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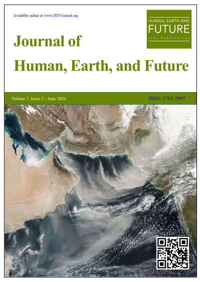

Innovation Allocation Dilemma: AI, R&D, and Policy Effects on U.S. Renewable Electricity

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Abstract

Despite holding the world's second-largest portfolio of green technology patents, the U.S. is still behind the developed economies in energy efficiency outcomes, which is responsible for creating an innovation allocation dilemma in renewable electricity deployment. This study addresses the fundamental question of the optimal resource allocation among competing innovation pathways by investigating the comparative impacts of artificial intelligence (AI) innovation, green technology innovation (GTI), research and development (R&D) expenditures, and environmental policy stringency (EPS) have on the U.S. renewable electricity contribution rate (ECR) over a period of 33 years (1990-2022). Applying the autoregressive distributed lag (ARDL) model, this study highlights the fact that the interaction between R&D investment and per capita gross domestic product (GDP) significantly influences ECR with a long-term elasticity of about 91%. Second, EPS also has a highly significant and robust elasticity of about 62% for ECR gains. AI innovation, however, shows mixed effects: the initial positive short-run contributions fade away in the long run without sustained complementary investments. With respect to asymmetric effects, negative shocks convey larger benefits to renewable energy than positive ones, a finding that questions the conventional technology deployment. The findings support policymakers making R&D investments a priority over patent-based strategies, reallocating government expenditures from direct spending to market mechanisms.

Keywords: Renewable Electricity Transition; Innovation Policy; ARDL Cointegration; Environmental Policy Stringency; Artificial Intelligence Patents; Green Technology Innovations.

1. Introduction

The U.S. holds the second-largest number of green patents, with $600 billion invested in low-carbon emissions and grid storage development [1], and more than $11 billion allocated to climate financing in 2024 [2]. Despite these large investments, the U.S. has lower efficiency in terms of clean energy outcomes than other countries such as the UK, Germany, and China. This weak performance in energy efficiency may suggest a suboptimal allocation of investment

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that is responsible for creating an "innovation allocation dilemma," a fundamental resource optimization challenge wherein policymakers have to decide how to distribute their finite R&D budgets and institutional capacity across competing technological pathways, each promising a distinct but uncertain contribution to renewable energy goals [3]. In contrast, Japan, with a lower energy intensity but higher technology innovation, has achieved superior performance in the energy transition due to considerable R&D spending [4]. In addition, R&D, when invested in carefully, can be a key explanatory variable contributing to a sustainable energy transition. Moreover, the Trump administration's current focus on reducing R&D expenditures may hinder R&D support for AI integration and limit systematic support for AI applications in energy management [5]. AI innovations' implications, such as intelligent grid management, have offered substantial contributions to energy enhancement and transition due to optimization goals, even if these innovations are not labeled green technology patents [6–8]. There are visible gaps in the understanding of whether it is a fundamental misallocation of R&D investments toward AI technology advancement in the energy system.

Investment in R&D and AI innovation has been influential, facilitating the renewable electricity contribution rate (ECR) within the contemporary energy landscape because R&D and AI can increase renewable energy toward electricity outputs [9, 10]. Recent studies have pointed out the huge potential of AI to optimize energy and electricity systems for efficient grid management [11, 12]. With capabilities related to system optimization, forecasting, and intelligent energy management, AI is increasingly considered one of the promising, transformative approaches within the energy sector, especially in integrating renewable energy contributions [11, 13]. Mose Solar Manufacturing reported that an AI-powered control system has achieved an energy efficiency of about 25% greater than that of traditional controls and is managing the majority of energy toward clean electricity [14]. Algburi et al. (2025) [13] provided prominent evidence with regard to AI-driven gains, observing a 2.5% increase in the efficiency of solar energy, 1.7% in wind energy, 4.5% in energy storage, and 1.2% in grid stability during three years (2020–2023) in a pilot project. The U.S. Department of Energy (2025) [15] also highlights the potential for integrating AI into the clean energy transition. AI can be incorporated into existing infrastructure to optimize energy generation and system performance [16], whereas traditional green technology patents may require additional infrastructure and the deployment of new technologies.

However, several gaps remain in understanding how different innovation pathways can enhance the ECR. First, prior studies have focused on capacity expansion [17], investment growth [18], and policy support mechanisms [19] as the primary drivers of higher ECR, without considering the transformative optimization benefits of AI in improving electricity outputs beyond traditional approaches. Second, previous research has generally viewed AI in electricity systems as a technical contribution and has focused on pilot programs related to energy efficiency and cost-effectiveness, rather than examining the broader integration effects of AI and its potential to increase the ECR through enhanced renewable electricity generation [11, 20, 21]. Third, conventional studies tend to emphasize linear innovation pathways in the energy transition while overlooking the synergistic benefits of integrating AI with other technological infrastructures to improve energy performance [22–24].

There are also methodological gaps in identifying the mechanisms through which innovation pathways can effectively drive higher ECR. For example, although previous studies have employed ARDL methods to investigate the clean energy transition, most have relied on consumption-based metrics, and only a limited number have focused on energy contribution rates or similar indicators [25–27].

To address these research gaps and methodological limitations, this study investigates the comparative impacts of AI innovation, green technology innovation, environment-focused policies, and per capita R&D expenditure on the U.S. ECR during the period 1990–2022. Advanced time-series econometric techniques, including the autoregressive distributed lag (ARDL) model and the nonlinear autoregressive distributed lag (NARDL) model, are employed to identify optimal pathways for accelerating renewable electricity integration and to provide evidence-based guidance for the design of sustainable energy transition policies. The study further examines the stability of model parameters across economic cycles and policy regime shifts, thereby validating the reliability of these variables for long-term policy planning.

In addition, the NARDL asymmetry test is conducted on AI innovation to determine how positive and negative AI-related shocks affect the ECR, revealing asymmetric effects. The core findings are subsequently verified using the fully modified ordinary least squares (FMOLS) model as a robustness check. Potential causal relationships are also examined using the Toda–Yamamoto Granger causality test. Furthermore, the study provides quantitative evidence regarding resource allocation among the investigated variables to assess their actual effectiveness in influencing the U.S. ECR.

Section 2 of this study provides the theoretical underpinning and review of existing literature on the respective variables. The limitations in previous studies and gaps are also identified. This is followed, in Section 3, by justification for the time-series econometric methodology through the diagnostic analysis, ARDL bounds cointegration analysis, error-correction modeling, and NARDL conclusions. The detailed empirical findings are described in Section 4, while the summary of the study, together with implications for policymakers and researchers, is given in Section 5.

2. Literature Review

2.1. Innovation Allocation Dilemma: Theoretical Foundations

The innovation allocation dilemma represents a resource optimization problem, with a conceptual grounding in three interlinked theoretical frameworks, which are endogenous growth theory, innovation systems theory, and general-purpose technology (GPT) adoption models [28–30]. Accordingly, for example, endogenous growth theory views technological development as being generated within the economic system itself, and proposes that heterogeneous effects might emanate from different forms of R&D, while highlighting careful budgeting as crucial in the process [31]. Such heterogeneous effects would also mean that strategic R&D spending is conducive to either capacity expansion or optimizing innovative technologies in order to derive actual efficiency gains. Recent literature also underlines the role of innovation systems theory and argues that successful transitions in technology require knowledge generation through R&D to support coordinated evolution in the deployment of AI in clean energy systems. However, most contributions so far have focused on technical and engineering research [32, 33]. The policy dilemma is further affected by the adoption of emerging GPTs, as policymakers have to choose between heavy investment in AI and R&D with uncertain near-term returns or invest in proven technologies like wind, solar, and hydropower [34]. Moreover, energy transition involves both capacity expansion and system optimization. Economists have focused on expanding renewable energy capacities, citing that such infrastructure within the energy system will contribute to reducing the use of fossil fuels, lowering dependencies, and increasing energy transitions [35]. However, only a well-designed capacity mechanism can incentivize this type of adequate infrastructure that will lead to long‐term sustainable benefits [36].

