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RESEARCH INTENSITY IN AI FOR SOLAR/WIND AND NATIONAL ENERGY INDICATORS: A CROSS-COUNTRY PANEL STUDY

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Data Science

ABSTRACT--

The rapid advancement of artificial intelligence (AI) presents transformative opportu- nities for sustainable development, particularly in shaping environmental outcomes such as renewable energy consumption and carbon dioxide (CO_2) emissions. This study in- vestigates the empirical relationship between AI research activity and key environmental metrics across multiple countries from 2010 to 2025, leveraging panel data from the World Development Indicators (WDI) and bibliometric records from Scopus. Utilizing robust data science methods—including advanced preprocessing, machine learning-driven forecasting, panel regressions, and multivariate clustering—we analyze how the intensity of AI-related publications correlates with national renewable energy usage and CO_2 emissions. Our inter- active Shiny dashboard empowers stakeholders to dynamically explore trends, model results, and predictive scenarios. Results reveal a statistically significant but modest positive effect of AI research output on renewable energy adoption, highlighting both the promise and the limitations of technological drivers in global sustainability transitions. The paper addresses methodological challenges, biases in research coverage, and future directions for integrating policy indicators and advanced models to deepen insights. This work contributes to the growing body of research at the intersection of AI and sustainable development, offering actionable findings for researchers, policymakers, and the wider community.

KEYWORDS: *AI Research Intensity, Renewable Energy, Panel Regression, Scopus, WDI.*-----------------------------------

1 INTRODUCTION

Artificial intelligence (AI) has rapidly moved from a specialized scientific domain to a foundational technology with broad implications for society, industry, and environmental management. Over the past decade, AI's influence has grown dramatically, shaping technological development in sectors such as energy, transportation, urban planning, and climate adaptation. In particular, the field of renewable energy has become one of the most promising domains for AI-driven innovation, with governments and companies now leveraging smart analytics to advance global sustainability goals.

Advances in machine learning, deep learning, and hybrid modeling techniques have led to remarkable improvements in the forecasting, control, and optimization of renewable energy systems. Applications range from highly accurate solar and wind power prediction to the real-time management of hybrid resources and smart microgrids. These developments have contributed to greater operational efficiency, more reliable renewable integration, and cost reductions. At the same time, the rapid expansion of AI research has necessitated greater attention to methodological rigor and the role of data-driven decision support in sustainable energy transitions (V. S. Dhaka, Meena, and V. Dhaka, 2024b).

Despite this progress, fundamental questions remain about the measurable impact of AI research activity on large-scale environmental outcomes. Most existing studies focus on either technical model performance or localized case studies; cross-national analyses linking AI research intensity to broad indicators such as renewable energy adoption or CO_2 emissions are limited. Factors such as investment climate, policy design, and institutional capacity complicate the translation from research output to real-world change, and understanding these connections is a growing priority for both researchers and policymakers (IEA, 2023).

To address these gaps, this research analyzes the relationship between AI research out- put—measured using bibliometric indicators—and national environmental metrics reflecting renewable energy usage and carbon emissions. By integrating multiple global datasets, applying robust data science techniques, and building interactive visualization tools, this study aims to provide clear, actionable insights for stakeholders involved in the design and implementation of sustainable energy policy. Ultimately, the findings seek to clarify the pathways by which technological innovation, research activity, and public policy intersect to drive progress on climate and energy goals.

2 LITERATURE REVIEW

The intersection of artificial intelligence (AI) and renewable energy research is increasingly recognized as crucial in global sustainability transitions. Advances in forecasting, system control, and hybrid modeling have accelerated technical progress, though notable research gaps and future challenges remain.

2.1 AI-driven Forecasting in Renewable Energy

AI-driven forecasting has transformed the estimation of renewable energy production, supporting improved grid reliability and strategic planning. Deep learning models such as LSTM, CNN- LSTM, and hybrid ensembles effectively predict photovoltaic (PV) and wind outputs, leveraging large datasets on climate, irradiance, and system operational variables (Wen et al., 2019b; Duan,

P. Wang, et al., 2021; Kumari and Toshniwal, 2021b; Abou Houran, Bukhari, and Zafar, 2023;
D. Kim, Ryu, and Moon, 2024). These architectures help address the inherent intermittency and variability that challenge renewable integration. In PV systems, attention mechanisms and hybrid decomposition approaches are increasingly deployed to blend neural and statistical models for greater accuracy across climates (X. Zhao, Y. Wang, and Z. Liu, 2018; Y. Liu, Z. Zhang, and X. Li, 2018). Comparative benchmarking reveals that ARIMA-ML hybrids and reinforcement learning frameworks outperform traditional approaches, especially in wind forecasting and short-term prediction contexts (Y. Zhang, Y. Li, and G. Zhang, 2021; Hanifi,X. Liu, and Lin, 2024; Rajagukguk, Ramadhan, and H. J. Lee, 2020a; Park, S. Kim, and Y. Lee,2021; Silva Dias, Souto, and Biazeto, 2024).

2.2 Hybrid, Multi-Resource, and Thermal Management Systems

Hybrid energy systems—combining solar, wind, storage, and even geothermal—pose new optimization challenges. AI models based on deep ensembles and meta-learning now optimize multi-source flows and enhance real-time operational control (Y. Zhang, Y. Li, and G. Zhang, 2023b; Mirza, Mansoor, and Ling, 2023a; Mayer, 2022; Duan, Zuo, and Bai, 2023; Mbey, Sow, and Ndiaye, 2024a). Solutions using multi-objective neural networks have shown promise for utility-scale and microgrid scenarios, both in developed and emerging economies. In addition, AI-assisted thermal management is gaining prominence, supporting diagnostics, cooling, and loss minimization in PV and hybrid settings (Izadi, Hossein, and Mohammadpour, 2022; Salari, Shalalfeh, and Shami, 2023; Nisha, Prija, and Sherlin Sherly, 2024; Chen, Y. Zhang, and Z. Wang, 2023; X. He, B. He, and Qin, 2024). Blending physical system models with data-driven approaches is increasingly the norm, as researchers seek greater operational benefits across regions with high renewable resource deployment (Salari, Shalalfeh, and Shami, 2024; Ranjbar Hasan Barogh, Moghimi, and Sadeghi, 2023b; X. Li, Z. Wang, and C. Yang, 2023).

