“Socioeconomic drivers and environmental pressure on renewable energy in Azerbaijan: Machine learning evidence”

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ARTICLE INFO	Anar Eminov, Ramil Hasanov, Jeyhun Mahmudov, Abbas Musayev and Mekhdi Bagirov (2026). Socioeconomic drivers and environmental pressure on renewable energy in Azerbaijan: Machine learning evidence. *Environmental Economics*, *17*(3), 154–167. doi:10.21511/ee.17(3).2026.10
DOI	http://dx.doi.org/10.21511/ee.17(3).2026.10
RELEASED ON	Friday, 04 September 2026
RECEIVED ON	Friday, 03 April 2026
ACCEPTED ON	Friday, 24 July 2026

JOURNAL	"Environmental Economics"
ISSN PRINT	1998-6041
ISSN ONLINE	1998-605X
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
38	5	3

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

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SOCIOECONOMIC DRIVERS AND ENVIRONMENTAL PRESSURE ON RENEWABLE ENERGY IN AZERBAIJAN: MACHINE LEARNING EVIDENCE

Abstract

This study explores potential factors associated with renewable energy consumption in Azerbaijan by examining the relationships among economic growth, human development, per capita CO_2 emissions, and urban population growth. The analysis applies an exploratory machine learning framework based on the XGBoost algorithm combined with SHapley Additive exPlanations (SHAP) to examine possible nonlinear associations and evaluate the relative contribution of selected socioeconomic and environmental variables. Correlation analysis indicates a negative relationship between renewable energy consumption and CO_2 emissions (–0.55), while human development and economic growth exhibit generally positive associations with renewable energy use, suggesting a possible role of socioeconomic development in the energy transition process. The exploratory model produced performance indicators of R^2 = 0.81, RMSE = 1.18, and MAE = 1.04, suggesting that the model captures variation within the available sample; however, given the limited dataset, these results should not be interpreted as evidence of strong or robust predictive performance. SHAP-based interpretation suggests that human development and environmental pressure may represent relatively important variables within the model framework, while the effects of economic growth and urbanization appear comparatively moderate and context-dependent. Overall, the study provides preliminary exploratory evidence regarding possible nonlinear patterns linking socioeconomic development, environmental conditions, and renewable energy consumption in Azerbaijan, offering directions for future research using larger datasets and complementary empirical approaches.

Type of the article: Research Article

Received on: 3rd of April, 2026
Accepted on: 24th of July, 2026
Published on: 4th of September, 2026

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Keywords environmental economics, sustainability, renewable energy, human capital, CO_2, machine learning, Azerbaijan

JEL Classification Q01, Q42, O15

INTRODUCTION

The transition to sustainable energy systems has become a central concern in both developed and developing economies, particularly amid rising environmental pressures and climate change. Economic growth, human capital, and renewable energy consumption constitute interconnected determinants in mitigating carbon emissions. Human capital, through enhanced education and skill development, promotes the adoption of renewable energy and improves energy efficiency, thereby reducing dependence on fossil fuels. Economic growth, despite its potential to increase emissions, simultaneously generates demand for cleaner technologies and facilitates the transition toward sustainable low-carbon development (Shabani, 2024; Pegkas, 2024). Therefore, understanding the dynamic interactions among these variables is essential for designing effective energy and environmental policies.

Conflict of interest statement:
Author(s) reported no conflict of interest

http://dx.doi.org/10.21511/ee.17(3).2026.10

Azerbaijan, as a resource-rich economy with a historical dependence on fossil fuels, is increasingly prioritizing the diversification of its energy mix through the expansion of renewable energy sources. However, renewables still contribute modestly: in 2022, they accounted for only 1.5% of total energy supply and 6% (1.8 TWh) of electricity generation (IEA, 2023). Despite this limited share, the country possesses substantial renewable energy potential. The technical potential of onshore renewable energy resources is estimated at 135 GW, while offshore potential reaches 157 GW. Furthermore, the economically viable renewable energy capacity is assessed at approximately 27 GW, including 3,000 MW of wind energy, 23,000 MW of solar energy, 380 MW of bioenergy, and 520 MW from mountain rivers (MERA, n.d.). These figures highlight significant opportunities for accelerating the transition toward a cleaner energy system.

From a macroeconomic perspective, Azerbaijan has experienced notable, albeit fluctuating, economic growth over recent decades. The real gross domestic product (GDP) growth rate reached 4.07% in 2024, with an overall increase of 27.17 percentage points observed between 1993 and 2024. However, this growth followed an uneven trajectory rather than a steady upward trend (SRD, 2026). At the same time, improvements in human capital have been evident, as reflected in the Human Development Index, which has remained above 0.70 over the past two decades, indicating sustained progress in health, education, and living standards (Knoema, n.d.; CE, n.d.). These developments suggest that both economic expansion and human capital accumulation may play a critical role in shaping energy consumption patterns and the adoption of renewable energy technologies.

Environmental considerations further reinforce the importance of this transition. Carbon dioxide emissions per capita in Azerbaijan stood at 3.61 tons, reflecting a slight decrease from 3.63 tons per person recorded in 2021 (Worldometer, 2024). Although this marginal decline may signal initial progress, continued economic and demographic changes, including urbanization, are likely to exert additional pressure on energy demand and environmental sustainability. In this regard, the urban population reached 5,798,042 in 2022, representing a 0.73% increase compared to the previous year (Macrotrends, n.d.), which may intensify energy consumption and emissions if not accompanied by sustainable energy policies.