2.2. AI as a Contributor to Energy Transition and System Optimization

AI implementation and involvement can be viewed in general-purpose theory as a single technology that can be widely adopted across different types of industrial integration due to its numerous benefits. The benefits have been seen through predictive analysis, real-time data, and process optimization [12, 28, 37]. For example, AI has proved to be an assistive technology for a renewable energy system that can provide better energy management and grid efficiency [11]. It can also facilitate predictive maintenance and dynamic systems-based load balancing for facilities of clean energy systems, where specific traditional green innovations are not that beneficial [38]. In addition, AI shows cost-effective energy system optimization by leveraging existing infrastructure to enhance efficiency, security, and resilience, besides developing grid management in terms of optimized energy management, fault prediction, and reduced transmission losses [8]. These could influence energy policy choices, since the U.S. government tends to highlight other subsidies and governmental spending as practical tools [39]. On the other hand, transformative AI technologies may rival these more traditional technologies in driving considerable energy contributions. Previous literature has focused on AI optimization in smart grids and clean energy systems and highlights the AI's role in dynamic management, automation, load supervision, value creation, resource assessment, forecasting, monitoring, and control [6, 7, 40]. However, the mentioned literature remains focused on simulations and pilot programming rather than national-level evidence. Algburi et al. (2025) [13] reported some major efficiencies in AI integration on energy systems that reached 2.5% for solar energy, 1.7% for wind energy, 4.5% for energy storage, and 1.2% for grid stability improvement in three years' time (2020-2023). However, these findings are context-specific and cannot provide insights into the differences between traditional technologies and AI.

2.3. Role of R&D Investment in Clean Energy Outcomes

Empirical evidence underscores how R&D investment is paramount for the attainment of energy outcomes. For example, Lee (2021) [41] observes that renewable energy investment can generally enhance the renewable energy capacity investment of G20 economies thanks to the favorable regulatory and economic policies of incentives. In the same way, green investment and financial development favor the energy transition by increasing energy capacity but do not integrate efficiency [42]. Correspondingly, studies using the ARDL have reported positive clean energy consumption and higher growth of the economy in emerging Asian and African economies [43, 44]. A substantial number of studies using ARDL cover a period of 20-40 years, demonstrating that renewable energy growth is driven by R&D from both short- and long-term perspectives across both developed and emerging countries [25–27]. However, these studies have elaborated more on the consumption-based matrices rather than the efficiency integration-based matrices, like CRIs, to assert their claims. While studies using ARDL approaches capture the long-term dynamics, they miss the separate pathways that influence energy outcomes, such as those between green patents and AI innovation driven by R&D investment.

2.4. Curated Environmental Policy in Energy Transition

Different forms of government intervention in the U.S. energy transition have been evaluated, including direct spending, tax incentives, and regulatory measures intended to make environmental policy stronger [19, 45-47].

Targeted mechanisms, such as tax incentives, grants, and research and development, are better than direct investments or loans, according to evidence from the European Union and Turkey [48]. Shahzad et al. (2021) [49] show that by emphasizing environmentally oriented policies and adopting methods for managing their environmental impact, 29 OECD countries enhanced clean energy production. Caglar & Ulug (2022) [46] also focused on how government spending can help improve the renewable energy transition. Climate policy is also another means of providing energy security for developing countries [50]; further support sustainability, as seen through the use of NARDL analysis by Dong et al. (2024) [51] in selected countries. According to endogenous growth theory, these targeted interventions, like R&D-focused measures or internal factor investments, generate more impacts compared to broad public spending or external forces [52]. Furthermore, feed-in tariffs can create temporary market distortions, which may overlook long-term efficiency. In contrast, internal R&D investment can be sustained with improved contribution rates over longer time periods by addressing technology issues in the longer term [53].

2.5. Research Positioning and Gap Identification

The review critically identifies several gaps in the literature. First, the literature extensively emphasizes different policy instruments for a renewable energy transition. Prior research has investigated individual policy instruments, especially R&D and green technology patents, in isolation without considering alternative innovation pathways to facilitate integration outcomes [54, 55]. There is a lack of systematic comparative analyses on the impact of AI innovation, green technology patents, fiscal and other mechanisms, particularly in relation to increasing rates of energy consumption. Although ARDL time series are applied [25-27, 44], they are rarely employed to evaluate different innovation pathways, especially AI-driven integration and the capture of dynamic adjustments to the effects. Although researchers have evaluated renewable energy programs for enhancement strategies [21, 25-27], these studies have focused primarily on integrating AI to maximize the energy contribution rate. This research addresses these gaps by showing a systematic comparison of their relative effects on the U.S. renewable energy contribution rate, applying ARDL bounds testing and analysis, which enables the assessment of dynamic relationships over both the short and long run.

3. Data and Methodology

3.1. Data Description

Our empirical analyses have been done on an annual time series for the U.S. from 1990 to 2022. By studying the use of innovations in AI, green technology, stringency of environmental policy, and R&D expenditures, we assess the overall ECR. We also cover 33 years that can capture important technological transitions, shifts in policy regimes, and innovation cycles relevant to the identification of long-run equilibrium relationships that can provide sufficient temporal variation and robust econometric analysis. The dependent variable, lnECR (log-transformed), refers to the share of renewable electricity output in total electricity output. It thus indicates the progress in the renewable energy transition and effectively evaluates federal energy policies toward transitioning to clean electricity. It contains both technological progress and the effectiveness of policies in clean energy deployment, and also a key metric for assessing the progress toward climate goals and energy security objectives. Improvements in the ECR would help the U.S. reduce carbon emissions, improve energy independence, and maintain economic competitiveness in the global clean energy transition, which also provides the reason why it has been a major policy concern. The log transformation reduces excessive skewness in this variable, and the interpretation of elasticity is thus facilitated.

Our key explanatory variable, AI patents (AI), is the log-transformed annual count of patent publications in the U.S. related to artificial intelligence technologies. The variable is a good proxy for the intensity of AI innovation because it captures commercially viable innovations that have demonstrated their market potential for energy applications. The reason behind our interaction term is grounded in the moderated technological change hypothesis, and Ahmed et al. (2021) [56] suggested that the level and adequacy of R&D investment relative to the economy's size are key policy concerns. Our interaction effect captures how the impact of R&D investment depends on the existing economic base, as we combine it with the U.S. per capita GDP (constant 2015 US$), two separate economic indicators, into a single measure, then take the natural log, making a robust measure of a nation's innovation intensity to prosperity amplify R&D's impact on ECR. A dollar spent on R&D in a high-income economy may have a different (and often greater) impact than the same dollar spent in a lower-income economy because of the presence of better infrastructure, skilled labor, and established innovation ecosystems.

The data for all predictors were obtained from well-established international databases, including the World Development Indicators (WDI), the National Center for Science and Engineering Statistics (NCSES), the Organisation for Economic Co-operation and Development (OECD), and the World Intellectual Property Organization (WIPO), all of which are recognized for providing reliable and consistent data for policy analysis. WDI data are sourced from reputable institutions, utilize consistent indicators, and are harmonized according to international statistical standards. The most recent datasets available were used to ensure consistency throughout the analysis.

Similarly, OECD R&D statistics follow the Frascati Manual, which provides internationally agreed-upon definitions, classifications, and guidelines for the collection of R&D statistics, thereby ensuring comparability across countries and over time. WIPO data are based on standardized intellectual property definitions, multisource integration, and databases that utilize Patent Cooperation Treaty (PCT) filings and patent counts by priority year. These datasets also follow internationally recognized definitions, classifications, and data collection procedures designed to ensure cross-country comparability.

