Means Clusters

Cluster	Countries	Count	Description
0	USA, IND, DEU, FRA, BRA, CAN	6	Broad and balanced profile. SHAP effects are moderate across most axes. Exhibits mid-level sensitivity to energy in investment and environmental dimensions. Indicates systemic stability.
1	AUS	1	Distinct country profile. Shows high sensitivity to energy in the growth (GDP) dimension. Moderate responses in investment and environmental indicators. Positioned uniquely.
2	GBR	1	Country with the highest SHAP impacts. Exhibits strong responsiveness to energy variables, particularly in investment (FDI) and environmental domains. Reflects a highly proactive renewable energy policy.

Table 10. K-Means Clustering Analysis by Country

Country	GDP_GEGR	GDP_ΔEDI	FDI_GEGR	FDI_ΔEDI	PM_GEGR	PM_ΔEDI	Cluster
USA	0.8519	0.7040	0.2605	0.2748	0.0626	0.1810	0
IND	0.8498	0.6140	0.2937	0.3980	0.1077	0.0611	0
DEU	1.0656	0.6519	0.4293	0.4193	0.0340	0.1138	0
GBR	0.6390	0.5296	2.1749	1.0519	0.1215	0.0730	2
FRA	0.9335	0.6091	0.5469	0.4137	0.0826	0.0755	0
BRA	1.7164	1.8932	0.2914	0.1467	0.0267	0.0471	0
CAN	0.4890	1.1320	0.5785	0.8768	0.0971	0.0625	0
AUS	0.4828	0.3046	1.0786	0.5369	0.0519	0.0627	1

The analysis of K-Means clustering reveals different structural responses among countries. The groupings are based on the indicators of renewable energy. Evidently, these prove something about the countries. The first cluster, Cluster 0, among which are the largest economies— the USA, India, Germany, France, Brazil, and Canada— presents very little effect from RiskAdjustedGreenScore, as indicated by SHAP values near zero. Rather, the related GreenEnergyGrowthRate and EnergyDiversityIndex show stronger effects on nearly all the economic variables for FDI and GDP growth. Indeed, the effects that have hitherto been wrought by these energy indicators on the environmental variable ParticulateDamage are relatively low within this cluster. It seems to highlight short-term economic outcomes in the consideration of energy policies. The second cluster, Cluster 1, whose membership is of Australia alone demonstrates moderate impacts of energy in FDI, GDP growth, and ParticulateDamage, wherein the SHAP score for GreenEnergyGrowthRate with respect to FDI is marked at approximately 1.07. This cluster may represent a balanced approach where investment activities are such that the environment is considered an issue that needs to be optimized jointly. The UK, in Cluster 2, is distinguished by the highest SHAP impact on FDI through Green EnergyGrowth Rate (about 2.17) concomitant with a very strong effect on GDP Growth. A more than positive relationship between the increment in production of green energy and that of FDI is observed in the case of the UK, underlining the prominence of the UK in channeling the green energy upswing for economic advancement. These clusters demonstrate the heterogeneity at which the countries' economies and environments respond to the dynamics of renewable energy and argue for the need for customized policy frameworks directed at specific country energy-economy-environmental interactions.