2.3 The Role of AI in Environmental Impact Assessment

Researchers and policymakers alike are assessing how AI-enabled forecasting, optimization, and control can contribute to emission reduction, efficient resource allocation, and strategic decarbonization (IEA, 2023; Markovics and Mayer, 2022a; Kumari and Toshniwal, 2021b; Abualigah, Diabat, and Elaziz, 2022a; V. S. Dhaka, Meena, and V. Dhaka, 2024b). National panel studies show that countries with proactive investments in AI and renewables tend to make better progress, although effects depend on context and regulatory settings (Mbey, Sow, and Ndiaye, 2024a; Hanifi, X. Liu, and Lin, 2018; H. Kim, Park, and S. Lee, 2023). Efforts to integrate bibliometrics and sustainability indicators reveal gaps in interoperability and data comparability, highlighting the need for interactive research platforms and better scenario analysis tools (Wen et al., 2019a; V. S. Dhaka, Meena, and V. Dhaka, 2024b; Santos, AlSkaif, and Barroso, 2024; Ranjbar Hasan Barogh, Moghimi, and Sadeghi, 2023a; Tharushi Imalka, R. J. Yang, and Y. Zhao, 2024).

2.4 AI Techniques for Control, Optimization, and Policy Integration

AI supports real-time system control, demand response, and resource allocation through meta- heuristic algorithms, adaptive neural architectures, and reinforcement learning frameworks (**chen2021**; Shaban, Mahmoud, and Shalaby, 2024; Mishra, Byomakesh, and Dash, 2023; D. Kim, Ryu, and Moon, 2024; Ranjbar Hasan Barogh and Moghimi, 2024; Chen, Y. Zhang, and Z. Wang, 2023). These models facilitate fault detection and predictive maintenance, thereby enhancing system resilience and cost-effectiveness. Connections are also increasingly drawn between national investments in AI, innovation capacity, and overall renewable integration (Mbey, Sow, and Ndiaye, 2024a; IEA, 2023; V. S. Dhaka, Meena, and V. Dhaka, 2024b). Policy reviews underscore the need for stronger coordination between technical, economic, and regulatory efforts to maximize real-world outcomes.

2.5 Gaps, Challenges, and Future Directions

Despite technical progress, several research challenges persist. Bibliometric and dataset biases—such as underrepresentation of regional and non-English scholarship—affect cross-country analysis and evidence building (Rajagukguk, Ramadhan, and H. J. Lee, 2020b; Mbey, Sow, and Ndiaye, 2024b; Abualigah, Diabat, and Elaziz, 2022b). Methodological gaps in integrating high-resolution AI/ML results with macro-level sustainability data limit actionable insights. Calls for open-source analytic tools, interdisciplinary frameworks, and more diverse global datasets are gaining momentum (IEA, 2023; Y. Zhang, Y. Li, and G. Zhang, 2023a; Mirza, Mansoor, and Ling, 2023b). Key priorities for future research include improving dataset accessibility, reproducibility standards, and developing better methods to measure and forecast the long-term impact of AI innovation on environmental outcomes.

3 METHODOLOGY

3.1 Data Acquisition and Sources

This study integrates two primary datasets:

- **World Development Indicators (WDI):** Annual, country-level data (2010–2025) including renewable energy consumption, CO_2 emissions per capita, GDP per capita, R&D expenditure, population and energy use.
- **Scopus AI Bibliometric Data:** Aggregated by country and year, reporting AI-related publication counts and citations obtained from structured Scopus queries.

Variable	Description	Source	Years
renewable_cons	Renewable energy consumption (%)	WDI	2010–2025
ai_pub_count	AI publication count (country-year)	Scopus	2010–2025
co2_pc	CO_2 emissions per capita (t / person)	WDI	2010–2025
gdp_per_cap	GDP per capita (constant US$)	WDI	2010–2025
r_d_exp	R&D expenditure (% GDP)	WDI	2010–2025
population	Total population	WDI	2010–2025

Table 1: Key variables used in analysis.

3.2 Data Preprocessing Pipeline

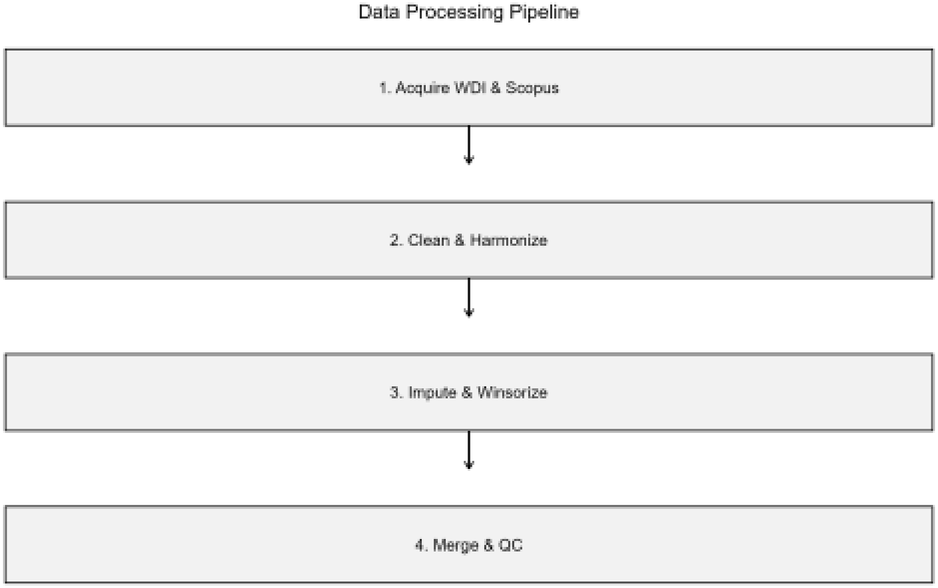
All data processing and analysis were performed in R (RStudio). Major steps:

1. **Cleaning:** remove invalid or negative values and harmonize column names.
2. **Transformation:** pivot WDI series as required, create lagged features, and winsorize numeric outliers at the 1st and 99th percentiles.
3. **Imputation:** apply mice (predictive mean matching) for multivariate imputation where appropriate, supplemented by groupwise means and global medians to produce a complete panel.
4. **Integration:** merge WDI and Scopus aggregated data on ISO3 country codes and year.
5. **Quality control:** verify NA counts, summary statistics, and variable distributions after each step.