The integration of these data sources helps ensure consistency and facilitates more robust cross-country and longitudinal analyses. The remaining predictors included in this study, along with their measurements, definitions, and data sources, are presented in Table 1, while Equation (1) represents the specified model used in the analysis.

$$\text{lnECR} = f(\text{AI, GTI, lnRNDxPGDP, EPS}) \quad (1)$$

Table 1. Description and sources of data

Study variables	Economic meaning	Measure	Data origins
Renewable Energy Contribution Rate (lnECR)	Substitution toward renewables	$\text{ECR} = \frac{\textit{Renewable electricity output}}{\text{Total electricity output}} * 100$; log transformed	WDI (2025)
AI Patents (AI)	Innovation in AI technologies	Log-transformed annual count of AI-related patent publications in the U.S.	WIPO (2025)
Green Technology Innovation (GTI)	Stream of innovations tied to environmental protection	Yearly tally of patent families related to the environment (green tech innovations); log-transformed	OECD (2025)
GDP Per Capita (PGDP)	Level of economic development	per capita GDP (constant 2015 US$)	WDI (2025)
Research and Development expenditure (RND)	Investment in research and development	Gross domestic expenditures on R&D as % of GDP	WDI, NCSES (2025)
Interaction between R&D and Per Capita GDP (lnRNDxPGDP)	Moderating effect of economic development on R&D	$lnRNDxPGDP = ln(RND * PGDP)$	Self-interpretation
Environmental Policy Stringency Index (EPS)	Stringency of environmental regulations	OECD Environmental Policy Stringency Index (scale from 0 to 6)	OECD (2025)

3.2. Estimation Strategy

Our study begins its diagnostic testing by employing two types of unit root testing procedures to identify the integration dynamics of our predictors, which is crucial for deciding the suitable methodology and for identifying clean energy and innovation variables that may exhibit trends due to technological progress or policy intervention changes common in long-term data series. We employ the augmented Dickey-Fuller (ADF) test [57] and the Phillips–Perron (PP) test [58] to investigate the stationarity characteristics of each time series. The test of ADF is specified as follows in Equation 2:

$$\Delta y_t = \alpha + \beta y_{t-1} + \sum_{i=1}^{k} \phi_i \, \Delta y_{t-i} + \varepsilon_t \quad (2)$$

where, Δ denotes the operator for the first difference, k represents the optimal lag length, α is a constant term, β is the coefficient on the lagged level of y_t, ϕ_i are the lagged first differences, and ε_t is the error term. Our analysis follows the unit root analysis by employing the ARDL approach developed by Pesaran et al. (2001) [59] in order to analyze long-run equilibrium relationships among the selected variables. This has clear advantages for our analysis: it can accommodate mixed orders of integration, where variables can be I(0), I(1), or fractionally integrated without imposing uniform integration assumptions. It is, therefore, particularly useful for energy economics applications-our proposed contribution in a small-sample situation where other techniques, like VAR, require at least 50 observations. In addition, the ARDL framework controls endogeneity by including lagged values of the dependent and explanatory variables, which yields more efficient coefficient estimates if some of the explanatory variables are potentially correlated with the error term. We also conduct FMOLS, non-parametrically adjusting for endogeneity. The ARDL test is specified in Equation 3 as follows:

$$\Delta \text{lnECR}_t = \alpha_0 + \alpha_1 \text{lnECR}_{t-1} + \beta_1 \text{AI}_{t-1} + \beta_2 \text{GTI}_{t-1} + \beta_3 \text{lnRNDxPGDP}_{t-1} + \beta_4 \text{EPS}_{t-1} + \sum_{i=1}^{m} \gamma_1 \, \Delta \text{lnECR}_{t-i} + \sum_{i=1}^{m} \gamma_2 \, \Delta \text{AI}_{t-i} + \sum_{i=1}^{m} \gamma_3 \, \Delta \text{GTI}_{t-i} + \sum_{i=1}^{m} \gamma_4 \, \Delta \text{lnRNDxPGDP}_{t-i} + \sum_{i=1}^{m} \gamma_5 \, \Delta \text{EPS}_{t-i} + \varepsilon_t \quad (3)$$

where m represents the optimal lag length quantified by the information criterion α_i, β_i are long-run coefficients, γ_i are short-run dynamic coefficients, m is the maximum lag order, and Δ denotes the first difference operator. The error correction model (ECM) we have used to decompose short-run dynamics from long-run equilibrium relationships, as specified in Equation 4:

$$\Delta \text{lnECR}_t = \alpha_0 + \sum_{i=1}^{m} \gamma_1 \, \Delta \text{lnECR}_{t-i} + \sum_{i=1}^{m} \gamma_2 \, \Delta \text{AI}_{t-i} + \sum_{i=1}^{m} \gamma_3 \, \Delta \text{GTI}_{t-i} + \sum_{i=1}^{m} \gamma_4 \, \Delta \text{lnRNDxPGDP}_{t-i} + \sum_{i=1}^{m} \gamma_5 \, \Delta \text{EPS}_{t-i} + \lambda \text{ECT}_{t-1} + \varepsilon_t \quad (4)$$

where ECT_{t-1} denotes the error correction term derived from the long-run cointegrating relationship, and where λ captures the speed of adjustment toward long-run equilibrium. The coefficient of ECT should be negative and statistically significant, which denotes that deviations from equilibrium are corrected over time.

To test the asymmetric impact of AI innovation on ECR, we further decompose our analysis with the NARDL approach introduced by Shin et al. (2014) [60]. The methodology decomposes the AI variable into positive and negative partial sum components, thus allowing for differential responses to increases versus decreases in AI innovation. It also captures nonlinearities for most macroeconomic and financial applications in a helpful way of approximating the nonlinear mechanisms to underpin an empirical relationship [61]. The NARDL specification is presented in Equation 5:

$$\Delta \ln ECR_t = \alpha + \beta^+ AI_{t-1}^+ + \beta^- AI_{t-1}^- + \sum_{i=1}^{p-1} \phi_i \, \Delta \ln ECR_{t-i} + \sum_{i=0}^{q-1} \left(\pi_i^+ \Delta AI_{t-i}^+ + \pi_i^- \Delta AI_{t-i}^- \right) + \varepsilon_t \quad (5)$$

where AI_{t-1}^+ and AI_{t-1}^- represent positive and negative partial sums of changes in AI, respectively, defined as:

$$AI_t^+ = \sum_{j=1}^{t} \Delta AI_j^+ = \sum_{j=1}^{t} \max\left(\Delta AI_j, 0\right) \quad (6)$$

$$AI_t^- = \sum_{j=1}^{t} \Delta AI_j^- = \sum_{j=1}^{t} \min\left(\Delta AI_j, 0\right) \quad (7)$$

Finally, our analysis includes the cumulative sum (CUSUM) stability test of Brown et al. (1975) [62] to test the consistency of parameters over the sample period. This technique tests the stability of the estimated coefficients in different sub-periods, making it a crucial assessment for confirming the reliability of our policy recommendations. The CUSUM statistic is calculated based on Equation 8:

$$W_t = \sum_{k=m+1}^{t} \frac{u_k}{\sigma} \quad (8)$$

where u_k represents standardized residuals, and σ is the standard error. We further elaborated our strategy that can also capture any latent causality. To do this, we have employed the Toda-Yamamoto (TY) Granger causality [63] test based on a VAR model, which is specifically designed for small samples. The core estimation strategy for our research is shown in Figure 1.