Given these dynamics, examining the influence of economic growth, human capital, and carbon emissions on renewable energy consumption in Azerbaijan is both timely and relevant. This analysis contributes to a deeper understanding of the structural factors driving the energy transition and provides empirical insights for policymakers seeking to promote sustainable development and reduce environmental degradation.

This study addresses the limited empirical evidence on the nonlinear and interactive effects of human development, economic growth, CO_2 emissions, and urbanization on renewable energy consumption in Azerbaijan. To overcome the limitations of traditional linear econometric approaches in capturing such complexities within a small-sample context, the study employs an XGBoost–SHAP framework to provide interpretable insights into variable importance and underlying relationships.

1. LITERATURE REVIEW

The interconnections between economic growth, human capital, renewable energy consumption, and carbon dioxide (CO_2) emissions have attracted considerable attention in empirical research, reflecting the complex and context-dependent dynamics that shape environmental sustainability. Economic growth can simultaneously exacerbate and mitigate emissions, depending on the adoption of cleaner technologies, the efficiency of human capital, and the broader institutional and economic context. Human capital, through education, skills, and innovation, is increasingly recognized as a key driver in moderating the environmental impacts of economic expansion, enabling the

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effective utilization of renewable energy and the adoption of low-carbon technologies. Renewable energy consumption constitutes a critical mechanism for reducing CO_2 emissions, although its impact often depends on complementary investments in human capital, governance, and technological innovation.

Empirical evidence highlights the nuanced interactions among these variables across countries and regions. Mahmood et al. (2019) examined the interaction effects of economic growth and renewable energy consumption on CO_2 emissions in Pakistan, incorporating human capital through three-stage least squares and ridge regression. Their findings revealed that while the interaction between income and renewable energy consumption contributed to increased emissions, and trade openness further amplified CO_2 emissions, human capital exerted a mitigating influence, and economic growth moderated the relationship, supporting the Environmental Kuznets Curve (EKC) hypothesis. Building on the conditional role of human capital, Khan (2020) demonstrated that at low levels of human capital, increased education intensified reliance on non-renewable energy and raised emissions. In contrast, beyond a critical threshold, higher education reduced CO_2 emissions by fostering environmental awareness and promoting cleaner technologies, emphasizing the contingent nature of the income–environment relationship.

Recent studies indicate that renewable energy consumption generally reduces CO_2 emissions while supporting sustainable economic expansion, particularly when economic growth is accompanied by efficient human capital investment (Bhuiyan et al., 2022; Egbe et al., 2024). Similarly, Gnangoin et al. (2022) examined 20 emerging market economies. They found that human capital played a dual role in influencing CO_2 emissions: directly contributing to emissions in some contexts while interacting with renewable energy to mitigate environmental degradation, with an overall inverted U-shaped effect. In contrast, Rahman et al. (2021) reported that economic growth and human capital improved environmental quality for newly industrialized countries, whereas energy consumption and exports intensified CO_2 emissions. Moreover, no empirical support for the EKC hypothesis was observed, underscoring regional and contextual heterogeneity.

Global analyses reinforce the importance of the interaction between human capital and renewable energy. Maftoon et al. (2025) analyzed 126 countries from 2001 to 2022. They found that although renewable energy consumption and human capital individually increased CO_2 emissions, their interaction significantly reduced emissions, highlighting the moderating role of human capital and supporting integrated policy approaches that combine green energy expansion with human capital development. Regionally, Yang et al. (2025) found that in Mercosur countries, economic development, green innovation, human capital, urbanization, and government effectiveness had marginal or negative short-term effects on renewable energy consumption but significant long-term impacts, with a strong error-correction mechanism ensuring convergence to a stable long-run relationship. Similarly, Amin et al. (2025) documented that renewable energy, human capital, and green growth contributed to reducing CO_2 emissions for the United States, whereas technological innovation and economic growth increased them, emphasizing the need for long-term, integrated strategies to achieve a low-carbon economy.

Collectively, these studies show that human capital functions both as a direct determinant of environmental outcomes and as a moderator that enhances the effectiveness of renewable energy in reducing emissions, while economic growth and technological innovation produce context-dependent effects that may either exacerbate or mitigate CO_2 emissions. Nonlinearities, threshold effects, and interaction terms are increasingly recognized as critical in understanding these relationships. This evidence underscores the need to design policies that simultaneously strengthen human capital, promote renewable energy adoption, and foster green innovation to achieve sustainable development and climate mitigation objectives (Mentel et al., 2022; Alvarado et al., 2022; Radulescu et al., 2025).

Recent studies have emphasized that the transition toward renewable energy was shaped by a complex combination of socioeconomic in-

http://dx.doi.org/10.21511/ee.17(3).2026.10

equality, environmental pressure, and institutional quality. Mehmood et al. (2022) found that income inequality played an important role in renewable energy consumption, showing that more equal income distribution increased renewable energy use, while higher CO_2 emissions were associated with greater adoption due to environmental pressure. Similarly, Eyuboglu and Uzar (2025) showed that income inequality negatively affected renewable energy consumption in Italy, whereas economic growth supported adoption, suggesting that development processes can both facilitate and hinder the energy transition depending on structural conditions. At the firm level, evidence from emerging economies indicated that environmental orientation, institutional support, and access to finance were more influential in driving renewable energy adoption than direct cost considerations (Abir et al., 2026). Institutional quality and policy stability were also consistently identified as key enabling factors that encouraged investment in renewable energy technologies. Pandey et al. (2025) further highlighted that renewable energy adoption is determined by an integrated set of economic, technological, policy, and sociocultural factors, while barriers such as financial constraints, infrastructure limitations, and policy uncertainty slow down its diffusion.