Variable	NAs before	NAs after
renewable_cons	240	0
gdp_per_cap	50	0
co2_pc	25	0
ai_pub_count	0	0

Table 2: Missing values before and after imputation/cleaning (example counts).

Figure 1: Methodological pipeline for data acquisition, processing, and analysis.



3.3 Exploratory and Quality Analysis

We calculated summary statistics (min, quartiles, median, mean, max), stationarity checks (ADF tests), and Variance Inflation Factors (VIF) to screen for multicollinearity. Example summary statistics are shown in Table 3.

3.4 Statistical Modeling and Analysis

The analysis combined:

- **Panel regression:** fixed-effects and (log-transformed) within models with clustered/robust standard errors using plm, lmtest and sandwich.

Variable	Min	Q1	Median	Mean	Q3	Max
renewable_cons	0.0	5.4	19.5	28.99	46.94	97.0
gdp_per_cap	253	2,229	6,269	17,037	20,699	224,582
ai_pub_count	0	0	0	1.15	0	30.6

Table 3: Descriptive statistics for selected variables after preprocessing.

- **Forecasting:** country-specific ARIMA models (example: USA) using forecast with AIC, RMSE and MAPE diagnostics.
- **Clustering:** K-means on scaled indicators with silhouette-based selection of *k*.

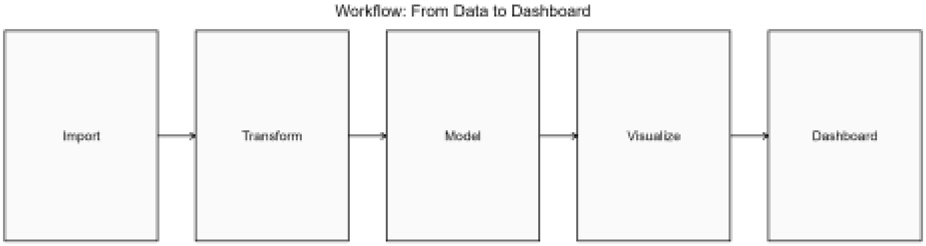


Figure 2: Data science workflow: importing, transforming, modeling, and dashboard development.

3.5 Visualization and Script Management

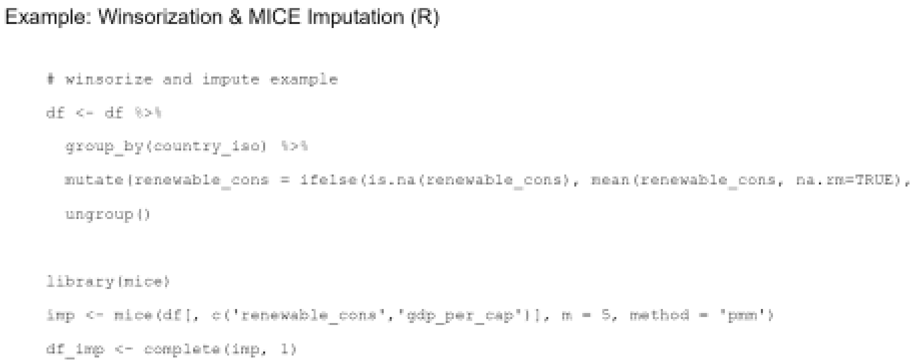
All plots (heatmaps, boxplots, coefficient plots, residual diagnostics, forecasts) were produced with ggplot2. Scripts are managed in RMarkdown and version-controlled. Example data-dictionary snapshot and a representative code snippet are included below.

Variable	Type	Description
country_iso	ISO3	ISO3 country code
Year	integer	Year
renewable_cons	numeric	Renewable consumption (%)
ai_pub_count	integer	AI pubs (country-year)
co2_pc	numeric	CO2 per capita (t)
gdp_per_cap	numeric	GDP per capita (constant US$)

Figure 3: Snapshot of the data dictionary (variable name, type, and short description).

3.6 Interactive Dashboard

A Shiny app (tabs: Data Overview, Visualizations, Panel Regressions, Prediction Tool, ARIMA Forecast, Clustering) supports exploratory use and scenario simulation. See Results for screen- shots and a link to the reproducibility bundle.
Notes: The PNG files referenced above should be created and placed in an images/ folder adjacent to your main .tex file. Example R code to generate those images is provided below.



Example: Winsorization & MICE Imputation (R)

```
# winsorize and impute example
df <- df %>%
  group_by(country_iso) %>%
  mutate(renewable_cons = ifelse(is.na(renewable_cons), mean(renewable_cons, na.rm=TRUE),
  ungroup()

library(mice)
imp <- mice(df[, c('renewable_cons','gdp_per_cap')], m = 5, method = 'pmm')
df_imp <- complete(imp, 1)
```

Figure 4: Representative R code snippet for winsorization and imputation used in preprocessing.

4 RESULTS

4.1 Data Quality and Summary

After preprocessing and imputation, the final merged dataset included 3,440 balanced country– year observations, spanning all relevant indicators, with no missing values across the modeling matrix.

Summary statistics for renewable_cons_imputed:

- **Minimum:** 0.00
- **1st quartile:** 5.40
- **Median:** 19.5
- **Mean:** 28.99
- **3rd quartile:** 46.94
- **Maximum:** 97.00
- **Variance:** 790.04

