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Drivers of Renewable Energy Adoption: Assessing the Role of Artificial Intelligence and Climate Finance in High-Income Economies

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Abstract

Renewable energy adoption (RNE) has become a worldwide concern owing to its fundamental role in achieving environmental goals. The literature has suggested diverse factors that can influence RNE. However, the role of artificial intelligence (AI) and climate finance in shaping RNE has received little attention. This research examines the role of AI and climate finance in shaping renewable energy, utilizing panel data from 29 high-income countries from 2000 to 2020. The empirical analysis is conducted using panel data estimators such as fixed and effects models and the system generalized method of moments. Moreover, the method of moments quantile regression is used to assess the nonlinear effects of AI on RNE. The results are estimated using Stata software. The empirical outcomes indicate that AI exerts a positive influence on renewable energy. This finding implies that AI initiatives can trigger efforts toward the renewable energy transition. Moreover, the results demonstrate that the marginal effects of AI on RNE vary across different levels of AI. Similarly, climate finance also positively and significantly contributes to renewable energy. Finally, the empirical outcomes demonstrate that climate finance moderates the role of AI in RNE. Policymakers need to focus on AI integration in renewable energy systems by prioritizing climate finance availability in AI applications that support renewable energy development.

Keywords: Renewable energy adoption, artificial intelligence, climate finance, trade activity, industry development.

1. Introduction

The world energy landscape has been going through a significant transformation during recent decades. It is driven by climate concerns, technological changes, and evolving energy policy frameworks (International Energy Agency, 2024). The transition toward renewable energy sources has become a fundamental strategy to achieve carbon neutrality and sustainable development goals. This transition has been particularly noticeable among high-income countries, which have shown a leading role in implementing advanced technologies and comprehensive policy frameworks to enhance renewable energy adoption (Mazhar et al., 2025).

It remains fundamental to understand the contribution of modern technological advances, such as artificial intelligence (AI), in renewable energy adoption (RNE). The advent of AI in recent years has been playing a crucial role in transforming numerous sectors, improving the efficiency, reliability, and sustainability of energy systems. The use of AI in the renewable energy sector helps to optimize renewable energy systems by improving forecasting, efficiency, and grid integration, supporting sustainable transition (Algburi et al., 2025; Li et al., 2025). Moreover, integrating AI technologies into renewable energy systems can resolve certain challenges linked to renewable energy deployment, such as intermittency, grid stability, and resource optimization (Ukoba et al., 2024).

In effect, integrating AI into the renewable energy sector is referred to as a regime shift in energy systems. It improves energy system conceptualization, management, and optimization. Moreover, machine learning algorithms help to manage energy demand forecasting and real-time grid balancing. In this way, AI overcomes key barriers that have historically hindered renewable energy penetration (Wang et al., 2025). Moreover, AI-linked optimization tools help to manage efficient resource allocation, improve system reliability, and reduce operational costs.

Although the studies have recommended the promising role of AI in supporting renewable energy transition, the empirical understanding of this relationship remains limited. The extant literature mainly focuses on country-specific experiences, which provide a limited understanding. Moreover, the country-specific case studies provide conflicting outcomes, which necessitate a broader understanding. For instance, Qin (2024) conducted an empirical analysis for China using monthly data over the period 2013-2023 and found the positive influence of AI on renewable energy. However, Qin (2024) also showed the negative influence of AI on renewable energy. This research gap is particularly important in the context of high-income countries, where both AI capabilities and renewable energy infrastructure have reached a sufficient level.

Meanwhile, the role of climate finance is also critical in shaping renewable energy adoption. The studies of AI and renewable energy overlooked the role of climate finance. Climate finance promotes renewable energy by lowering the cost of capital for renewable energy finance. It is considered an important financial innovation that improves energy efficiency and facilitates pathways to renewable energy adoption (Briera & Lefèvre, 2024). The existing studies, such as Aquilas & Atemnkeng (2022) and Borojo et al. (2024), demonstrated the favorable role of climate finance in renewable energy adoption, but these studies did not model the crucial role of AI in determining RNE.

This study contributes to the extant literature in the following distinct ways. First, the existing research on the role of AI in renewable energy has mainly focused on country-specific case studies, which provide a limited understanding. In contrast, this study focuses on high-income countries and provides broader findings that are not only useful for technologically advanced economies (Mazhar et al., 2025) but also provide insights for the rest of the world. Besides, high-income countries have upfront capital, advanced digital infrastructure, and skilled labor forces, which are necessary to harness the advantages of AI integration in energy systems. Second, this study allows heterogeneous experiences of sampled economies by allowing non-linear effects of AI on renewable energy, depending upon the diverse exposure of economies to renewable energy adoption. Third, unlike prior studies, which consider the role of financial development in renewable energy, the present research considers the role of climate finance, which is a more direct and accurate measure of the role of finance in supporting renewables.

