Business Analytics for Green Electricity Transition Planning: Explainable Forecasting of Renewable Electricity Shares from Cross-Country Energy Indicators

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Abstract

Renewable electricity growth is central to sustainable development, decarbonization, and green-technology planning. However, much of the forecasting literature remains focused on plant-level or narrow-horizon technical prediction, with limited attention to country-level decision support for investment screening, transition monitoring, and strategic benchmarking. This study develops a business analytics framework to forecast the renewable share of electricity generation and classify countries by renewable-transition level using a cross-country panel based on the *Our World in Data* Energy database. The empirical sample comprises 5,162 country-year observations from 213 countries over the period 2000–2025 and includes measures of electricity demand, electricity generation, primary energy use, greenhouse-gas emissions, and energy-system structure. Three regression models and three classification models were evaluated using a fixed train–test de sign. The random-forest regressor achieved the best continuous forecasting performance, with MAE = 3.536, RMSE = 6.466, and $R^2 = 0.960$, while the random-forest classifier delivered the best tier-classification performance, with 93.998% accuracy and macro-F_1 = 0.940. Feature-importance analysis identified greenhouse-gas emissions, energy intensity, electricity generation, electricity demand, and per-capita electricity consumption as the most influential p redictors. The findings indicate that renewable-transition benchmarking can be framed as a managerial analytics problem, extending sustainability research beyond descriptive monitoring toward practical decision support for business and policy planning.

Keywords: Renewable electricity; Green technology; Sustainable development; Business analytics; Machine learning; Energy transition; Explainable forecasting

1. Introduction

The transition toward low-carbon electricity systems has become one of the central pillars of sustainable development and green-technology strategy. Renewable electricity matters not only for environmental policy but also for industrial planning, corporate procurement, infrastructure investment, and the competitive positioning of economies attempting to decarbonize without constraining growth. Recent international analyses continue to show rapid expansion of renewable electricity capacity and strong policy momentum, while at the same time emphasizing that transition pathways remain uneven across countries and require better planning intelligence [8–10]. In practical terms, decision-makers often need answers to questions that are managerial rather than purely technical: which indicators best signal renewable-transition progress, how reliably can countries be grouped into practical transition tiers, and what data-driven tools can support cross-country benchmarking? Much of the forecasting literature has concentrated on narrow technical tasks such as short-term wind, solar, irradiance, or electricity-price prediction [11,16–18]. These contributions are valuable, but they do not fully address the business and policy need for reproducible country-level analytics that support strategic transition planning. For example, investors, sustainability officers, energy-intensive firms, and public-sector planners may wish to screen markets according to renewable-electricity maturity, identify structural predictors of greener electricity systems, and convert high-dimensional energy data into operationally interpretable decision tools. That type

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of decision support aligns closely with sustainability-oriented business intelligence.
To address this gap, this paper proposes an explainable business analytics framework for forecasting the renewable share of electricity generation and classifying countries into renewable-transition tiers using the *Our World in Data* Energy database [13]. The analysis treats renewable-transition measurement as a country-level analytics problem suited to managerial benchmarking and sustainability planning, rather than as a narrowly defined plant-level or weather-driven forecasting task.
The study makes four contributions. First, it introduces a reproducible country-level modeling pipeline built on a contemporary cross-country energy panel. Second, it compares linear, ensemble, and boosting methods for forecasting renewable electricity shares. Third, it converts the continuous transition indicator into actionable low-, medium-, and high-transition tiers. Fourth, it extracts interpretable drivers of renewable-transition performance to support managerial reasoning. This framing makes the paper appropriate for a sustainability and green-technology journal while preserving a clear business orientation.

2. Related Work

2.1. Forecasting in renewable electricity and energy-transition research

Forecasting has long occupied a central place in electricity and renewable-energy research. Early work emphasized price forecasting and load forecasting, while later studies expanded to wind, solar, and integrated smart-grid applications. Reviews by Weron [17], Voyant et al. [16], Mosavi et al. [12], and Hong et al. [7] showed that machine learning and hybrid approaches often outperform purely linear baselines in complex energy settings. More recent reviews and empirical studies have highlighted the growing role of deep learning, explainability, and integrated analytics for renewable-energy planning [4,6,15,19].
However, the literature is still dominated by high-frequency technical forecasting tasks. Many studies focus on short-term wind power, solar irradiance, photovoltaic output, or electricity prices, using weather features or local operational data [15,16,18]. Other studies emphasize critical infrastructure implications of energy-transition dynamics, including sustainability constraints in the digital economy and supply-planning pressure under rapid electricity demand growth [5]. These streams are important but do not directly provide a country-level business-analytics framework that can translate broad energy-system indicators into renewable-transition tiers suitable for strategic benchmarking.