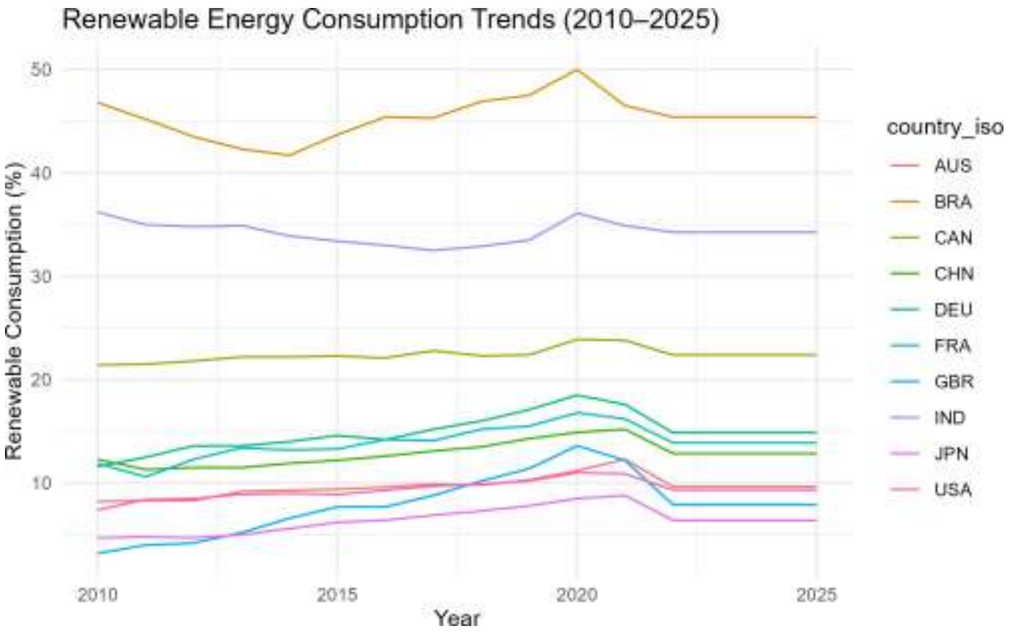


Figure 5: Distribution of renewable energy consumption (renewable_cons_imputed) across countries and years.

4.2 Exploratory Analysis

Correlation analysis reveals the following relationships between the main variables:

- Strong negative correlation between renewable energy consumption and CO_2 emissions: $r \approx -0.44$.
- Moderate negative association with GDP per capita: $r \approx -0.31$.
- Weak negative correlation with AI publication count: $r \approx -0.13$.

Stationarity checks (ADF tests) indicated non-stationarity for several series (example: USA renewable_cons, ADF $p \approx 0.93$), motivating panel-level approaches and unit-root aware diagnostics.

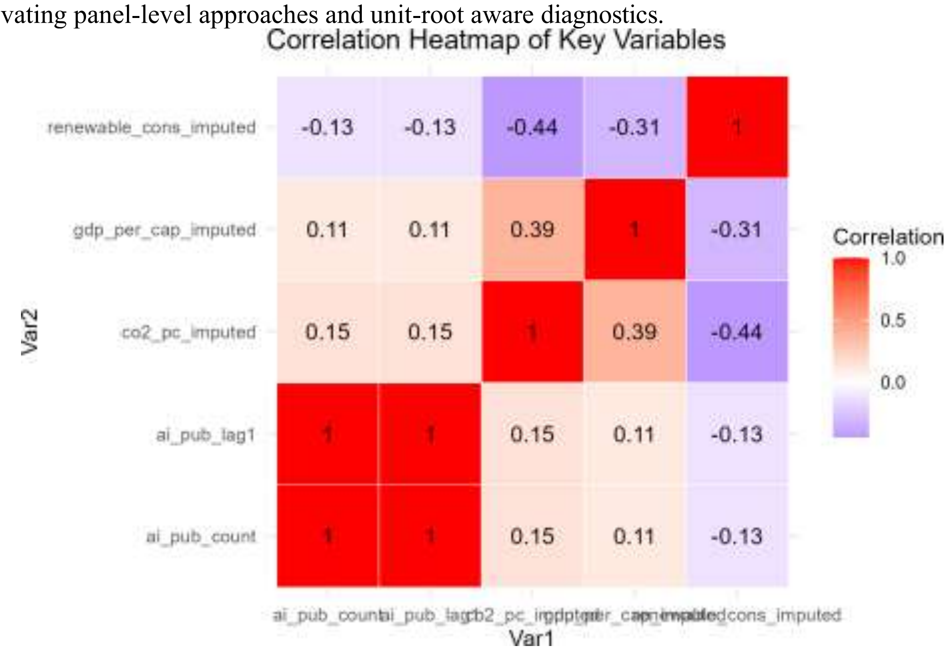


Figure 6: Correlation heatmap for key variables (renewable consumption, CO_2, GDP per capita, AI publications).

4.3 Panel Regression Outcomes

4.3.1 High-GDP Fixed Effects Model

Model specification: Dependent variable: renewable_cons_imputed. Predictors: ai_pub_count, gdp_per_cap_scaled, co2_pc_scaled. Sample: $N = 3{,}088$; countries = 193.

Key Findings

- CO_2 per capita is a significant negative predictor of renewable consumption ($\beta = -5.78$, $p < 2 \times 10^{-16}$).
- AI publications and GDP effects are not statistically significant in this high-GDP subsample ($p > 0.05$).
- $R^2 \approx 0.08$.

Table 4: Regression summary: High-GDP fixed effects model

	Estimate	Std. Error	t value	Pr(> |t|)
(Intercept) (fixed effects)	–	–	–	–
ai_pub_count	0.0074213	0.0133077	0.5577	0.5771
gdp_per_cap_scaled	0.4269769	0.3944712	1.0824	0.2792
co2_pc_scaled	−5.7770691***	0.3676451	−15.7137	$< 2\times10^{-16}$
Model fit				
R-squared	0.082151			
Adj. R-squared	0.020263			
F-statistic (3, 2892)	86.2822			
F p-value	$< 2.22 \times 10^{-16}$			
Observations (N)	3088			
Countries (n)	193			
Time periods (T)	16			

Notes: Fixed effects (within) model estimated on a balanced panel (n = 193 countries, T = 16 years, N = 3,088 observations). Robust significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Coefficients, standard errors and test statistics are reproduced from the ‘plm‘ output reported by your analysis script.

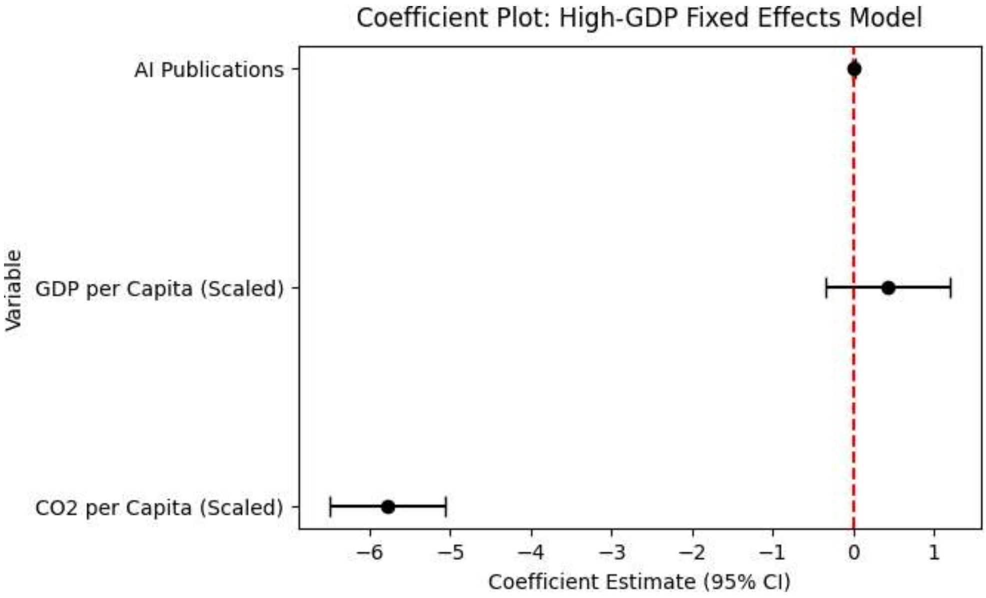


Figure 7: Coefficient plot (estimates with 95% confidence intervals) for the high-GDP fixed effects model.