The literature generally indicates that renewable energy consumption is shaped by a complex interplay of socioeconomic, environmental, and structural factors rather than being driven solely by economic growth or environmental degradation. However, relatively few studies simultaneously examine economic growth, human capital, and carbon emissions within a unified analytical framework, particularly in developing country contexts such as Azerbaijan. This limitation is further reflected in the scarce application of machine learning approaches, where evidence on nonlinear relationships and predictive modeling of renewable energy determinants in Azerbaijan remains limited. Therefore, the present study addresses this gap by investigating the effects of economic growth, human capital, and carbon emissions on renewable energy consumption in Azerbaijan using an advanced machine learning framework. Accordingly, this study aims to investigate the relative and potentially nonlinear contributions of economic growth, human development, CO_2 emissions, and urbanization to renewable energy consumption in Azerbaijan using an interpretable XGBoost–SHAP framework.

2. METHOD

The empirical analysis investigates the influence of economic growth, human capital, carbon emissions, and urbanization on renewable energy consumption (REC) in Azerbaijan. The key variables included in the analysis are defined as follows.

REC (Renewable Energy Consumption) is measured as the proportion of renewable energy in total energy consumption, capturing the adoption of sustainable energy sources in Azerbaijan. Data are sourced from the World Bank (2026) and SSCRA (2026). ECG (Economic Growth) is represented by the annual percentage growth of real GDP, reflecting overall economic activity and its potential influence on energy demand. HDI (Human Development Index) is a composite indicator of health, education, and standard of living, serving as a proxy for human capital, which affects the population's capacity to adopt renewable energy technologies (UNDP, 2022). CO_2 (Per Capita Carbon Emissions) is measured in metric tons per person, representing environmental pressures associated with energy use and industrial activity (Worldometers, 2026). UPG (Urban Population Growth) is annual percentage change in urban population, reflecting urbanization trends that influence energy consumption patterns and infrastructure development (SSCRA, 2026; UNDP, 2026).

These variables collectively capture the economic, human, and environmental dimensions hypothesized to drive renewable energy consumption in Azerbaijan. The dataset consists of annual time-series observations for Azerbaijan covering the period 2001–2022, providing a total of 22 observations for all selected variables. The variables are collected from internationally recognized databases and capture the economic, human, demographic, and environmental dimensions hypothesized to be associated with renewable energy consumption. Given the relatively limited sample size, the machine learning framework is applied primarily

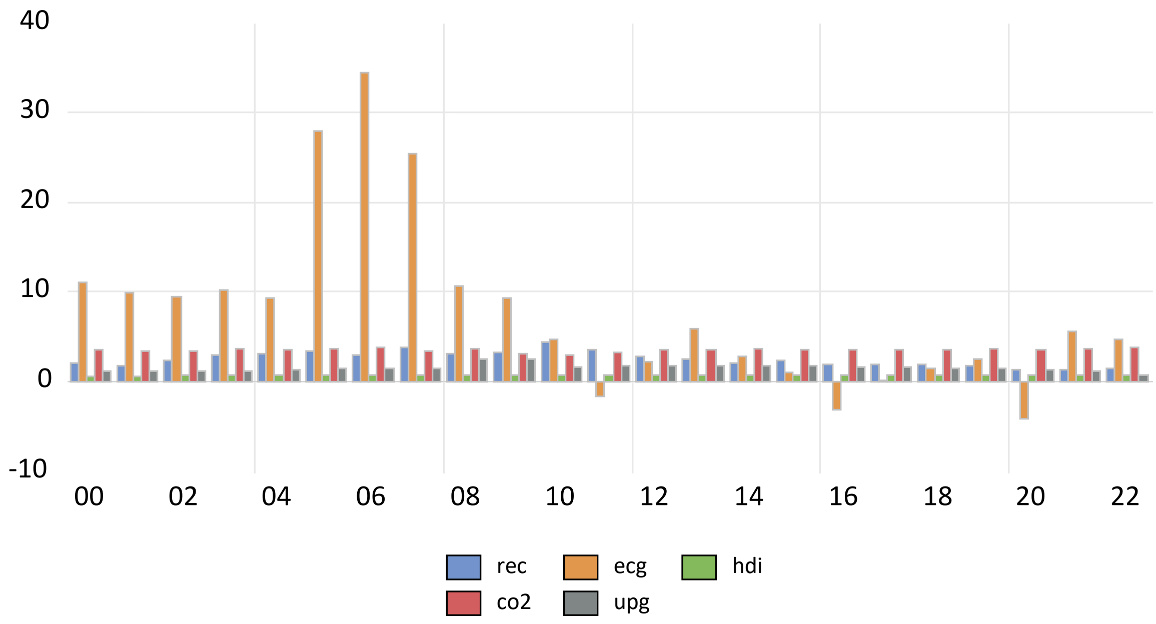

Figure 1. Time-series dynamics of selected indicators

as an exploratory analytical approach intended to identify potential nonlinear associations rather than to establish robust predictive inference.

Figure 1 presents a bar chart depicting the temporal dynamics of five variables over a 22-year period. Among them, economic growth (ECG) exhibits the greatest volatility, with a pronounced peak between 2005 and 2007, followed by intermittent negative deviations. In contrast, renewable energy consumption (REC), Human Development Index (HDI), per capita CO_2 emissions (CO2), and urban population growth (UPG) remain relatively stable, maintaining values near the baseline throughout the period. Overall, the trends suggest that while most indicators demonstrate consistency over time, ECG experienced a distinct expansion phase in the mid-2000s before stabilizing at a lower level.