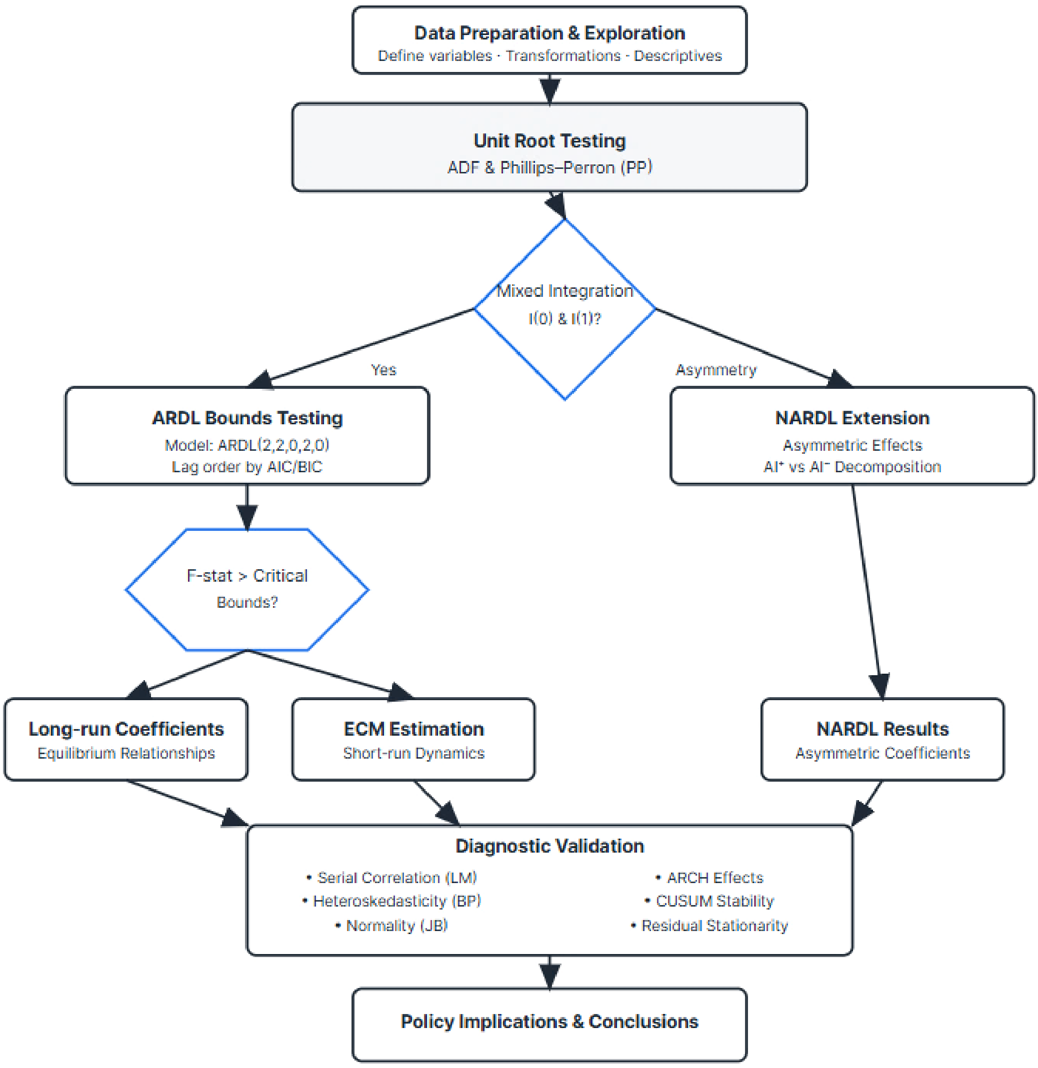

Figure 1. Empirical Workflow

4. Results and Discussion

Table 2 presents the descriptive statistics, which capture most of the variability in the main variables over the 1990–2022 period. The variable lnECR reflects the moderate energy transition trajectory of the United States, ranging from 2.005 to 3.009, with a mean value of 2.456 and a standard deviation (S.D.) of 0.273. The positive skewness of 0.745 suggests that renewable energy transitions accelerated in the later years of the sample period, consistent with the clean energy transition gaining momentum over time. AI exhibits remarkable growth patterns, with a mean value of 8.837 and an S.D. of 1.258, accompanied by a notable negative skewness of −0.630. This indicates an accelerated growth trajectory that aligns with the well-documented AI boom beginning around 2010. In contrast, GTI shows moderate variability around a mean of 19.547 patents, with an S.D. of 8.938, indicating a steady flow of innovation that differs from the more rapid acceleration observed in AI development. The near-zero skewness value of 0.026 suggests a relatively symmetric distribution over time. The interaction term lnRNDxPGDP has a mean value of 1.943 and an S.D. of 0.208, while EPS has an average value of 1.818 with an S.D. of 0.775, ranging from 0.833 to 3.028. The positive skewness observed for both variables reflects the gradual strengthening of environmental policies and R&D intensity throughout the sample period.

Table 2. Descriptive statistics

Predictors	mean	S.D.	min	max	skewness	kurtosis
lnECR	2.456	0.273	2.005	3.009	0.745	2.500
AI	8.837	1.258	6.593	10.119	-0.630	1.787
GTI	19.547	8.938	7.624	34.379	0.026	1.512
lnRNDxPGDP	1.943	0.208	1.678	2.451	0.936	3.033
EPS	1.818	0.775	0.833	3.028	0.387	1.579
Observations = 33						

The time series plots in Figure 2 also display some distinct temporal patterns where we see that the lnECR increases overall, with a steep fluctuation in 2005 and further acceleration after 2015. This oscillating phenomenon is consistent with the major renewable energy policy initiatives such as the American Recovery and Reinvestment Act and subsequent Clean Power Plan implementations. AI innovation exhibits the expected exponential growth with a modest increase until 2010 and then rapid acceleration. It reflects the current revolution in AI innovation with breakthroughs in machine learning and improvements in computing power. However, GTI is seeing much more volatility, with cyclical ups and downs, but an overall increasing trend with some periodical spikes that are likely to be related to major environmental policy initiatives and international climate agreements. The interaction term, lnRNDxPGDP, increases steadily over time, which implies that R&D investments are increasing along with economic growth. Also, the EPS shows stepwise increases consistent with major environmental legislation periods, around 2005-2010 and 2015-2020. Figure 3 presents a correlation heatmap emphasizing the most important relationships and pointing out several critical econometric considerations. The interdependencies among the predictors are complex, thus justifying our multivariate approach; while the correlations point to potential multicollinearity issues that we address by the VIF analysis in Table 3, which also shows the correlations are within acceptable bounds for ARDL estimation. The mean VIF of 6.41 indicates that there is some degree of multicollinearity that does not substantially affect our results [64, 65].