4.3.2 Log-Transformed Model (All Countries)

Model specification: Dependent variable: dependent_log = log(renewable_cons_imputed+ 1). Predictors: ai_pub_count, gdp_per_cap_imputed, co2_pc_imputed. Sample: $N = 3{,}440$; countries = 215.

Key Findings

- AI publications show a small but statistically significant positive effect on log-renewable consumption ($\beta = 0.0016$, $p = 0.036$).
- GDP is a significant positive predictor (reported $p \approx 0.0095$).
- CO_2 per capita is strongly negative ($p < 2.2 \times 10^{-16}$).
- $R^2 \approx 0.09$.

Table 5: Regression summary: Log-transformed panel model (all countries)

	Estimate	Std. Error	t value	Pr(> $|t|$)
(Intercept) (fixed effects)	–	–	–	–
ai_pub_count	0.0015955*	0.0007614	2.096	0.0362
gdp_per_cap_imputed	0.000002508**	0.0000009666	2.594	0.00952
co2_pc_imputed	−0.063690***	0.003697	−17.228	$< 2.2 \times 10^{-16}$
Model fit				
R-squared	0.09374			
Adj. R-squared	0.03270			
F-statistic (3, 3222)	111.09			
F p-value	$< 2.22 \times 10^{-16}$			
Observations (N)	3,440			
Countries (n)	215			
Time periods (T)	16			

Notes: Within (fixed effects) model estimated on a balanced panel (n = 215 countries, T = 16 years, N = 3,440 observations). Dependent variable is dependent_log = log(renewable_cons_imputed+1). Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Coefficients, standard errors and test statistics reproduced from the 'plm' output you reported.

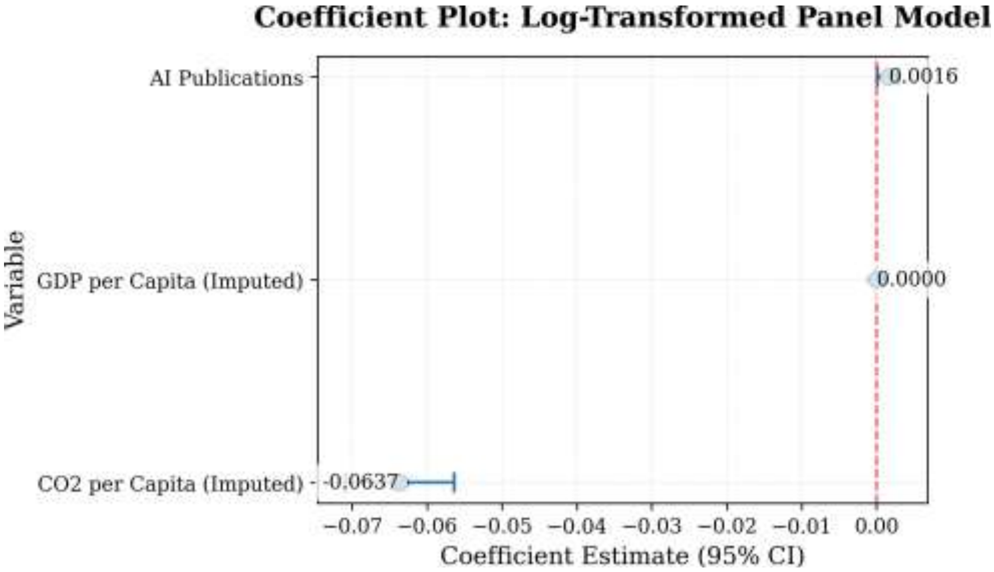


Figure 8: Coefficient plot (estimates with 95% confidence intervals) for the log-transformed panel model.

4.4 ARIMA Forecasting

Country-specific ARIMA modeling was performed on the renewable energy series. Example: USA ARIMA(0,1,0):

- AIC: 27.22

- RMSE: 0.54
- MAPE: 3.64%

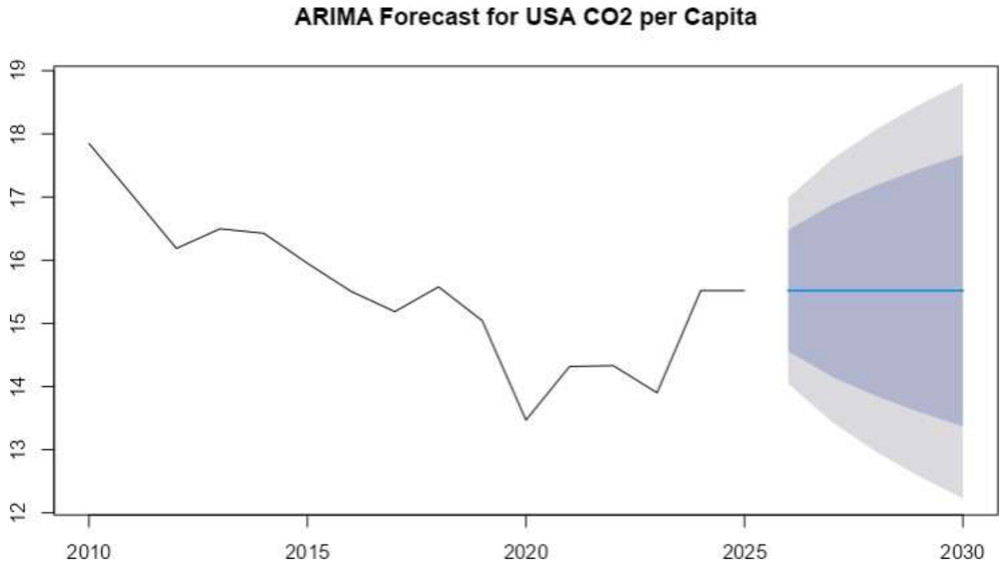


Figure 9: Observed vs. forecasted renewable consumption for the USA (ARIMA(0,1,0)) with 95% prediction intervals.