2.2. Business analytics and sustainability-oriented decision support

A second literature stream concerns business analytics in sustainability and transition contexts. The core idea is that environmental datasets should not only support reporting but also managerial decision-making. In energy contexts, this means moving beyond descriptive dashboards to predictive and classification tools that help organizations monitor market conditions, compare jurisdictions, and anticipate structural change. Recent work links big-data analytics with renewable forecasting and carbon reduction in decision settings [2], while broader transition reviews emphasize inclusiveness, policy readiness, and system-level transformation factors [3].
Despite these advances, three limitations remain. First, many studies are either purely technical or purely conceptual, leaving a gap between predictive modeling and actionable transition tiers. Second, reproducibility is often constrained by proprietary or highly localized datasets. Third, interpretability is still underdeveloped in many machine-learning studies, which reduces managerial trust. This paper responds by combining a recent cross-country energy panel with a transparent workflow and an explicit decision-oriented classification layer.

2.3. Summary of representative published studies

Table 1 summarizes representative published studies related to renewable-energy forecasting, energy-transition analytics, and sustainability-oriented decision support. The table highlights both the maturity of the forecasting literature and the relative scarcity of studies that combine current public country-level energy data, interpretable machine learning, and business-facing transition-tiering.

Table 1: Representative published studies related to renewable-energy forecasting and sustainability analytics.

Study	Main focus	Data context	Method emphasis	Key contribution	Limitation relative to the present study
Weron (2014) [17]	Electricity-price forecasting review	Electricity markets	Statistical and ML review	Foundational synthesis of forecasting models and evaluation issues	Focused on prices, not renewable-transition benchmarking
Voyant et al. (2017) [16]	Solar radiation forecasting review	Solar-resource data	ML review	Benchmarked learning methods for solar forecasting	Technical solar focus rather than country-level sustainability analytics
Mosavi et al. (2019) [12]	ML in energy systems	Broad energy systems	Systematic review	Consolidated ML applications across energy domains	Broad review without explicit transition-tier decision layer

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Study	Main focus	Data context	Method emphasis	Key contribution	Limitation relative to the present study
Hong et al. (2020) [7]	Energy forecasting review and outlook	Multiple energy series	Comparative review	Clarified forecasting horizons, metrics, and methodological directions	Not specific to renewable-share forecasting or managerial tiers
Ahmad et al. (2020) [1]	Renewable-energy and electricity requirement forecasting review	Energy planning studies	Systematic review	Connected forecasting to energy-planning decisions	Review article without reproducible panel modeling pipeline
Lago et al. (2021) [11]	Day-ahead electricity-price forecasting	Market data	Benchmarking review	Open-access benchmark and best-practice discussion	Price focus; not sustainability transition measurement
Benti and Chaka (2023) [4]	Renewable-generation forecasting review	Renewable generation studies	ML/DL systematic review	Detailed assessment of ML and DL forecasting approaches	Review format; no country-year business analytics setting
Ying et al. (2023) [19]	Deep learning for renewable-energy forecasting	Bibliometric and literature data	Deep-learning review	Identified strong DL momentum in renewable forecasting	Did not target interpretable cross-country transition analytics
Talwariya et al. (2023) [14]	Renewable generation and forecasting review	Solar and wind studies	ML review	Discussed future research directions in renewable generation forecasting	Focused on generation forecasting at technical level
Chatterjee et al. (2024) [6]	ML applications in variable renewable energy	VRE studies	Systematic review	Compared forecasting and optimization uses of ML in VRE	Review-centered and not country-panel decision support
Castro et al. (2024) [5]	Renewable-energy limits under digital data demand	Global energy sustainability	Forecasting and policy analysis	Linked renewable constraints to digital-economy sustainability	Broader sustainability warning, not classification of transition tiers
Arman et al. (2024) [2]	Big-data analytics for renewable forecasting and carbon reduction	U.S. clean-energy context	Big-data analytics	Positioned analytics as support for carbon reduction	Not based on a multi-country public panel dataset
Awolesi et al. (2024) [3]	Inclusive and sustainable energy transition review	Energy-transition literature	Systematic review	Synthesized drivers of equitable transition pathways	Conceptual rather than predictive
Yang et al. (2024) [18]	Wind-power forecasting survey	Wind forecasting literature	ML survey and knowledge mapping	Structured overview of technical progress in wind forecasting	Narrow wind-power scope
Teixeira et al. (2024) [15]	Comparative forecasting for renewable production	PV and wind datasets	Comparative empirical study	Compared forecasting methods for renewable production	Technology-specific rather than country-level renewable-share modeling