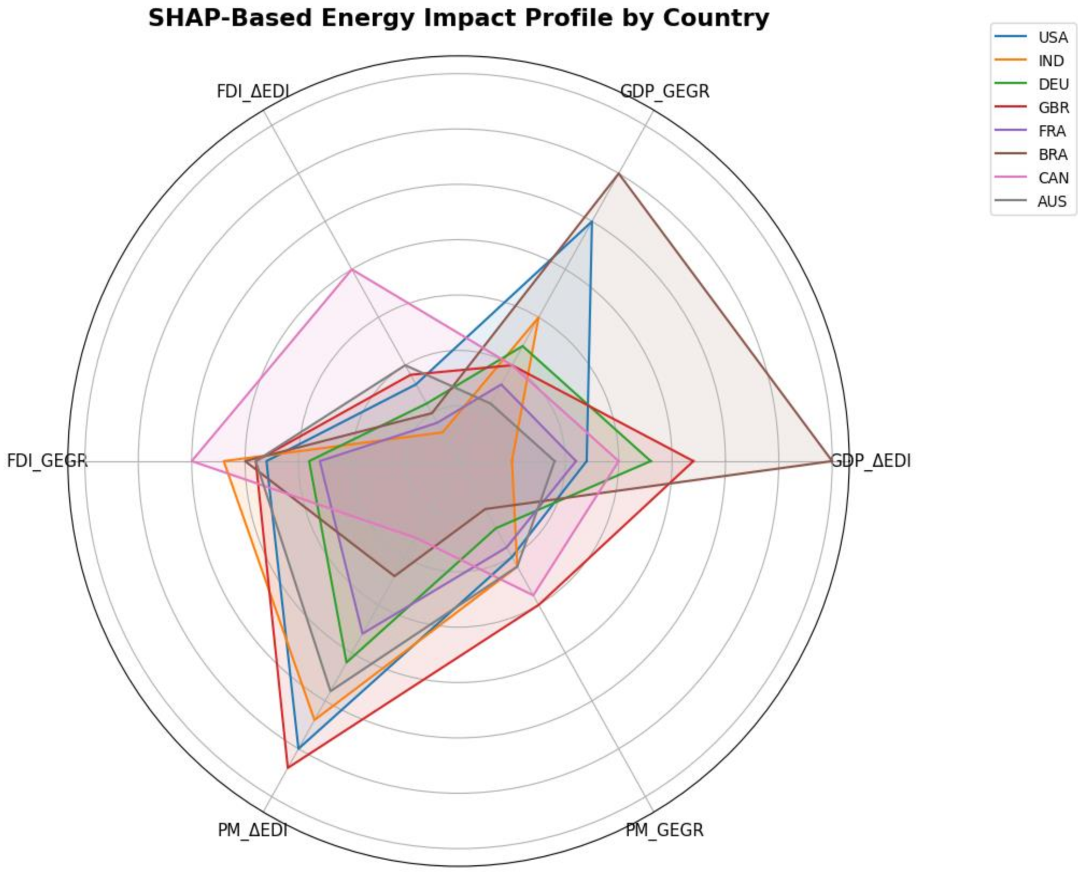

Figure 4. SHAP-Based Energy Impact Profile by Country

5. CONCLUSION

This study aimed to deepen the understanding of how renewable energy systems influence national macroeconomic and environmental outcomes by moving beyond traditional capacity-based evaluations. Focusing on seven countries—Australia, Brazil, Canada, Germany, France, the United Kingdom, and the United States—over the 2000–2023 period, the research sought to capture not only the scale but also the structural qualities of renewable energy production. To this end, the analysis began with raw production data disaggregated by renewable sources such as solar, wind, hydroelectric, and other renewables. From these foundational data, three composite indicators were constructed: the Green Energy Growth Rate (GEGR), reflecting the annual percentage increase in total renewable energy output; the Energy Diversity Index (EDI), based on Shannon entropy, quantifying the balance and variety in energy portfolios; and the Risk-Adjusted Green Score (RAGS), measuring the stability of growth by normalizing expansion rates against their volatility. These indicators collectively enable a multifaceted evaluation of renewable energy systems, incorporating both quantitative and qualitative dimensions critical for sustainability assessments. Following the development of renewable energy indicators, the study rigorously tested the stationarity of all variables using the Augmented Dickey-Fuller (ADF) test under both constant and trend specifications. The stationarity of differenced series at a 5% significance level ensured the appropriateness of subsequent time series and machine learning analyses. Correlation matrices and heatmaps unveiled mostly non-linear and intricate interactions between renewable energy indicators and macroeconomic-environmental factors, thus motivating a preference for non-linear models. We based our modeling work on the XGBoost Regressor, the gradient boosting variant reputed for its application in solving problems with high non-linearities. The model was trained using a grid over all possible combinations of parameters and further fine-tuned using cross-validation to account for all problem intricacies. In several instances, the modeling work delivered very high R^2 values for major targets like fiscal metrics and particulate damage greater than 90%, hence proving how well the machine can catch the involved trends within the energy-economy-environment relationship. To remedy the ''black-box'' concern often associated with machine learning, the current study applied SHapley Additive exPlanations (SHAP). This enabled us to quantitatively measure the contribution of each indicator of renewable energy to the predicted results, thus ensuring a transparent view of their relative importance and directions. This bridges the gap between explanatory clarity and policy conclusions, though most of the previous studies on the impact of renewable energy were based on capacity only. Structural and qualitative aspects have not received enough consideration in research. Measures of diversity and instability are equally salient. Much conventional empirical modeling is wanting in the face of such dynamic, non-linear processes that could directly inform policy in an intelligible manner. To address this issue, the present study incorporates composite quality indicators (GEGR, EDI, RAGS) with state-of-the-art explainable artificial intelligence (XGBoost with SHAP) and unsupervised clustering algorithms (KMeans) into a single analytical framework that not only models the nuanced energy-economy-environment interaction but also facilitates country classification due to structural response profiles. This, in turn, facilitates more context-sensitive analysis and policy prescription. Findings indicate that a country's structural response profile is an important determinant of the effectiveness of a policy prescription. The RAGS (Risk-Adjusted Green Score) came out to be decisive in lowering particle pollution and improving fiscal health, showing that sustainability is more about resilient and balanced growth than capacity expansion. This is in line with the new sustainability direction that calls for integrated actions reconciling economic development, environmental care, and social equality. Further, the diversity among the clusters of countries shows that energy policies cannot be uniform. For instance, countries like the UK, showing strong sensitiveness in terms of energy expansion toward renewable sources as well as investment and environmental targets, need a different strategic focus compared to Australia or the USA. Thus, making interventions at the policymaking level to correspond with structural national features will help use energy diversity as well as stability metrics for the dual betterment of economic as well as ecological returns. In summary, the methodological innovations and empirical insights of this study argue for a paradigm shift in renewable energy policy and investment from an emphasis on "more renewable energy" to greater consideration of "better, diversified, and stable renewable energy." The latter is necessary for achieving the Sustainable Development Goals and transforming the world's post-Covid-19 recovery into a precept of a fair and resilient energy future. This research adds to existing literature by providing a solid, fact-based analytical framework that not only offers cross-cutting, foresight strategic opportunities for optimization at the structural level but also goes toward capturing the multi-faceted nature of renewable energy systems and some of its differential impacts across countries to better inform more adaptive and equitable policy development. This calls for a consideration in future research, thus: how to go about it, plus the added dimensions of the technological innovation diffusion, social acceptance metrics, and geopolitical factors. Longitudinal analyses monitoring real-time effects of policy interventions should add one more step toward understanding and responding to the issues. Ultimately, though, the real need for getting used to complex interpretative energy system analyses will be important in dealing with the unprecedented dilemmas and, indeed, opportunities of the global energy transition.

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