Table 1 presents the descriptive statistics for the analyzed variables. ECG emerges as the most volatile variable, exhibiting the highest mean (7.83), a substantial standard deviation (9.70), and a wide range from −4.19 to 34.47. Jarque–Bera tests indicate that REC, HDI, CO_2, and UPG are normally distributed ($p > 0.05$), whereas ECG significantly deviates from normality ($p = 0.01$). In contrast, the Human Development Index (HDI) is the most stable variable, characterized by the lowest standard deviation (0.04).

This study employs a machine learning-based approach to investigate the influence of economic growth, human capital, carbon emissions, and urban population growth on renewable energy consumption (REC) in Azerbaijan. Specifically, Extreme Gradient Boosting (XGBoost) is used as

Table 1. Descriptive overview of selected variables

Statistic	REC	ECG	HDI	CO2	UPG
Mean	2.5173	7.8288	0.7179	3.5145	1.5215
Median	2.4	5.61644	0.733	3.5269	1.4796
Maximum	4.4	34.4662	0.762	3.8875	2.4780
Minimum	1.3	−4.1989	0.635	2.9417	0.7310
Std. Dev.	0.8348	9.7026	0.0400	0.2126	0.4002
Skewness	0.3984	1.3848	−0.8233	−0.8975	0.7093
Kurtosis	2.3612	4.3827	2.3064	3.8928	3.8879
Jarque–Bera	0.9995	9.1840	3.0595	3.8522	2.6844
Probability	0.6066	0.0101	0.2165	0.1457	0.2612

http://dx.doi.org/10.21511/ee.17(3).2026.10

the primary predictive model due to its robustness in handling nonlinear relationships, multicollinearity, and complex interactions among variables. To interpret the model outputs and quantify the contribution of each predictor, Shapley Additive Explanations (SHAP) analysis is applied, providing a transparent framework for feature importance and facilitating policy-relevant insights.

XGBoost is an ensemble learning algorithm based on gradient-boosted decision trees, which iteratively fits regression trees to the residuals of previous models to minimize a specified loss function. The objective function in XGBoost combines a loss term L that measures the predictive accuracy and a regularization term Ω that penalizes model complexity to prevent overfitting:

$$Obj(\theta) = \sum_{\{i=1\}}^{\{n\}} L(y_i, \hat{y}_i) + \sum_{\{k=1\}}^{\{K\}} \Omega(f_k), \quad (1)$$

where y_i represents the observed values, $\hat{y}_i$ is the predicted values, f_k is the individual trees, and K *is* the total number of trees in the ensemble (Chen & Guestrin, 2016). The regularization term $\Omega(f)$ is defined as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{\{j=1\}}^{\{T\}} w_j^2, \quad (2)$$

where T denotes the number of leaves in a tree, w_j represents the leaf weights, and γ and λ are regularization parameters controlling model complexity and penalization, respectively.

While XGBoost provides high predictive accuracy, interpreting complex tree ensembles can be challenging. To address this, Shapley Additive Explanations (SHAP) are applied, which decompose model predictions into additive contributions of each feature based on cooperative game theory. For a given instance x, the SHAP value ϕ_i for feature i is calculated as:

$$\varphi_i = \sum_{\{S \subseteq F\ \{i\}\}} \left(|S|!\left(|F|-|S|-1\right)! - |F|! \right) \cdot \left[f_{\{S \cup \{i\}\}}\left(x_{\{S \cup \{i\}\}}\right) - f_{S(x_S)} \right], \quad (3)$$

where F denotes the set of all features, S is a subset of features excluding i, $fS(xS)$ represents the model prediction using only the subset S, and ϕ_i measures the marginal contribution of feature i to the prediction (Lundberg & Lee, 2017). SHAP values allow identification of the most influential determinants of REC and provide an interpretable ranking of economic, human, and environmental factors.

Given the relatively small sample size of 22 annual observations, the machine learning framework is applied as an exploratory nonlinear analytical tool rather than a predictive forecasting model. The objective is not to establish highly generalizable predictive performance, but rather to identify potential nonlinear associations and variable interaction patterns. Consequently, model performance metrics should be interpreted cautiously, as small-sample machine learning applications may produce unstable estimates sensitive to sample partitioning and model specification choices.

3. RESULTS

Figure 2 illustrates the correlation patterns among renewable energy consumption (REC) and key socioeconomic and environmental variables. A strong negative association is observed between REC and CO_2 emissions (–0.55), indicating that higher emission levels are generally linked to lower renewable energy adoption. Economic growth (ECG) shows a moderate positive correlation with REC (+0.45), suggesting that increasing energy demand is partly met through renewable sources. Furthermore, the Human Development Index (HDI) correlates positively with urban population growth (+0.35) but negatively with ECG (–0.47), highlighting the complex interplay between socioeconomic development, urbanization, and energy consumption dynamics.

Table 2 reveals that the model achieves a high level of explanatory power, indicating that most of the variation in renewable energy consumption is effectively captured. Despite the modest prediction deviations, the results suggest that the model successfully identifies the complex, nonlinear relationships between the predictors and renewable energy outcomes.