3. Research Gap, Questions, and Contributions

The literature review reveals a gap at the intersection of renewable-energy analytics, sustainability planning, and business intelligence. Existing studies are strong in technical forecasting or conceptual transition analysis, but fewer provide a compact and reproducible framework that uses country-year energy indicators to generate both continuous forecasts and operational transition tiers. That gap matters because organizations increasingly need benchmarking tools that are transparent, portable, and methodologically verifiable.
Accordingly, the study addresses the following research questions:

- **RQ1:** Which country-level energy and macro indicators are the strongest predictors of the renewable share of electricity generation?
- **RQ2:** Which machine-learning model best forecasts the renewable share of electricity across countries?
- **RQ3:** Can countries be classified accurately into low-, medium-, and high-transition renewable-electricity tiers?

The study contributes by combining a contemporary cross-country energy panel, a business-facing target variable, a dual regression–classification design, and interpretable feature analysis. In this sense, the contribution lies not in proposing a new algorithm, but in constructing an operationally useful analytics framework for sustainability benchmarking.

4. Data and Methodology

4.1. Data source and sample construction

The empirical analysis draws on the *Our World in Data* Energy database, a harmonized international panel that consolidates major energy and electricity indicators from sources such as the Energy Institute Statistical Review, the U.S. Energy Information Administration, and Ember's yearly electricity data [13]. Its country-year structure is well suited to cross-country modeling of transition dynamics.
For this study, the dataset was filtered to observations satisfying three conditions: (i) a valid three-letter ISO country code, (ii) year $\geq$ 2000, and (iii) a non-missing value for the target variable *renewables_share_elec*.

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This produced a final modeling sample of 5,162 country-year observations from 213 countries covering the period 2000–2025.

4.2. Target variable and predictors

The target variable is the **renewable share of electricity generation** (percentage), denoted by y_i. This variable captures the extent to which a country's electricity mix is sourced from renewables and serves as a practical transition indicator. A second decision layer transforms the continuous indicator into three balanced classes using empirical tertiles:

$$T_i = \begin{cases} \text{Low}, & y_i \leq q_{0.33} \\ \text{Medium}, & q_{0.33} < y_i \leq q_{0.67} \\ \text{High}, & y_i > q_{0.67} \end{cases}$$

where $q_{0.33}$ and $q_{0.67}$ are the 33rd and 67th empirical percentiles, respectively.
The predictor set combines macro-scale and electricity-system variables reported in the database:

- year
- GDP
- population
- electricity demand
- electricity generation
- primary energy consumption
- greenhouse-gas emissions
- energy use per unit of GDP
- per-capita electricity consumption
- net electricity imports as a share of demand
- country identity

This predictor design was chosen to keep the framework business-oriented and policy-relevant rather than narrowly engineering-specific.

4.3. Modeling pipeline

The workflow consists of two stages. In the first stage, the study forecasts the continuous renewable-electricity share. In the second stage, it classifies country-years into practical transition tiers. Missing numeric values were imputed with medians and standardized before model fitting. Country was one-hot encoded to preserve country-level heterogeneity while keeping the workflow transparent.
Three regression models were evaluated:

1. Linear Regression
2. Random Forest Regressor
3. Gradient Boosting Regressor

Three classification models were also evaluated:

1. Logistic Regression
2. Random Forest Classifier
3. Gradient Boosting Classifier

A reproducible hold-out design was used with 80% of observations for training and 20% for testing (`random_state=42`). Regression performance was assessed using mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination (R^2). Classification performance was assessed using accuracy, macro-precision, macro-recall, and macro-F_1.