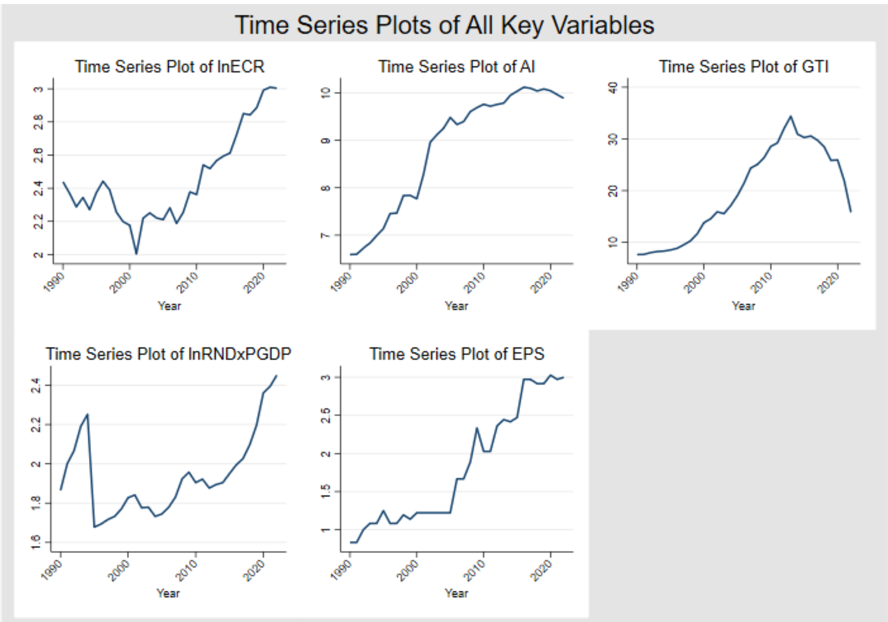

Figure 2. Time series plots

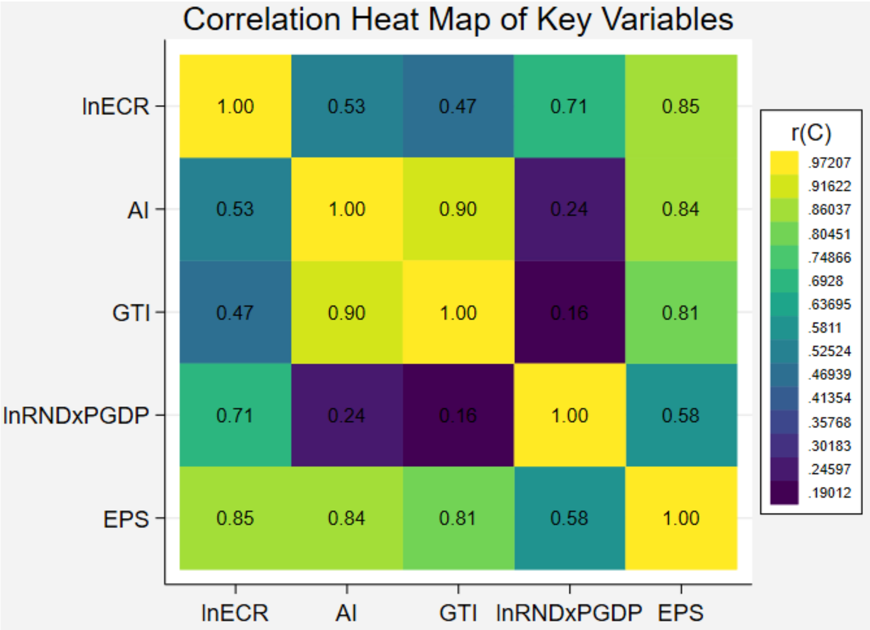

Figure 3. Correlation heatmap

Table 3. VIF results

Variable	VIF	1/VIF
EPS	8.99	0.111237
AI	7.11	0.140564
GTI	6.8	0.146982
lnRNDxPGDP	2.72	0.367096
Mean VIF	6.41	

Table 4 shows the results of the unit root test, which confirms our approach of ARDL bounds testing since it indicates that the variables have mixed integration properties. The ADF and Phillips-Perron test results indicate that all predictors are nonstationary in levels but become stationary after first differencing, thus confirming normal I(1) integrations characteristic of economic time series, which often exhibit trending patterns. These mixed orders of integration therefore justify the application of the ARDL approach, which can be applicable for the predictors with different integration properties and does not necessarily need the data to be uniformly stationary. This is further reflected in Table 5, where the ARDL (2,2,0,2,0) specification is identified as the best trade-off between explanation and parsimony. Model selection criteria reflect this specification to have the lowest AIC of -89.725 and a reasonable BIC of -73.952, respectively, based on 31 observations. Comparisons across alternative lag structures confirm that the chosen model effectively captures the dynamic association without any overfitting.

Table 4. Unit Root Test Results

Variables	ADF (Level)	ADF (First Diff.)	PP (Level)	PP (First Diff.)
lnECR	-1.743	-6.668***	-1.668	-6.833***
AI	0.062	-4.779***	0.049	-4.744***
GTI	2.711	-2.435***	1.726	-2.261***
lnRNDxPGDP	-1.326***	-5.536***	-1.349***	-5.752***
EPS	-2.327	-6.425***	-2.244	-6.641***

Note: ***, **, and * refer to significant levels (1%, 5%, and 10% levels), respectively.

Table 5. Model selection criteria

Model	Obs.	Log-likelihood	AIC	BIC	R^2	Adj. R^2	RMSE
ARDL(1,0,0,0,0)	32	40.842	-69.684	-60.889	0.388	0.270	0.075
ARDL(2,2,0,2,0)*	31	55.863	-89.725	-73.952	0.786	0.678	0.05
ARDL(2,3,0,3,0)	30	57.638	-89.276	-71.061	0.829	0.708	0.047

* Model selected on the basis of the AIC and BIC.

Table 6 presents the core ARDL estimation results, with the long-run coefficients illustrating the relationships among innovation, policy variables, and renewable energy contribution. In particular, the coefficient of AI is −0.07 and statistically insignificant, contrary to expectations of an immediate positive aggregate effect of AI on the clean energy transition. This insignificant result may indicate that AI innovation contributes to the clean energy transition through indirect channels and with considerable deployment lags, requiring complementary investments in grid modernization, energy efficiency improvements, and smart-system integration. This interpretation is consistent with emerging evidence, including Fang et al. (2025) [66], who demonstrate that state-level AI development provides immediate benefits for the transition toward clean energy and moderates the effects of economic policy uncertainty.

Practical applications, such as those implemented by the California Independent System Operator (CAISO), have employed AI-powered probabilistic solar forecasting to improve system reliability and energy efficiency [67]. Zhao et al. (2024) [20] also provided evidence that sector-wide AI adoption can accelerate renewable energy transitions and related adaptations. These findings imply that, although the immediate effect may be limited, AI has considerable latent potential to displace fossil fuel-based systems and accelerate the clean energy transition. Realizing this potential will require policymakers to provide enabling conditions through targeted infrastructure investments and appropriately designed policy frameworks.

However, the coefficient of GTI is small and statistically insignificant at 0.009. This suggests that green technology innovation alone may not be sufficient to increase lnECR, which is consistent with the broader innovation-systems literature documenting weak linkages between patents and commercialization, as noted by Iqbal et al. (2021) [3]. This finding challenges the conventional assumption of a direct relationship between green innovation and clean energy deployment and indicates that patent-based measures may not adequately reflect actual implementation and deployment activities. In contrast, the coefficient of the interaction term lnRNDxPGDP is 0.910, which is positive and statistically significant at the 10% level. This finding shows that the underlying level of economic development is an important determinant of how effectively R&D expenditure translates into renewable electricity output.

In other words, R&D investments may generate substantially higher returns in economies with stronger economic fundamentals. This result is also consistent with Ziesemer (2025) [52], who identifies CES spillover effects of R&D in OECD countries through the interaction of private R&D in promoting firm-level endogenous growth. The positive effect of R&D further supports the earlier argument based on endogenous growth theory, which emphasizes that coordinated policies can combine research investment with the capacity to absorb and deploy technology effectively.

The coefficient of the EPS stands at 0.483 and is significant at the 1% level, and it confirms that stringency in environmental regulation is indeed one of the critical drivers of clean energy transitions. With this magnitude, it also reports that a one-unit change in policy stringency corresponds to a renewable energy contribution rate that is approximately exp(0.483) –1 or 62% higher in the long run, also underlining the impactful role of regulatory frameworks in making the transition to clean energy possible. This finding perfectly aligns with the study of Deschenes et al. (2023) [68], where they proposed an average 44% increase in clean electricity with the help of wind-related technologies by employing the right renewable policies. Haseeb et al. (2025) [69] reported that to achieve SDG 7, which is to be able to afford clean energy, the U.S. needs to utilize the benefits of EPS and increase the consumption of cleaner fuels and energy. Moreover, the error correction term (ECT) coefficient of -0.288, which is statistically significant at the 1% level, confirms that the long-term equilibrium relationship is stable.

The short-term dynamics of the coefficient of AI show positive and highly significant results in both lags. This shows the immediate optimization benefit of AI innovation, which points toward the immediate optimization benefits that dissipate in the long-run equilibrium, without sustained complementary investments. Nevertheless, when it reaches its full potential, it has the potential to yield the most positive benefits for clean energy, as has also been observed in long-term findings. However, our interaction term, lnRNDxPGDP, showed short-term adverse effects but provided evidence of significant long-term benefits. The ARDL bounds test results in Table 7 provide evidence for long-run cointegration relationships among our chosen predictors. The F statistic of 11.028 substantially exceeds the upper critical bounds at all conventional significance levels (10%, 5%, and 1%), confirming the existence of a stable long-run equilibrium relationship. The corresponding t statistic of -2.592 provides additional support for long-run cointegration. However, it falls between the I(0) and I(1) bounds and is consistent with the mixed integration properties.