Table 3 presents feature importance based on the XGBoost gain metric, which measures each pre-

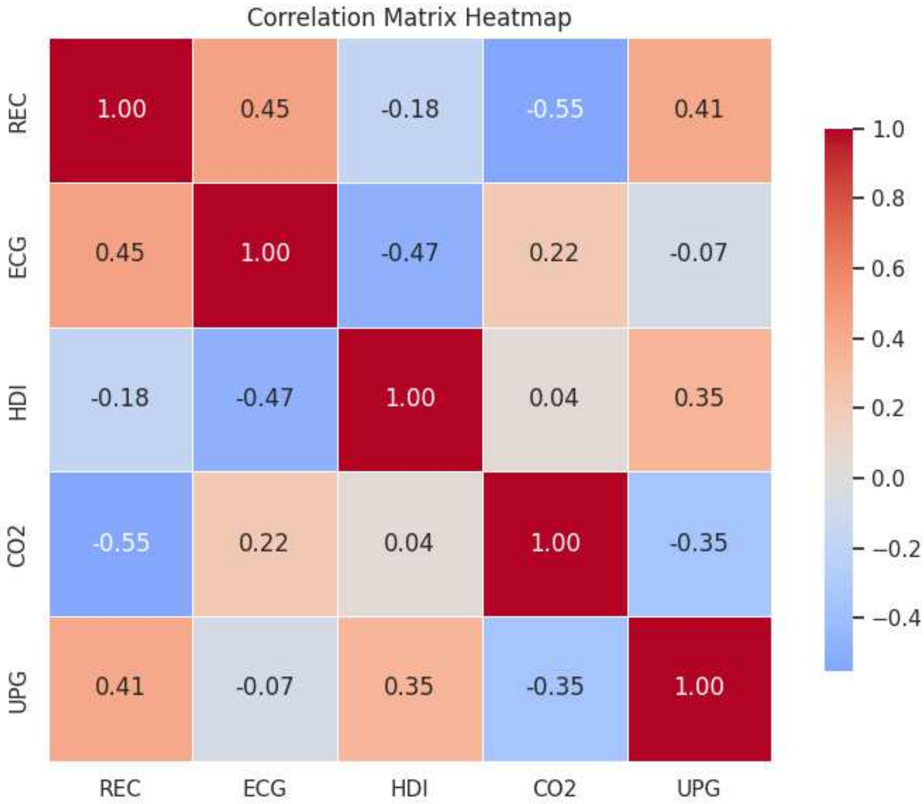

Figure 2. Correlation of renewable energy and socioeconomic variables

Table 2. XGBoost model performance metrics

Metric	Value	Interpretation
R^2	0.81	81% of the variation in renewable energy consumption is explained by the model, indicating strong predictive ability.
RMSE	1.18	Average deviation of predicted values from actual REC is moderate, showing good model fit.
MAE	1.04	Mean absolute error confirms moderate predictive accuracy.
MAPE	0.74	Relative prediction error; high percentage due to small scale of REC values, but absolute errors (RMSE, MAE) are more informative.

Note: The results demonstrate the model's ability to capture complex, nonlinear influences of economic, demographic, and environmental factors on renewable energy consumption.

Table 3. Feature importance (XGBoost gain)

Feature	Importance (Gain)	Interpretation
HDI	0.34	Highest impact; higher human development facilitates renewable energy adoption.
ECG	0.28	Strong influence; economic growth enables investment in renewable energy.
CO2	0.22	Moderate impact; higher emissions can trigger policy-driven renewable energy adoption.
UPG	0.16	Small but positive contribution; urbanization increases energy demand and indirectly promotes renewable energy.

Note: Gain reflects each feature's contribution to error reduction, with HDI and GDP growth showing the strongest influence on renewable energy adoption.

dictor's contribution to reducing model error during the tree-building process. According to this criterion, HDI demonstrates the highest importance score (0.34), indicating that human development contributes most strongly to model optimization. Economic growth (ECG) ranks second (0.28), followed by CO_2 emissions (0.22) and urban population growth (UPG = 0.16). These re-

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sults specifically reflect tree-based optimization importance and should be interpreted independently from alternative explainability frameworks such as SHAP analysis.

Figure 3 illustrates the internal feature importance distribution generated by the XGBoost model based on split contribution patterns during tree construction. Unlike the aggregated gain values reported in Table 3, this visualization reflects the relative contribution of variables through model-specific decision-tree splitting behavior. In this representation, CO_2 emissions appear visually dominant, followed by HDI, while ECG and UPG demonstrate comparatively smaller contributions. Since this measure reflects internal model structure rather than global predictive contribution, the ranking should be interpreted separately from both gain-based importance and SHAP-based feature attribution.

The SHAP summary plot in Figure 4 provides a global interpretability framework by measuring the average marginal contribution of each feature to individual model predictions. Under this approach, HDI demonstrates the highest mean absolute SHAP value (0.306), followed closely by CO_2 emissions (0.282), indicating that these two variables contribute most substantially to prediction variability across observations. Unlike XGBoost gain metrics, SHAP values capture observation-level predictive influence rather than tree-construction importance, and therefore ranking differences across methods are expected.

The variation between XGBoost and SHAP importance rankings is expected because XGBoost measures feature contribution based on tree-splitting optimization during model training, while SHAP quantifies the average marginal effect of each variable on prediction outcomes, thereby capturing different dimensions of variable importance within the same nonlinear model. The three feature importance approaches applied in this study capture different dimensions of predictor relevance. XGBoost gain (Table 3) measures each variable's contribution to reducing prediction error during tree optimization and identifies HDI as the highest-ranked predictor. The XGBoost internal feature importance visualization (Figure 3) reflects split-based contribution patterns, where CO_2 appears visually dominant. In contrast, SHAP analysis (Figure 4) evaluates the average marginal contribution of variables to individual predictions and indicates that HDI (0.306) slightly exceeds CO_2 (0.282). Because these methods quantify different aspects of model behavior, their ranking structures do not necessarily coincide and should be interpreted as complementary rather than contradictory evidence.