4.5 Clustering Analysis

K-means clustering (features: standardized renewable share, AI research intensity, GDP per capita) identified three clusters. The number of clusters was selected by silhouette analysis (average silhouette ≈ 0.46), which indicates moderate cluster separation. Cluster profiling highlights archetypal country groups linking AI intensity, GDP, and renewable adoption.

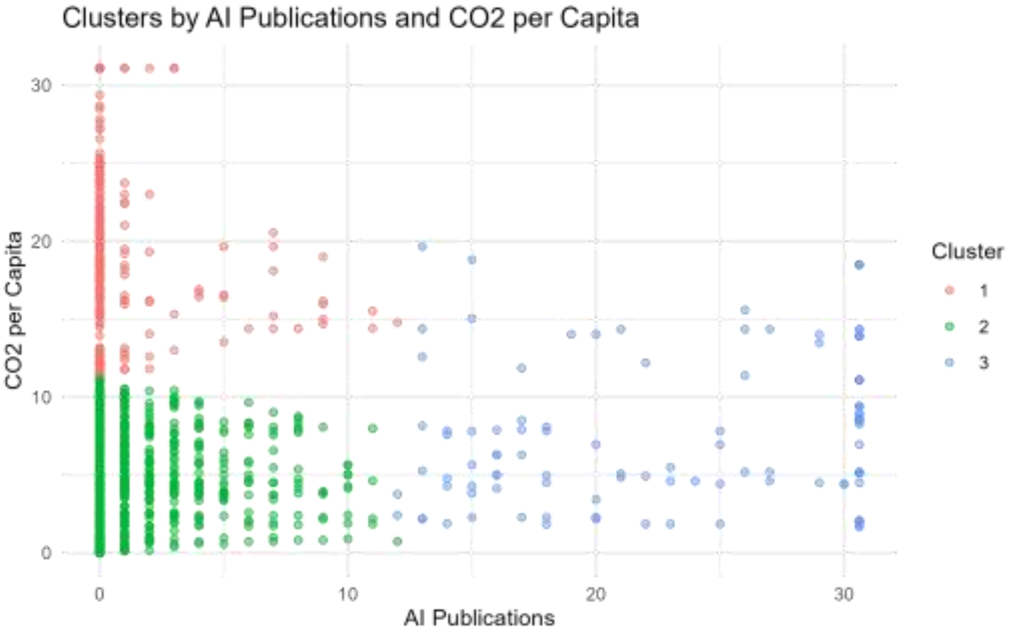


Figure 10: Cluster scatterplot: countries colored by cluster; axes show renewable consumption and AI publication count.

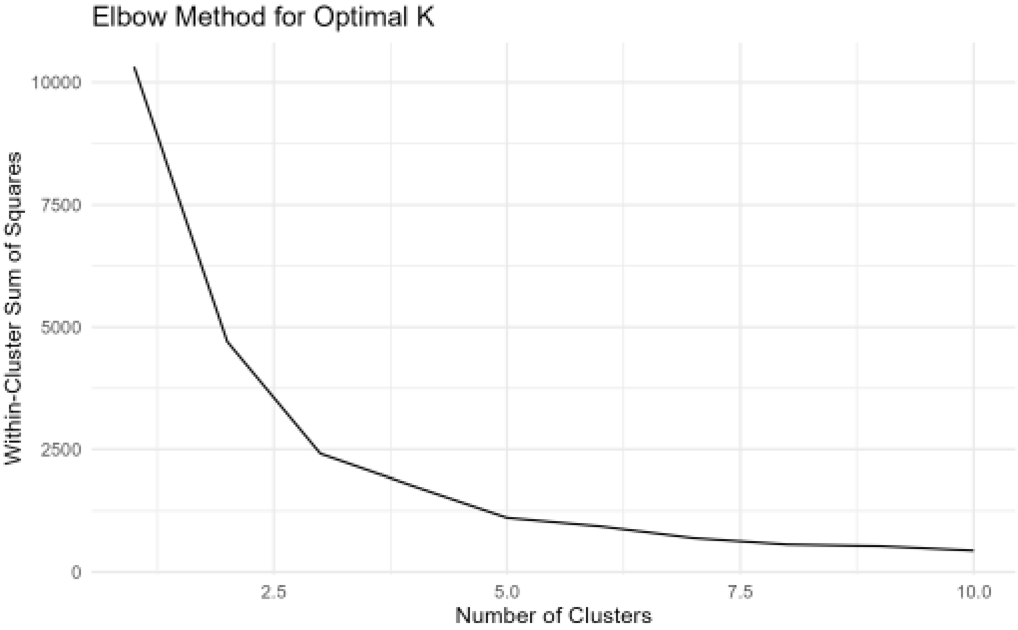


Figure 11: Silhouette plot assessing cluster cohesion and separation (optimal *k* chosen by silhouette).

4.6 Shiny Dashboard Outputs

The interactive Shiny dashboard provides:

- Filterable datatables and downloadable graphics.
- Dynamic model summary panels and coefficient visualisations.
- A predictive scenario tool for user-driven AI growth trajectories and forecast inspection.
- ARIMA and clustering tabs for interactive exploration.