Table 6. ARDL estimation results

Dependent Variable: Energy Contribution Rate (lnECR)	
Long-Run Relationships	**Coefficients**
AI	-0.07
GTI	0.009
lnRNDxPGDP	0.910*
EPS	0.483***
Short-Run Dynamics	Coefficients
ΔlnECR(-1)	-0.339**
ΔAI	0.067
ΔAI(-1)	0.287***
Δ(lnRNDxPGDP)	-0.265***
Δ(lnRNDxPGDP)(-1)	-0.389***
Constant	0.072
Model Statistics	
Observations	31
R²	0.786
Adjusted R²	0.678
ECT(-1)	-0.288***
Log Likelihood	55.863
Root MSE	0.05

*Note: ***, **, and * refer to significant levels (1%, 5%, and 10% levels), respectively.*

Table 7. ARDL bounds test for long-term relationships

Test Statistic	Value	10% Critical Bounds		5% Critical Bounds		1% Critical Bounds		p value (I(0))	p value (I(1))
		I(0)	I(1)	I(0)	I(1)	I(0)	I(1)		
F-statistic	11.028	2.730	4.103	3.377	4.971	5.003	7.138	0.000	0.001
t-statistic	-2.592	-2.509	-3.632	-2.895	-4.091	-3.700	-5.049	0.087	0.352

The diagnostic tests of ARDL, shown in Table 8, confirm the reliability and robustness of the chosen specification. From there, we have seen that the Breusch-Godfrey LM test gives $\chi^2(2) = 3.640$ with a p value of 0.162, showing that no significant serial correlation exists in the residuals. The Breusch-Pagan test for heteroskedasticity has $\chi^2(1) = 1.00$ with a p value of 0.317, suggesting homoskedastic error terms. The joint skewness-kurtosis test for normality provides a $\chi^2(2) = 3.43$ with a p value of 0.180, indicating the residuals are normally distributed. The ARCH-LM test is passed at the p value of 0.212, revealing no significant conditional heteroskedasticity. Most importantly, the unit root test on residuals gives a Z(t) of -4.548 with a p value less than 0.01, confirming the stationarity of the residuals and therefore the cointegration relationship among the predictors. The foregoing diagnostic results collectively point to the fact that the specification of the model is convincing and that the coefficient estimates are reliable. The CUSUM stability test, using CUSUM6 and the custom CUSUM plots in Figures 4 and 5, generally suggests that parameters are stable over most of the sample period. During this period, the CUSUM statistic stays within the 5% critical bounds. A slight deviation occurs toward the end of the sample period and may reflect the increasingly volatile renewable energy markets and policy environments in recent years, especially from 2020-2022, related to the COVID-19 disruptions and accelerated climate policy initiatives.

Table 8. Postestimation diagnostic tests

Diagnostic Test	Test Statistic	p value	Remarks
Serial Correlation (Breusch-Godfrey LM)	$\chi^2(2) = 3.640$	0.162	No serial correlation
Heteroskedasticity (Breusch–Pagan)	$\chi^2(1) = 1.00$	0.317	Homoscedastic errors
Normality (Skewness-Kurtosis)	$\chi^2(2) = 3.43$	0.180	Normally distributed residuals
ARCH Effects (LM test)	$\chi^2(1) = 1.560$	0.212	No conditional heteroskedasticity
Unit Root in Residuals (ADF)	Z(t) = -4.548	<0.01	Stationary residuals (cointegration confirmed)

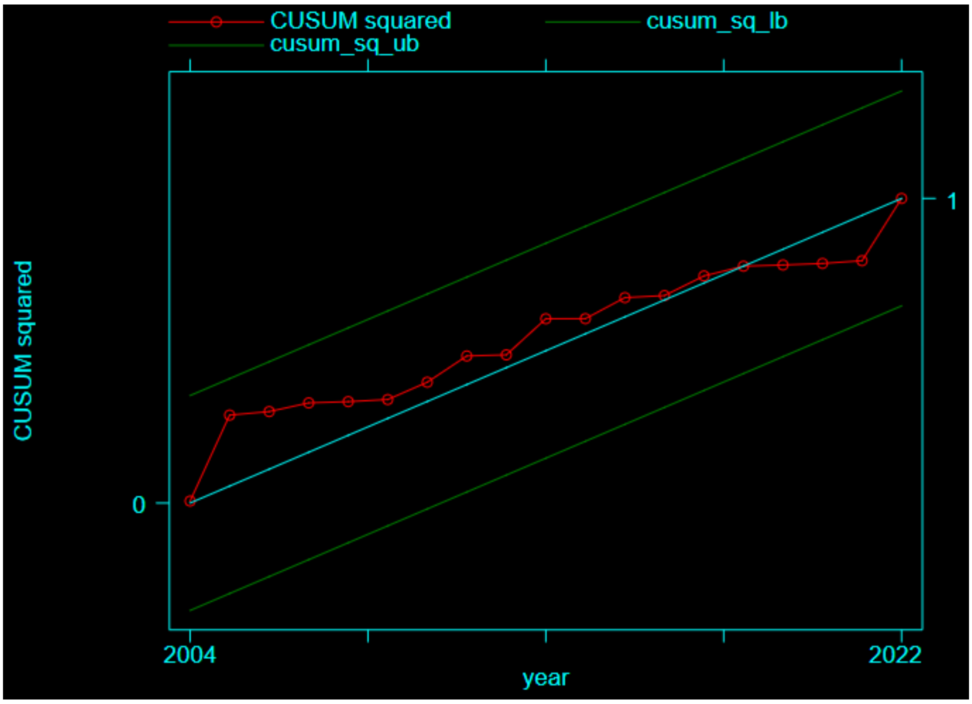

Figure 4. Model stability test via the 'CUSUM6'

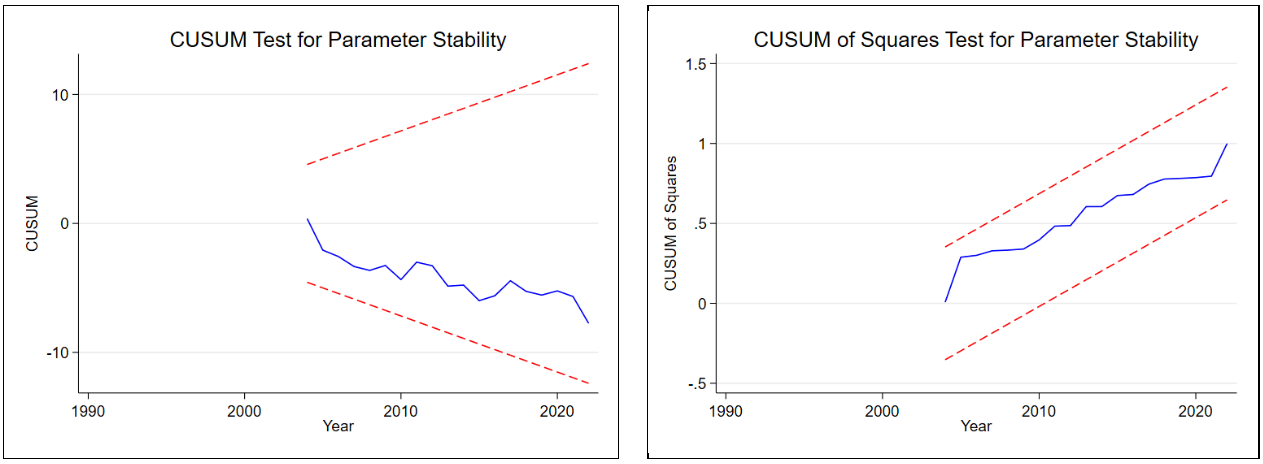

Figure 5. CUSUM and CUSUMQ plots for parameter stability

To investigate the potential asymmetric effects of AI innovation on ECR, we proceed to the NARDL methodology. It is specifically designed to collect different responses to positive and negative changes in AI innovation. The positive AI shocks (lnAI_pos) have a coefficient of -0.0815, which is statistically insignificant, and suggest that the increases in AI innovation do not significantly increase ECR in the long run when considered in isolation. On the other hand, negative AI shocks (lnAI_neg) have shown a positive score of 0.6569 at the 10% significance level. This type of counterintuitive finding is particularly aligned with the verdicts of the study conducted by Tian et al. (2024) [70], who showed that renewable energy development is prone to negative shocks rather than positive shocks. This is because slowing down the development of AI technologies can impact the development of new energy technologies through reduced rates and efficiency. That, in turn, affects the creation and deployment of clean technologies and hampers the growth of the clean energy sector.