An empirical analysis of the effects of AI on renewable energy adoption is crucial for the following reasons. First, the analysis will provide insights into the mechanisms through which technological innovation can accelerate sustainable energy transitions. Second, it will provide valuable guidance for developing countries seeking to leverage technological leapfrogging opportunities in their energy transitions. This study extends the empirical literature on renewable energy in the following ways. First, it provides the first comprehensive empirical analysis of the AI-renewable energy relationship using cross-country panel data for high-income countries. Second, this study models the role of climate finance along with AI, which has been ignored in past literature. Third, this study investigates the moderating role of climate finance and AI in influencing renewable energy. Finally, this study explores the heterogeneous effects of AI on renewable energy across diverse levels of existing renewable energy adoption in sampled economies.

The study is useful as it offers direct policy relevance for both academic understanding and policy practice. From an academic perspective, the study advances knowledge on the role of general-purpose technologies in facilitating energy transition. From a policy perspective, it provides evidence-based guidance for policymakers seeking to design integrated strategies that harness AI's potential to accelerate REN. Particularly, this study highlights the importance of an integrated policy framework instead of siloed policy choice by highlighting the moderating role of climate finance in AI applications to support efficient and optimized energy systems.

2. Literature Review

AI is increasingly becoming a transformative force in the renewable energy sector. It helps with grid optimization management, energy production forecasting, and improving smart management strategies.

2.1 Artificial Intelligence and Renewable Energy

The literature has offered diverse perspectives to link AI development with renewable energy. One important channel through which AI matters for renewables is its role in forecasting and grid integration. AI techniques such as machine learning and deep learning are widely used for forecasting renewable energy production, managing grid stability, and improving load balancing. Such technologies are helpful in improving the accuracy of resource prediction and system optimization, which is essential for the intermittent nature of renewable power. Ukoba et al. (2024) provided a comprehensive review of the literature on AI and renewable energy and concluded that AI systems enable real-time grid optimization and load balancing. They highlighted the role of AI in predictive maintenance. Moreover, they argued that AI-based tools facilitate smart grids management, decentralized energy systems, and the development of autonomous energy management.

Recently, Rajaperumal & Columbus (2025) provided a review study to assess the significance of AI in smart grid management. They argued that AI integration supports grid management in the following ways: First, it addresses the issues of the early grid. Second, Furthermore, it enhances the current smart grid's capabilities. Third, it is essential in creating a next-generation grid that is dependable, effective, and flexible enough to meet changing demands. They maintained that by facilitating automated fault detection, demand-response optimization, predictive maintenance, and real-time data analysis, AI increases the grid's operating efficiency.

Energy storage is another significant way that AI affects the use of renewable energy. AI helps hybrid and renewable energy storage systems by enhancing efficiency, guaranteeing stability, and optimizing energy storage systems. In energy storage regulation and DC bus voltage stability, AI solutions such as fuzzy logic controllers and adaptive neuro-fuzzy inference systems (ANFIS) perform better than conventional approaches (Kechida et al., 2024). Rajaperumal & Columbus (2025) assert that AI's role in advanced energy storage will ensure "future grids are resilient, sustainable, and responsive to growing energy demands." AI also assists in optimizing battery charge-discharge cycles, boosting overall system performance. Besides, advancement in AI offers solutions by improving energy efficiency and optimizing smart grids that potentially reduce costs and support a sustainable and economically viable energy transition (Song et al., 2025).

To examine the role of AI in renewable energy, Senyapar et al. (2025) conducted a qualitative analysis of literature, reports, and policy documents over the period 2020–2025. They discussed links between technological, behavioral, and ethical dimensions of AI that assist consumers in making complex energy decisions with increased assurance, awareness, effectiveness, and trust. They argued that connecting these dimensions can resolve systematic challenges in green energy transition by promoting sustainable behavioral change towards renewable energy adoption. They emphasize that integration in a renewable energy system needs to align with transparency, fairness, and regulatory alignment. They emphasize the role of technological, behavioral, and ethical insights in AI integration in renewable energy systems.

Contrary to this, the literature also highlights the potential challenges of AI integration in renewable energy. The studies suggest that AI adoption in renewable energy confronts obstacles such as data quality issues, computational costs, cybersecurity risks, and the lack of explainable AI models (Rajaperumal & Columbus, 2025; Verma et al., 2024).

2.2 Empirical Literature

Qin (2024) conducted an empirical analysis for China using monthly data from January 2013 to October 2023. The quantitative discussion reveals both positive and negative influences of AI on renewable energy. They suggest that negative effects appear of less cost of non-renewable energy.