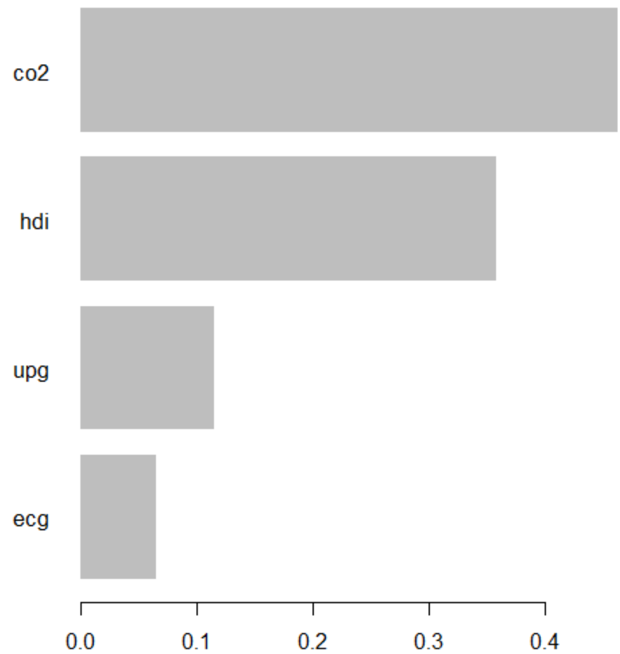

Figure 3. XGBoost feature importance of renewable energy factors

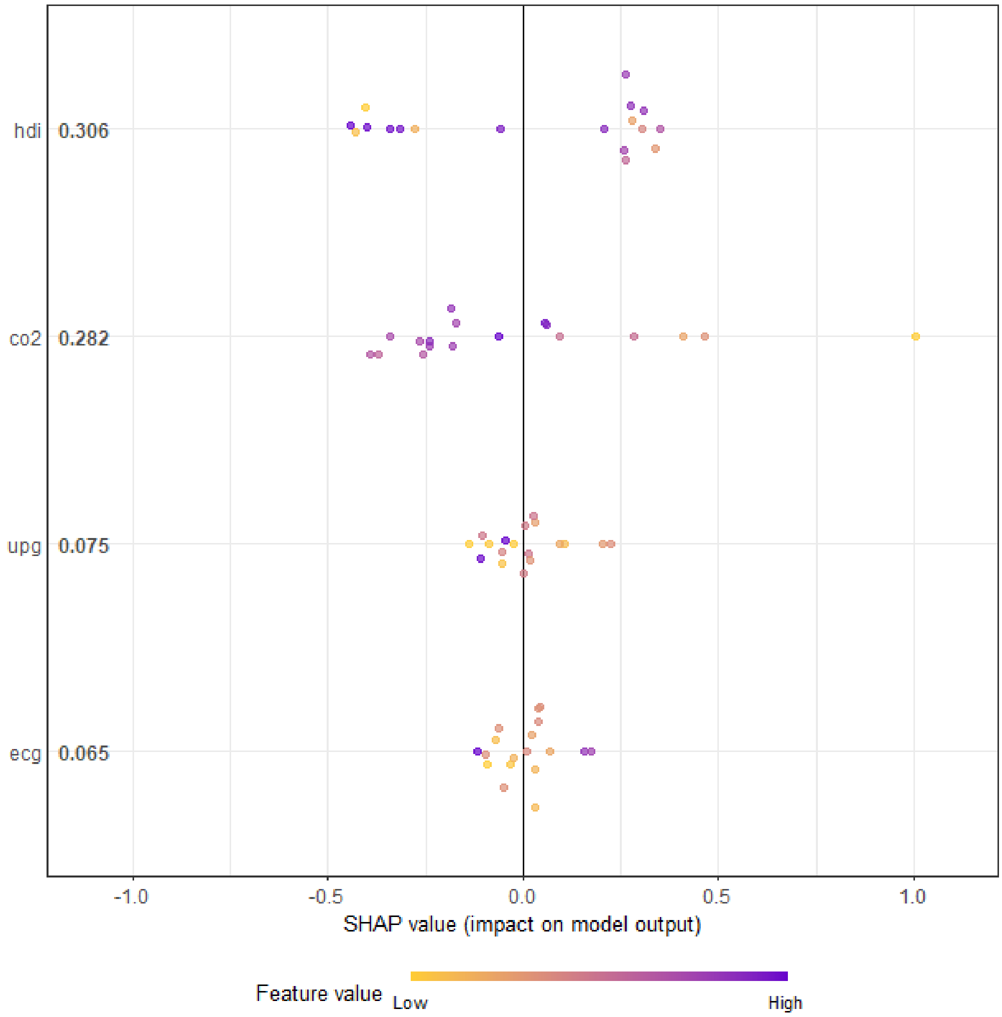

Figure 4. SHAP feature importance of renewable energy predictors

Figure 5 visually depicts the numerical distribution of SHAP values, highlighting the heterogeneous impacts of individual features on renewable energy consumption. Per capita CO_2 exhibits substantial variance of nearly 0.5 units, indicating a strong yet uneven suppressive effect across different national contexts. The Human Development Index (HDI) shows the widest positive range, with SHAP values reaching up to +0.4, reaffirming its consistent role as a structural driver of renewable energy adoption. In contrast, GDP growth displays a narrow clustering around ±0.1, suggesting episodic, context-dependent influences rather than systemic effects. Urban population growth remains concentrated near zero, with deviations below 0.1, underscoring its limited explanatory contribution within the predictive model.