This finding also suggests that the consequences of AI for clean energy depend on the direction of change, with adverse AI shocks potentially creating opportunities for alternative renewable energy pathways. This is because when AI activity contracts, the disruption of the AI-intensive trajectory can relax resource and attention constraints and allow capital, policy focus, and complementary innovation to shift toward non-AI-intensive renewable options, which is consistent with ideas from the technological transition and innovation portfolio literature [71]. Policymakers should consider broader innovation ecosystems in the development of policies for AI and renewable energy. In such systems, both non-AI and AI components have the potential to contribute on an equal footing, so policy must not lean solely on AI but also encourage other clean technologies. Theoretically, resource competition and dynamics in innovation ecosystems can explain asymmetric NARDL results. For example, when there is a negative shock to the investment in AI, some research funding and skilled talent previously focused on the development of AI can be shifted to other renewable energy technologies. This can create a "resource spillover effect, in which reduced competition for researchers, venture capital, and R&D budgets allows greater emphasis on the innovation and deployment of renewable energy [72]. Conversely, positive AI shocks may create resource crowding-out effects, where the AI sector attracts funding and expertise away from renewable energy projects, temporarily slowing the progress of clean energy until complementarities between AI and renewable systems are fully realized [73].

The dynamics of the short-run NARDL are complex, with significant coefficients of both positive and negative AI shocks at various lags. While the first lag of positive AI shocks and the first lag of negative AI shocks yield positive coefficients significant at the 1% level and at the 10% level, respectively, these alternating effects suggest that positive AI innovations have oscillating short-term impacts on renewable energy systems-a reflection of cycles of technology diffusion, adjustment costs, and reallocation benefits that eventually require additional investment in innovation. However, the second lag of the positive shock gives a negative coefficient of -0.2235, and the negative shock has a coefficient of -1.0054, and both are statistically significant at the 5% level. Magnitudes are consistent, indicating that negative AI shocks have significant, persistent effects on renewable energy systems, supporting our interpretation that AI and traditional renewable energy technologies might compete for resources and attention within innovation ecosystems. The explanatory power of this estimated NARDL model is superior, with an R-squared of 0.9759 and an adjusted R-squared of 0.9683, much higher than the linear specification in ARDL, which is an R-squared of 0.786. The added value of accounting for asymmetric effects has again improved knowledge of the AI-renewable energy relationship. The root mean squared error is lower at 0.0537 compared to that of the linear specification, indicating an improved predictive accuracy (see Table 9).

Table 9. NARDL Estimates

Variable	Coefficient
Long-run estimates	
ECT (-1)	-0.5796***
lnAI_pos	-0.0815
lnAI_neg	0.6569*
lnAI_asym	-0.7384*
Short-run dynamics	
lnECR (-1)	0.5796***
lnECR (-2)	0.3253**
lnAI_pos (-1)	0.2708***
lnAI_pos (-2)	-0.2235**
lnAI_neg (-1)	0.6247*
lnAI_neg (-2)	-1.0054**
Model diagnostic	
Sample Period	1990-2022
Number of Observations	31
Specification	ARDL(2,0,0,0,2,2)
AIC	-70.48
R-squared	0.9759
Adjusted R-squared	0.9683
Log Likelihood	43.24
Root MSE	0.0537

Note: ***, **, and * refer to significant levels (1%, 5%, and 10% levels), respectively.

These results are free from any measurement bias and lag effects, as the selected lag specification has the lowest AIC values and is also validated through the RESET test, which gives an F-statistic of 0.7753 and a p value of 0.3889, thus confirming the correct functional form. Furthermore, the Breusch-Pagan LM test, as reported in Table 10, generates a statistic of 0.2553 with a p value of 0.6132, which indicates no problem of serial correlation. The asymmetry coefficient (lnAI_asym) of -0.7384 is statistically significant at 10%, formally confirming that the relationships between AI innovation and renewable energy transitions are asymmetrical. The ECT coefficient of -0.5796 is highly significant at the 1% level of significance, reflecting that the adjustment speed is about 58% per period, which is much faster compared to the linear ARDL model. Therefore, this means that asymmetric models better capture the adjustment dynamics in renewable energy markets, where the responses against positive and negative shocks may have different channels of transmission. The Wald test for asymmetry yields a statistic of 3.049, which is significant at the 10% level, thereby formally confirming the existence of asymmetric effects and justifying the innovation of the nonlinear specification. The ARCH test results in a statistic of 0.4387 with a p value of 0.5075, indicating the absence of heteroskedasticity concerns. Finally, the normality test indicates a χ^2 statistic of 1.8725 with a p value of 0.3921, confirming that the residuals follow a normal distribution. The bound test of NARDL, as shown in Table A1, confirms strong evidence of a long-run equilibrium relationship, as the value of the F statistic, 11.028, exceeds every percentage of the critical bounds scores, suggesting strong cointegration.

Table 10. Diagnostic test of the NARDL model

Test	Statistic	p value	Conclusion
Wald Test for Asymmetry	3.049	0.097	Asymmetry is statistically significant at the 10% level
ARCH Test	LM = 0.4387	0.5075	No heteroskedasticity
RESET Test	F = 0.7753	0.3889	Correct functional form
LM Serial Correlation	LM = 0.2553	0.6132	No serial correlation
Normality Test	χ^2 = 1.8725	0.3921	Residuals are normally distributed

However, to verify the reliability of our ARDL long-run estimates and address potential endogeneity concerns through alternative econometric approaches, we employ FMOLS and obtain similar results from the table shown in Table A2, which aligns with our verdicts and suppresses endogeneity concerns through nonparametric adjustments to OLS standard errors. The nearly identical magnitudes of AI and continued statistical insignificance validate our interpretation that the impact of AI operates through asymmetric channels that require NARDL decomposition rather than uniform linear effects. For the remaining variables, GTI shows a borderline significant positive effect, but we have seen that the impact has been lost in the long-run ARDL situation. The coefficient power of the interaction term has decreased, but is still positive. Most importantly, FMOLS of EPS is highly robust compared with ARDL, at 0.492 against 0.483, both at the 1% significance level, indicating that policy needs to be strengthened to reach a green and sustainable economy. The Toda-Yamamoto Granger causality tests reported in Table A3 provide evidence for three directions of causality for renewable electricity contributions. There is unidirectional causality from the interaction term to lnECR in accordance with endogenous growth theory, whereby R&D decisions are determined prior to output realizations. In contrast, AI presents a bidirectional relationship through TY causality analysis, supporting the so-called innovation allocation dilemma wherein priority is not given to the innovations with the greatest potential.

5. Conclusion

This study provides evidence-based insights into strengthening the ECR through various innovations and policy approaches in the United States. It offers a comparative assessment of the effects of AI, GTI, GDP-supported R&D, and EPS on ECR enhancement. The 33-year time-series analysis reveals that per capita R&D has a strong and statistically significant positive effect on ECR, with a long-run coefficient of 0.91 at the 10% significance level. This finding implies that, in the long run, increases in per capita R&D can lead to substantial and promising improvements in the contribution of renewable electricity, provided that U.S. GDP continues to support the required budgetary allocations.

Similarly, EPS has a significant positive effect at the 1% significance level. The recent U.S. federal budget has also highlighted the important role of environmental policy in promoting clean energy innovation and the effectiveness of government spending in supporting the transition to renewable energy. The Inflation Reduction Act has maintained a portfolio investment of $369 billion and continued to provide tax incentives for solar, wind, and battery technologies, with the aim of achieving meaningful gains in renewable energy output.