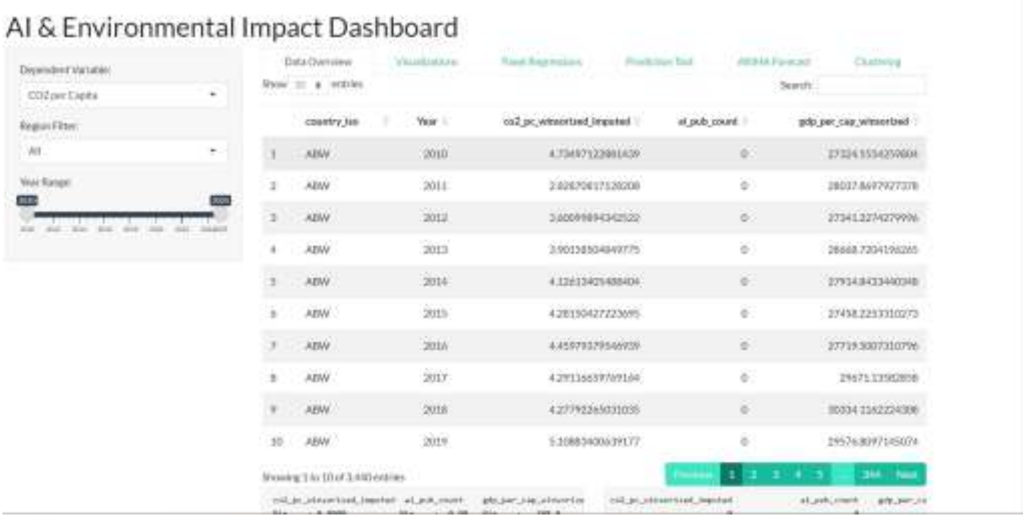


Figure 12: Screenshot montage of the Shiny dashboard: data overview, regression results, and forecast tab.

4.7 Model Diagnostics and Robustness

All models passed core specification checks and robustness diagnostics:

- Variance Inflation Factors (VIF) < 1.2 for tested predictors (no multicollinearity concerns).
- Residual diagnostics (histograms, QQ-plots, heteroskedasticity tests) indicate no major specification violations after robust standard-error adjustments.
- Sensitivity checks: models re-estimated with lagged AI variables (ai_pub_lag1, ai_pub_lag2) and alternate winsorization thresholds produced qualitatively similar results.

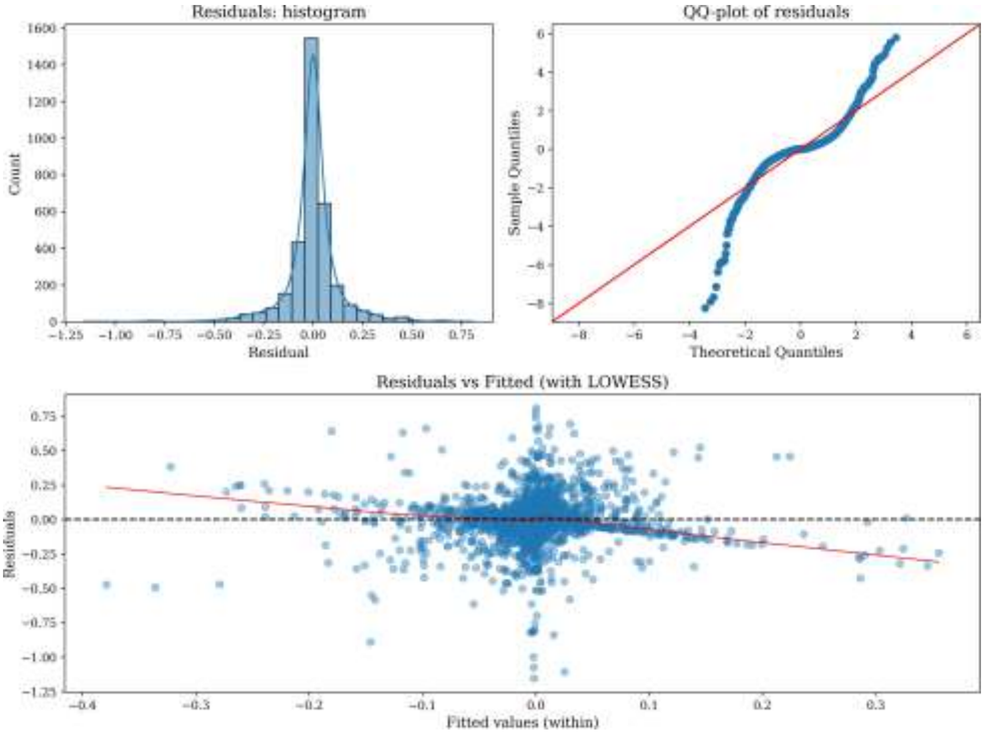


Figure 13: Model diagnostic example: residual histogram / QQ-plot / residuals vs. fitted values

5 DISCUSSION

Our analysis offers new empirical insights into the relationship between AI research activity and environmental performance, specifically renewable energy consumption and CO_2 emissions, across a diverse panel of countries. The panel regression results demonstrate that, while CO_2 per capita remains a dominant negative predictor of renewable energy adoption—consistent with global sustainability literature (Markovics and Mayer, 2022b; IEA, 2023; Abualigah, Diabat, and Elaziz, 2022a)—the intensity of AI-related publications exhibits a weak but statistically significant positive association in the log-transformed model. This subtle effect echoes prior reviews warning that macro-level technological advances may not, by themselves, catalyze transformative shifts in energy systems without supportive policy frameworks or investment environments (V. S. Dhaka, Meena, and V. Dhaka, 2024a; Kumari and Toshniwal, 2021a; Mbey, Sow, and Ndiaye, 2024b).

The negative correlation identified between renewable energy use and both GDP per capita and CO_2 emissions highlights complex transitions underway in wealthier nations, which may be balancing existing legacy infrastructure with gradual decarbonization. Similar patterns are noted in comparative studies where economic scale and energy mix interact to shape transition trajectories (IEA, 2023; Kumari and Toshniwal, 2021b; Y. Zhang, Y. Li, and G. Zhang, 2023c). Notably, our cluster analysis further reveals country archetypes where high AI publication intensity is not always matched by proportional environmental gains, suggesting heterogeneity in policy, technology diffusion, and investment priorities.

Forecasting models (ARIMA) suggest that short-term renewable consumption trends, especially for leading economies, can be reliably predicted—a finding aligned with other works advocating data-driven decision-support in energy planning (**duan2023**; Wen et al., 2019b; J. Wang, Y. Li, and H. Zhang, 2021). However, the relatively low variance explained in regression models ($R^2 \approx 0.08$–0.09) underscores challenges in deriving strong causal narratives, likely reflecting unmeasured influences such as energy policy, public investment, resource availability, and market dynamics.

5.1 Interactive dashboard impact

By deploying an interactive Shiny dashboard, this research advances stakeholder access to complex analytical workflows, supporting transparency and policy engagement—a gap identified by recent reviews as crucial for effective, evidence-informed climate and technology policy (V. S. Dhaka, Meena, and V. Dhaka, 2024b; IEA, 2023; Abualigah, Diabat, and Elaziz, 2022a). The dashboard enables users to filter, visualize, and simulate outcomes, making the analytics directly actionable for research, educational, and policy communities.