4. DISCUSSION

The machine learning analysis provides preliminary exploratory evidence regarding possible nonlinear associations between renewable energy consumption and the selected socioeconomic and environmental variables in Azerbaijan. Rather than establishing robust predictive relationships, the findings should be interpreted as identifying potential structural patterns that may warrant further investigation using larger datasets and alternative empirical frameworks.

The analysis provides exploratory evidence on the relationships between renewable energy consumption (REC) and its potential determinants in Azerbaijan. The XGBoost and SHAP results suggest that the Human Development Index (HDI) is

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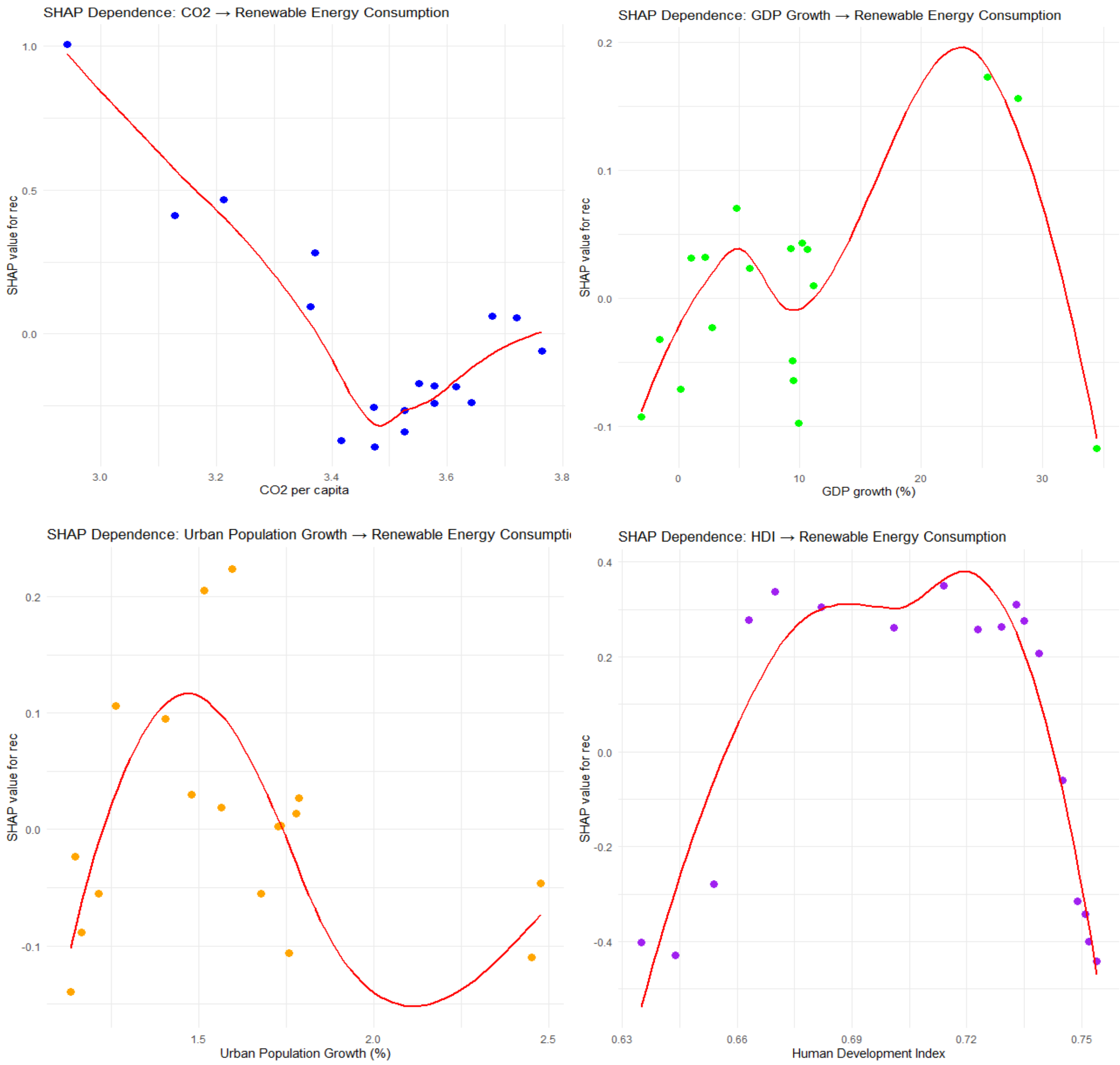

Figure 5. SHAP value distribution of features

the most influential variable in the model, which may indicate that education, institutional capacity, and technological readiness are closely associated with renewable energy consumption. This interpretation is broadly consistent with Hasanov et al. (2024), who reported that improvements in HDI were linked to reductions in CO_2 emissions, implying that human capital development may play an important role in supporting environmental sustainability and broader economic transformation.