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4.4. Explainability

To support managerial interpretability, feature importance was extracted from the best-performing random-forest regression and classification models. The objective was not only to identify the best forecasting model, but also to clarify which structural indicators matter most in renewable-transition benchmarking.

5. Results

5.1. Descriptive patterns

The sample exhibits substantial cross-country heterogeneity. Across the 5,162 country-year observations, the mean renewable share of electricity was 31.20%, with a standard deviation of 32.69 percentage points, a minimum of 0%, and a maximum of 100%. The lower quartile was only 1.77%, while the upper quartile reached 55.29%, confirming strong international dispersion in renewable-electricity maturity. Figure 1 shows that the global average renewable-electricity share in the sample increased over time, although progress remained uneven.

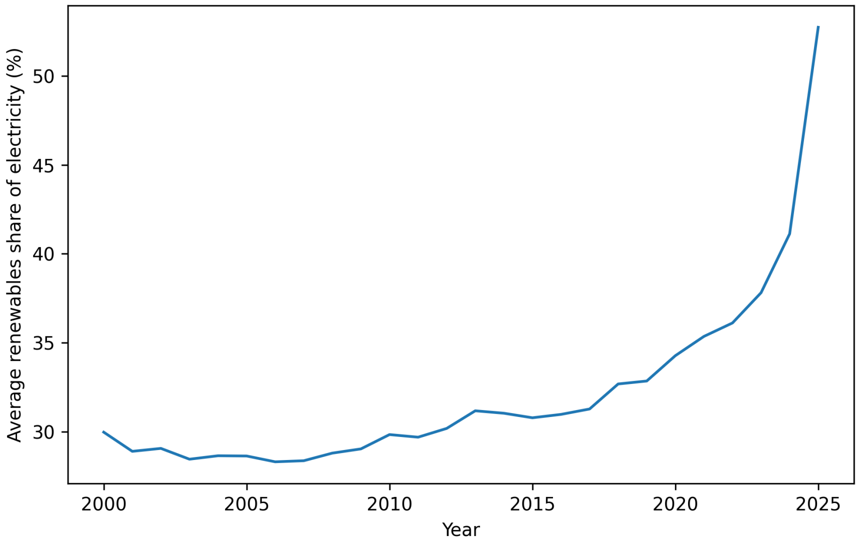

Figure 1: Average renewable share of electricity in the modeling sample, 2000–2025.

5.2. Regression performance

Table 2 reports the regression results. The random-forest regressor produced the best forecasting performance with MAE = 3.536, RMSE = 6.466, and $R^2 = 0.960$. Linear regression ranked second and still performed reasonably well ($R^2 = 0.918$), which suggests that part of the renewable-transition signal is structurally linear. Gradient boosting was clearly weaker in this specific country-level setting.

Table 2: Regression performance for forecasting renewable share of electricity.

Model	MAE	RMSE	R^2
Random Forest	3.536	6.466	0.960
Linear Regression	5.973	9.304	0.918
Gradient Boosting	10.428	12.605	0.850

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Figure 2 confirms the strong predictive agreement between actual and predicted renewable shares in the best model. Most points cluster closely around the 45-degree line, with larger deviations appearing mainly in more extreme transition cases.