The positive effects of AI-based innovation and optimization can generate measurable efficiency improvements that contribute substantially to national electricity grids. However, the small and statistically insignificant effect of GTI presents a dilemma regarding the allocation of the U.S. budget toward innovations that can deliver tangible long-term benefits. Moreover, the oscillating effect of AI observed in the NARDL results may be explained by the absence of sufficient complementary measures to support AI deployment. Nevertheless, the overall impact of AI suggests substantial untapped potential for AI-enabled optimization in renewable energy systems, indicating that AI innovations can generate rapid, although fluctuating, improvements in renewable electricity contribution.

5.1. Policy Implications and Recommendations

Prioritizing federal R&D investment by restructuring governmental expenditures: As our investigation revealed that R&D investments can significantly contribute to transitioning, the federal government should prioritize targeted R&D investment as a means to increase the maximum energy contribution rate. However, Trump’s 2026 plan to reduce R&D expenditures could be a contradictory policy approach to these benefits in the energy transition [5].

Instead, the Trump administration should revise the policy and expand R&D investment for the upcoming years because even other options of different innovations may not guarantee maximum effects. The targeted R&D-based interventions should focus on system integration, grid optimization, and deployment acceleration to maximize the potential for the longer term. Our research findings also suggest that EPS and R&D have positive effects on ECR in the longer term, which is why the federal government should restructure governmental expenditures for renewable energy deployment and emphasize research-based mechanisms more. Although these expenditures can provide short-term results, they may crowd out private sector investment, which would not be beneficial for the country [74]. Instead, market-based and research-based mechanisms such as production tax credits, investment tax credits, and competitive grant programs can leverage private sector investment [19] and avoid crowding-out effects.

Accelerate AI innovation and rebalance policies: On the basis of our results, AI has the untapped and unrealized potential to increase ECR. However, targeted policy interventions are necessary to achieve greater and practical outcomes in this case. Federal agencies can implement tax incentive programs for AI innovation among renewable energy companies, which can also ensure the potential optimization benefits [75] and ensure enhanced contributions to ECR. The Department of Energy should also establish sector-specific roadmaps for the innovation of AI into renewable energy systems. As green technology patents have minimal and steady effects, the federal government should shift its emphasis away from green technology patents to increase renewable electricity contributions. The U.S., which holds the second-largest number of green patents, may not ensure its leadership in energy efficiency [76]. The focus should be on optimization and system integration capabilities. Policies can prioritize R&D investments to make innovations capable of directly assessing challenges through integrated R&D strategies with strict environmental policies. The government should provide rewards for innovations on the basis of actual deployment success and improvements in the ECR.

Emphasize long-term strategic frameworks: The findings demonstrated persistent R&D effects over a long-term period. Even if it sustains its effectiveness for ECR over extended periods, the Federal government should emphasize long-term strategic policy reconstruction, integrating policies such as R&D. The federal government can establish a renewable energy trust fund to ensure the consistency of outputs over a long period and create a roadmap for achieving ECR through tailored strategies for the renewable energy transition.

5.2. Limitations and Future Research Directions

Our study has several limitations. First, the study employs aggregate national relationships, and there may be sectoral heterogeneity in the deployment patterns of renewable energy, AI integration, and green patent applications. This heterogeneity made it challenging to depict sector-specific results. Second, focusing solely on national-level data obscures the actual analysis results, as it does not consider the distributional effects from states, regions, and utilities. Considering the distributional effects can be important for policymakers, as they may help them understand the actual scenario for appropriate R&D investments. Third, AI's true contribution may also obscure actual benefits to ECR. For example, some AI applications, even without being patented, can still drive high efficiency and energy contribution enhancements by underestimating accurate ECR counts through AI integration. Although stability analysis depicted the robustness of the relationships in earlier shocks and economic disruptions, there is no guarantee that different innovation pathways can sustain this stability in future shocks that fundamentally alter system dynamics.

Our findings explore several research priorities but limit direct generalizability to other advanced economies. This is because U.S. energy policy operates across 50 state regulatory regimes with heterogeneous renewable portfolio standards (RPS) as well as diverse siting, permitting, and interconnection rules, but there are still gaps in adopting these standards statewide. For example, California mandates 100% clean electricity by 2045, but Wyoming has no RPS [77]. This fragmentation creates deployment bottlenecks, which justifies the minimal impact of GTI despite enormous investments and is a potential factor for the innovation paradox. However, the innovation allocation dilemma is a general challenge in energy transitions, with country-specific manifestations that depend on the characteristics of each innovation system. Other countries, such as those in the EU, Japan, and China, have responded more quickly to this issue than the U.S. Germany's centralized Energiewende policies enable faster patent commercialization, and Olbrich et al. (2024) [4] document that German green patents achieve commercial deployment 2.3 years faster than U.S. equivalents do. They also showed that Germany's feed-in tariff system (2000-2020) achieved 55% renewable electricity, primarily through direct price support. Japan received just 3% of public R&D GDP annually but achieved 22% renewable electricity by 2023, despite having lower patent counts than the U.S. [78]. China is also in the lead in transitioning to a clean energy system, with its centralized deployment mandated and benefiting from its innovations.

Future research can examine the optimal design of per capita R&D funding mechanisms to help compare the effectiveness of basic research with that of applied development programs. Future policy research should also examine the cost-effectiveness of different ECR enhancement strategies by forecasting their impacts under pre- and post-budget-cut scenarios before any major policy changes are implemented. These types of research can provide policymakers with insights into allocating budgets in accordance with their priorities. Additionally, the political economy can explore and investigate the implementation barriers to rebalancing innovation portfolios. Moreover, research on federal-state policy coordination can help optimize multilevel governance approaches to increase ECR.

6. Declarations

6.1. Author Contributions

Conceptualization, M.E.A., M.F.I., and C.A.G.; methodology, M.E.A., M.Z.H., C.A.H.G., and M.F.I.; software, C.A.G. and M.Z.H.; validation, J.P. and M.F.I.; formal analysis, M.F.I., M.E.A., C.A.G., M.Z.H., and C.A.H.G.; investigation, J.P., C.A.H.G., and M.F.I.; resources, J.P. and M.F.I.; data curation, M.E.A., C.A.G., C.A.H.G., and M.Z.H.; writing—original draft preparation, M.E.A., and M.F.I.; writing—review and editing, J.P. and M.F.I.; visualization, C.A.G. and C.A.H.G.; supervision, J.P.; project administration, M.E.A. and M.F.I.; funding acquisition, M.F.I. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that there are no conflicts of interest concerning the publication of this manuscript. Furthermore, all ethical considerations, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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Appendix I

Table A1. Bound test of NARDL

Test Statistic	Value	10% Critical Bounds		5% Critical Bounds		1% Critical Bounds	
		I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
F-statistic	11.028	2.73	4.103	3.377	4.971	5.003	7.138

Table A2. Robustness check with FMOLS

Variable	FMOLS Coefficient	FMOLS Std. Err.
AI	-0.088	0.031
GTI	0.008*	0.004
lnRNDxPGDP	0.128	0.114
EPS	0.492***	0.056
cons	2.284***	0.309

Note: ***, **, and * refer to significant levels (1%, 5%, and 10% levels), respectively.

Table A3. Granger Causality Check

Direction	Statistic	p value	Has Causality
AI → lnECR	18.42***	0.000	Yes
GTI → lnECR	3.24	0.198	No
lnRNDxPGDP → lnECR	18.37***	0.000	Yes
EPS → lnECR	0.57	0.753	No
lnECR → AI	7.85**	0.020	Yes
lnECR → GTI	1.62	0.446	No
lnECR → lnRNDxPGDP	0.61	0.738	No
lnECR → EPS	2.47	0.291	No

Note: ***, **, and * refer to significant levels (1%, 5%, and 10% levels), respectively.