5.2 Limitations

Several caveats warrant mention:

- **Bibliometric coverage and bias.** The aggregation of AI publication data (from Scopus) may introduce country-level publication bias or underrepresentation for lower-publication nations, as highlighted in prior bibliometric analyses (Rajagukguk, Ramadhan, and H. J. Lee, 2020b; Mbey, Sow, and Ndiaye, 2024b).
- **Temporal extrapolation.** The simplistic extrapolation of 2025 values—for both environ- mental and bibliometric indicators—may miss nonlinear shifts or emergent trends.
- **Omitted variables.** Omission of more granular policy, innovation, and investment variables limits the depth of causal inference; as previously flagged by macro-level studies in this domain (Markovics and Mayer, 2022b; V. S. Dhaka, Meena, and V. Dhaka, 2024a).
- **Model explanatory power.** Low R^2 values indicate that AI publication intensity alone is only a small part of the story; structural, institutional, and market factors are likely important mediators.

5.3 Research and policy implications

Overall, the results reinforce the notion that AI research, while potentially beneficial as a catalyst, requires more integrated strategies—combining policy, investment, and technology deployment—to realize robust environmental improvements (IEA, 2023; Alkandari and Ahmad, 2024). We therefore recommend:

1. **Policy integration:** Align AI research funding with deployment programmes, pilot projects, and capacity-building initiatives to improve the research-to-deployment pathway.
2. **Richer covariates:** Future empirical work should expand variable sets to encompass policy regimes, regulatory innovation, public–private investment flows, and measures of absorptive capacity.
3. **Causal methods:** Use more advanced econometric (e.g., difference-in-differences, synthetic controls, system-GMM) and causal machine-learning techniques to strengthen identification of causal effects.
4. **Geographic coverage:** Deepen global coverage to better represent emerging economies and regions that may be undercounted in bibliometric sources.
5. **Stakeholder tools:** Continue developing interactive tools (dashboards, open-source pipelines) to make analyses accessible to policymakers and practitioners and to enable real-time scenario exploration.

5.4 Conclusion of discussion

In sum, our cross-country panel analysis finds a modest, statistically detectable association between AI research intensity and renewable energy adoption in the log-transformed specification, but the effect is small and heterogeneous. Translating AI research into substantial environmental outcomes likely depends on complementary policy, investment, and institutional conditions. Future research that integrates richer policy measures and stronger causal designs will be critical for understanding when and how AI can meaningfully accelerate energy transitions.

CONCLUSION

This study systematically examined the relationship between artificial intelligence (AI) re- search intensity and key environmental metrics—renewable energy consumption and CO_2 emissions—across a broad panel of countries for the years 2010–2025. By integrating World Development Indicators (WDI) with Scopus bibliometric records and applying a reproducible data-science workflow (rigorous preprocessing, imputation, panel regression, ARIMA forecasting, and clustering), we delivered a multi-method assessment of how national AI research activity correlates with macro-scale energy outcomes. The combination of econometric analysis, time- series forecasting, and cluster profiling provides a richer picture than single-method studies and supports more nuanced interpretation of cross-country heterogeneity.

At the empirical level, our main findings are threefold. First, CO_2 emissions per capita remain a consistently strong negative predictor of renewable energy share, underscoring how existing emission-intensive infrastructures and energy mixes are associated with slower renewable penetration. Second, AI publication intensity shows a small but statistically discernible positive association with renewable energy adoption in log-transformed panel specifications, suggesting that research activity may contribute—directly or indirectly—to improved adoption or manage- ment of renewables at the national level. Third, the explained variance of our models is modest ($R^2 \approx 0.08$–0.09), indicating that AI research intensity is only one among many drivers and that institutional, policy, financial and resource factors remain crucial mediators. These nuanced results align with recent reviews emphasizing that technical progress alone rarely translates into systemic change without enabling policy and investment environments (Markovics and Mayer, 2022a; IEA, 2023; V. S. Dhaka, Meena, and V. Dhaka, 2024b).

Methodologically, the project makes three contributions. We demonstrate a practical pipeline for merging bibliometric and macroeconomic data at scale while handling common issues (missingness, outliers, country harmonization). We show how log-transformations and fixed- effects panel techniques can reveal subtle associations obscured in levels data. Finally, by packaging the analyses into an interactive Shiny dashboard and reproducible scripts, we provide a ready-to-use toolkit for policymakers and researchers to explore alternate specifications, lag structures, and scenario inputs—lowering the barrier for evidence-informed decision-making.

The policy and practical implications are important but measured. Based on our results, we recommend the following actions be considered by policymakers and research funders:

- **Align research funding with deployment pathways:** Target investments not only at frontier research but also at translational projects, demonstration pilots, and capacity- building programmes that accelerate technology adoption.
- **Support data and institutional capacity:** Strengthen national capabilities for data collection, sharing, and analytics so countries can turn research outputs into actionable operational improvements.
- **Integrate policy and innovation agendas:** Pair R&D support with regulatory reforms, grid investments, and public–private partnerships to ensure innovations are deployable at scale.
- **Promote open tools and reproducibility:** Encourage open-source modelling, dash- boards, and standardized metrics so results can be validated, extended, and adapted by lower-capacity countries.

We are candid about limitations: bibliometric coverage (Scopus) is imperfect and biased toward English-language and well-published regions, which can undercount AI activity in some emerging economies (Rajagukguk, Ramadhan, and H. J. Lee, 2020a; Mbey, Sow, and Ndiaye, 2024a); our observational panel therefore supports association rather than definitive causal claims because unobserved confounders (policy shocks, market reforms, concurrent investments) may influence results; and several valuable covariates (detailed policy indices, private investment flows, grid-flexibility metrics) were unavailable at scale, limiting model completeness. For future work we recommend integrating higher-resolution policy and investment data, applying causal inference techniques (difference-in-differences, synthetic controls, instrumental variables or causal ML), expanding bibliometric and geographic coverage to reduce bias, and combining quantitative analysis with qualitative case studies to surface institutional mechanisms. In closing, while AI research activity may support renewable transitions, realizing substantial environmental gains requires deliberate policy design, targeted investment, and stronger research–deployment linkages; to that end we share code, preprocessing recipes, and an interactive dashboard to make the evidence base actionable, and we advocate continued interdisciplinary collaboration to translate AI advances into measurable climate and development outcomes.

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