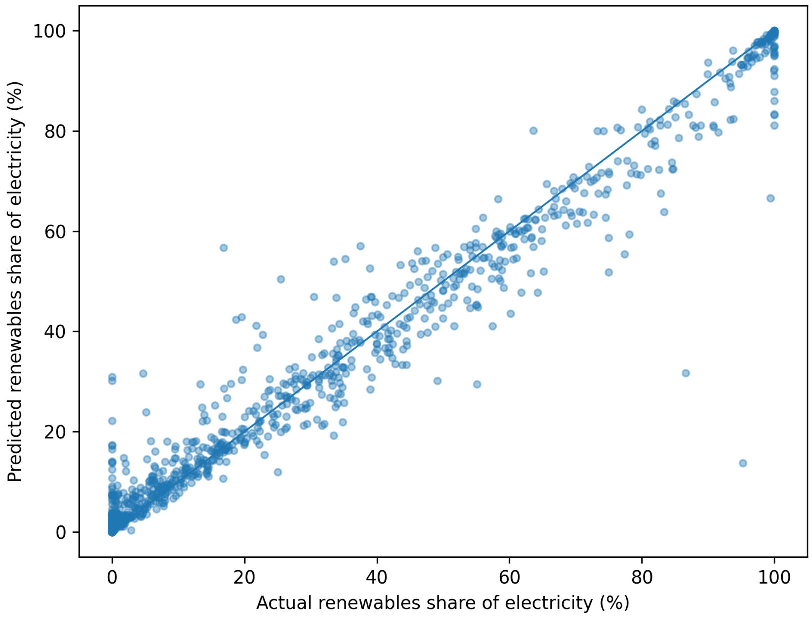

Figure 2: Actual versus predicted renewable share of electricity for the best regression model (Random Forest).

5.3. Classification performance

The classification results in Table 3 show that the random-forest classifier was again the strongest model, achieving 93.998% accuracy with macro-F_1 = 0.940. Logistic regression also performed strongly, while gradient boosting was moderately weaker. These results indicate that country-year observations can be grouped into practically meaningful renewable-transition tiers with high reliability.

Table 3: Classification performance for renewable-transition tiers.

Model	Accuracy	Precision$_{macro}$	Recall$_{macro}$	$F1_{macro}$
Random Forest	0.940	0.940	0.940	0.940
Logistic Regression	0.891	0.890	0.891	0.889
Gradient Boosting	0.882	0.881	0.882	0.881

Figure 3 presents the confusion matrix for the best classifier. Misclassification errors are limited and concentrated mainly at the boundaries between adjacent tiers rather than across distant classes, which is consistent with an ordered transition structure.

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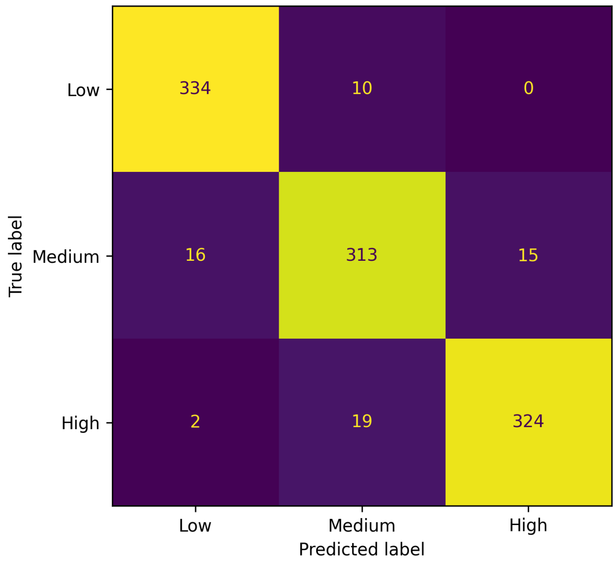

Figure 3: Confusion matrix for the best classification model (Random Forest).

5.4. Explainability findings

Feature-importance analysis provides an interpretable view of the structural determinants of renewable transition. For the best regression model, the most influential predictors were greenhouse-gas emissions, energy use per unit of GDP, electricity generation, per-capita electricity consumption, electricity demand, and net electricity imports as a share of demand. The same broad pattern appeared in the classification model, although population and primary energy consumption became relatively more important.