Per capita CO_2 emissions also show a meaningful association with renewable energy consumption, suggesting that higher emission levels may be linked with increased attention to renewable energy adoption, potentially reflecting policy responsiveness to environmental pressure. However, this relationship should be interpreted cautiously, as the small sample size limits the ability to draw strong conclusions about directionality or causality. GDP growth exhibits a nonlinear and context-dependent pattern, implying that its relationship with renewable energy consumption may vary across different phases of economic development and structural conditions. Urban population growth shows a relatively weaker but generally positive association with renewable energy consumption, which may reflect changes in energy demand patterns and infrastructure development in more urbanized settings. Nevertheless, all findings should be considered exploratory due to the limited dataset of approximately 22 annual observations, which restricts statistical robustness and generalizability. Accordingly, the machine learning results are used primarily to identify potential patterns and associations rather than to provide definitive evidence of causal relationships or policy effects.

The empirical findings of this study aligned with the growing body of literature suggesting that renewable energy systems had become central elements of low-carbon transitions, where socioeconomic and environmental drivers jointly shaped adoption dynamics. Consistent with Sumon et al. (2024), the results confirmed that machine learning approaches, particularly ensemble-based models such as XGBoost, effectively capture complex nonlinear relationships between renewable energy systems and environmental outcomes, outperforming traditional econometric methods in both predictive accuracy and interpretability. The strong influence of human development observed in this study was also in line with Magazzino et al. (2025), who emphasized that socioeconomic capacity and structural development factors significantly shaped environmental performance and energy transition pathways. Moreover, the positive role of CO_2 emissions in stimulating renewable energy adoption supported the environmental pressure hypothesis, indicating that higher emission levels act as a catalyst for policy responses and clean energy investment. In contrast to studies that highlighted economic growth as a dominant driver, the present findings revealed a nonlinear, context-dependent effect of GDP, suggesting that economic expansion alone did not guarantee renewable energy uptake without complementary human capital and institutional support. Together with Zhao et al. (2024), these results reinforce the view that renewable energy expansion is a multidimensional process driven by the interaction of environmental pressures, socioeconomic development, and structural conditions, and that machine learning methods provide a robust framework for capturing these complex relationships.

Integrating machine learning and AI-based approaches provided additional insights beyond traditional econometric models. Dong et al. (2025) and Khan et al. (2025) demonstrated that interpretable machine learning and artificial intelligence revealed complex, nonlinear, and interactive relationships among economic, demographic, technological, and environmental factors affecting carbon emissions. These approaches highlighted that human capital, renewable energy, and clean energy adoption interacted synergistically to mitigate emissions, while structural variables such as industrial composition, population density, and economic development exhibited threshold-dependent effects. For Azerbaijan, these findings indicated that policies targeting human development, urbanization, and emissions management needed to be designed in an integrated manner, leveraging both economic and technological levers to optimize renewable energy adoption and promote sustainable development.

Overall, the combined evidence from traditional econometric and machine learning analyses highlighted the importance of adopting multidimensional, context-specific strategies, where investments in human development, regulatory frameworks, and technological innovation collectively drove the transition toward a low-carbon, sustainable energy system.

CONCLUSION

The aim of this study was to investigate the relative and potentially nonlinear contributions of human development, economic growth, CO_2 emissions, and urbanization to renewable energy consumption in Azerbaijan using an interpretable XGBoost–SHAP framework. The empirical analysis provides exploratory evidence on the relationships between renewable energy consumption (REC) and key socioeconomic and environmental factors in Azerbaijan. The results suggest that human development (HDI) is consistently associated with higher levels of renewable energy consumption across the machine learning framework, indicating that improvements in education, health, and institutional capacity may be linked to more favorable conditions for renewable energy adoption. However, this relationship should be interpreted as an association rather than a definitive ranking of importance, given differences across model interpretability measures.

http://dx.doi.org/10.21511/ee.17(3).2026.10

CO_2 emissions and GDP growth also appear to play relevant roles in explaining variations in REC, although their effects are less stable across different importance metrics. In particular, CO_2 emissions show a heterogeneous relationship with renewable energy consumption, which may reflect complex interactions within the energy-environment system rather than a simple directional effect. Similarly, GDP growth exhibits a context-dependent pattern, suggesting that its association with renewable energy consumption may vary across different economic conditions. Urban population growth demonstrates a comparatively weaker relationship with renewable energy consumption, indicating that demographic change alone may not be a dominant factor in explaining renewable energy dynamics in the Azerbaijani context. Overall, the results highlight that renewable energy consumption is likely shaped by a combination of human development, economic conditions, and environmental factors. However, the relative importance of these drivers differs across modeling approaches.

The findings are based on a limited dataset of approximately 22 annual observations and should therefore be interpreted as exploratory and hypothesis-generating rather than confirmatory evidence. The use of XGBoost and SHAP provides useful insights into potential nonlinear relationships and variable interactions; however, the results do not establish causal relationships or definitive predictor rankings. Future research with longer time series or panel data is required to validate these patterns and to further investigate the underlying mechanisms linking socioeconomic development, environmental pressure, and renewable energy consumption in Azerbaijan and comparable economies.

AUTHOR CONTRIBUTIONS

Conceptualization: Anar Eminov, Ramil I. Hasanov, Jeyhun Mahmudov.
Data curation: Ramil I. Hasanov.
Formal analysis: Anar Eminov, Ramil I. Hasanov, Jeyhun Mahmudov, Abbas Musayev, Mekhdi Bagirov.
Investigation: Anar Eminov, Ramil I. Hasanov, Jeyhun Mahmudov, Abbas Musayev, Mekhdi Bagirov.
Methodology: Anar Eminov, Ramil I. Hasanov.
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