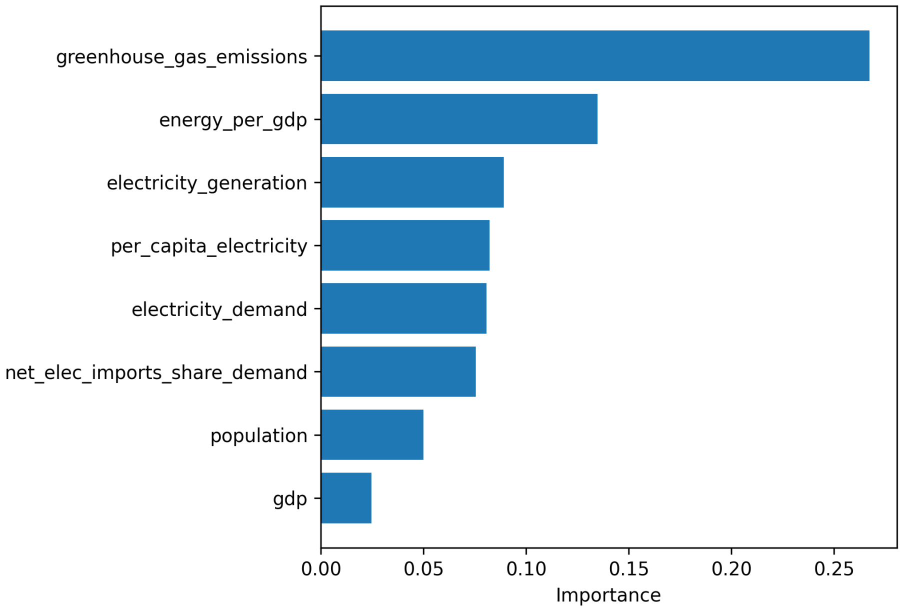

Figure 4: Top numeric feature importances for the best regression model.

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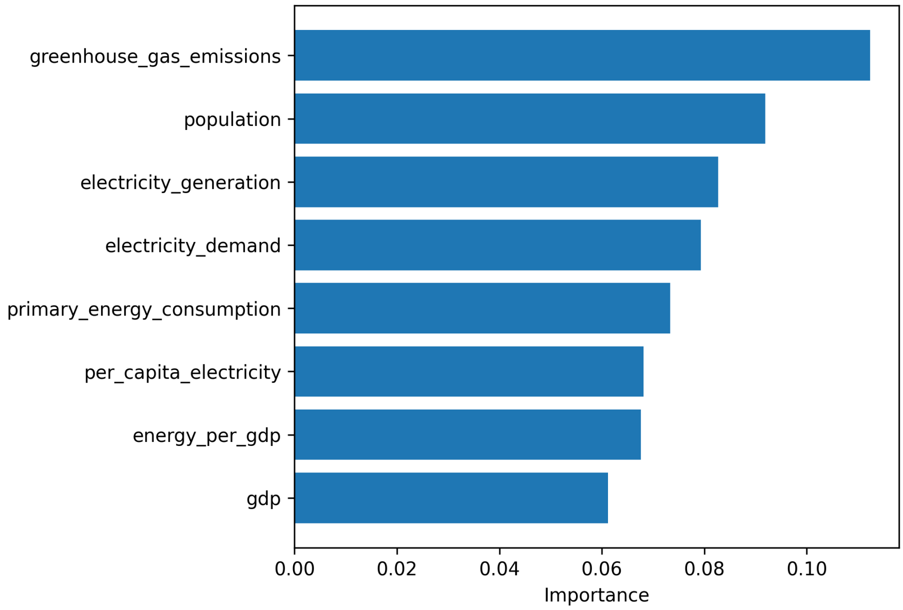

Figure 5: Top numeric feature importances for the best classification model.

The boxplot in Figure 6 confirms that the empirical tiering process creates clearly separated low-, medium-, and high-transition groups, which supports its use as a practical benchmarking device.

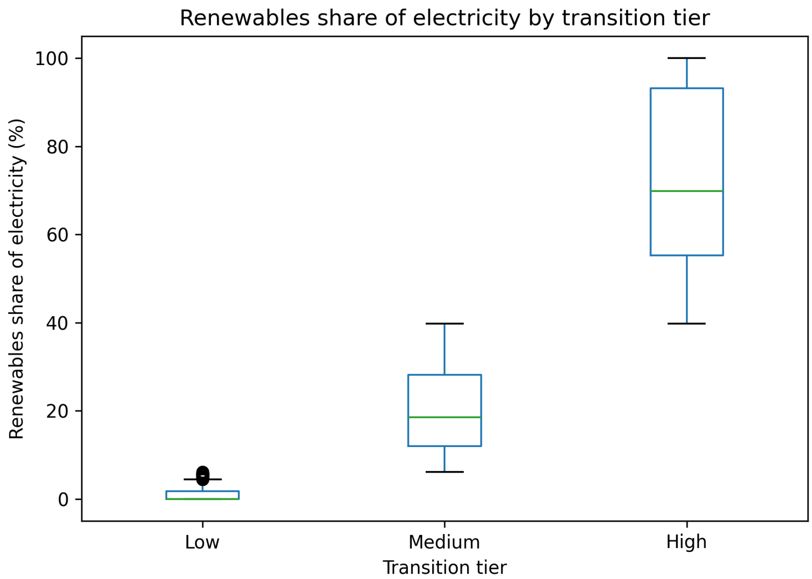

Figure 6: Distribution of renewable share of electricity by transition tier.

6. Discussion

The empirical results support three main observations. First, renewable-transition analytics can be modeled effectively at the country-year level using a harmonized international energy panel. This matters because reproducibility remains a recurring weakness in sustainability forecasting research. The data structure used here allows the analysis to be verified, extended, and compared across national settings [13]. Second, the results suggest that renewable-transition positioning is strongly associated with broad structural indicators rather than only highly technical variables. Greenhouse-gas emissions, energy intensity, and electricity-system scale dominate the importance rankings, indicating that transition maturity is tied to the wider organization of national energy systems.

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Third, the classification results are particularly relevant from a business perspective. Many sustainability dashboards present continuous values but do not convert them into action-oriented states. The tiering mechanism proposed here makes the data easier to use in practice. For example, firms evaluating international investment destinations, large electricity buyers considering decarbonization opportunities, or development institutions benchmarking transition readiness can use the low/medium/high classification as an interpretable first-screening tool.

The findings also complement broader concerns raised in recent work about the relationship between rising electricity demand, digital growth, and renewable-system adequacy[5]. If electricity demand expands rapidly while renewable transition remains uneven, then cross-country benchmarking becomes even more important for investment strategy and policy coordination.

7. Managerial and Policy Implications

The study has several practical implications. First, firms can use the framework for **market screening**. Rather than relying on single environmental headlines, they can benchmark countries using a structured renewable-transition indicator and predicted transition tier. Second, the framework supports **sustainability-oriented procurement and location strategy**. Companies seeking greener electricity environments for energy-intensive operations or digital infrastructure can prioritize locations with stronger renewable profiles. Third, policymakers can use the results for **transition monitoring**. Because the models identify the most influential structural variables, they help clarify whether weak renewable performance is primarily associated with demand scale, energy intensity, import dependence, or broader system characteristics.

From a journal-scope perspective, the paper shows how green-technology progress can be translated into business analytics outputs. The contribution is therefore managerial as much as technical: it demonstrates that renewable-transition assessment can be organized as a reproducible data product for strategic planning.

8. Limitations and Future Work

Several limitations should be acknowledged. First, the study relies on annual country-level indicators, which are appropriate for strategic benchmarking but not for operational short-term dispatch or plant-level forecasting. Second, although country identity improves predictive power, it may absorb institutional and geographic effects that are not modeled explicitly. Third, the present analysis focuses on one target variable—renewable share of electricity—and does not separately model technology-specific subcomponents such as wind or solar deployment. Future work could extend the framework to multi-output forecasting, regional clustering, or scenario analysis linked to industrial demand, digital infrastructure, and green investment flows.

9. Conclusion

This paper developed a reproducible business analytics framework for forecasting renewable electricity shares and classifying renewable-transition tiers using a cross-country energy panel derived from the *Our World in Data* Energy database. The analysis was based on 5,162 country-year observations from 213 countries between 2000 and 2025. Among the tested models, the random-forest regressor achieved the strongest forecasting performance (MAE = 3.536; RMSE = 6.466; $R^2 = 0.960$), while the random-forest classifier achieved the best tier-classification performance (accuracy = 93.998%; macro-F_1 = 0.940). Feature-importance analysis indicated that emissions, energy intensity, electricity-system scale, and demand-related variables are central to transition benchmarking.

Overall, the findings show that renewable-transition evaluation can be structured as a managerial analytics problem supported by cross-country energy indicators and interpretable machine learning. This orientation is well suited to sustainability and green-technology research that seeks not only to measure transition progress, but also to inform practical business and policy decisions.

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