Zhao et al. (2024) analyzed whether AI can accelerate the transition to renewable energy in China from November 2015 to July 2023, employing a wavelet-based quantile approach. Their findings suggest that AI accelerates the transition to renewable energy. However, they also demonstrated that AI negatively influences renewable energy in the short and medium terms. Moreover, they suggest that the non-renewable energy sector temporarily takes more benefit than the renewable energy sector. Wang & Jin (2025) conducted a cross-country empirical study of 51 countries from 1993 to 2019 to examine the role of AI in renewable energy innovation. They found that AI significantly promoted renewable energy innovation by enhancing R&D investment, labor productivity, and institutional quality. However, the study also revealed spatial spillovers: AI promoted innovation domestically but suppressed it in neighboring countries. Using panel data for 31 Chinese provinces over the period 2000-2022, Song et al. (2025) demonstrated that the integration of AI in the renewable energy system enhances the economic growth impact of renewable energy. Following the literature (Ukoba et al., 2024; Qin, 2024; Zhao et al., 2024), Figure 1 illustrates the potential pathways through which AI can influence RNE.

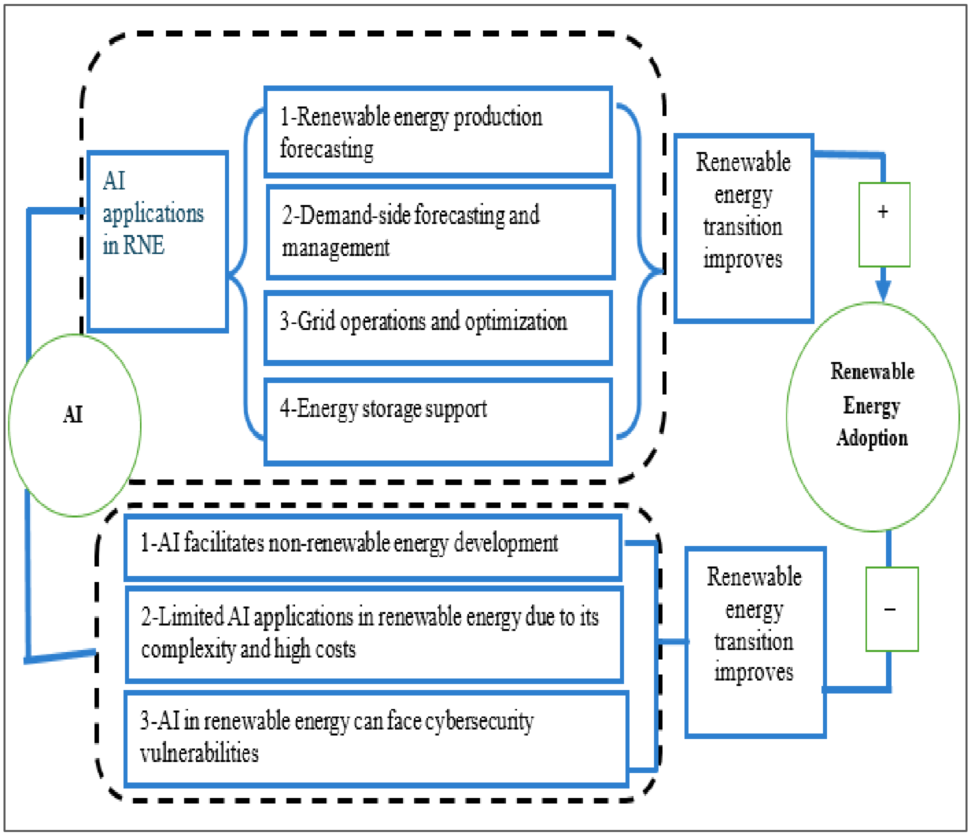

Figure 1: AI and Renewable Energy Adoption

2.3 Climate Finance and Renewable Energy

Climate finance promotes RNE by lowering the cost of capital for renewable energy finance. It is considered an important financial innovation that improves energy efficiency and facilitates pathways to renewable energy adoption. In this respect, Briera & Lefèvre (2024) argued "climate finance reduces investment risks by providing concessional loans, guarantees, or blended finance, which lowers the cost of capital for renewable projects. This is critical in developing countries, where high financing costs are a major barrier to variable renewable energy deployment."

Empirical literature also supports the favorable effects of climate finance on RNE. For instance, Aquilas & Atemnkeng (2022) investigated the effect of climate finance on RNE for the Congo Basin over the period 2002-2020 and found that climate-related mitigation finance significantly supports renewable energy adoption.

However, some studies also question these favorable effects. Borojo et al. (2024) examined the diverse effects of climate finance on RNE for 81 developing economies over the period 2002-2009, employing the method of moments quantile regression (MMQR) approach to explore distributional and unobserved individual heterogeneity. The favorable effect of climate finance is not observed across lower-income countries and higher quantiles of renewable energy. The authors argue that the renewable energy effect of climate finance is climate-dependent, as favorable effects are observed in middle-income countries. Figure 2 illustrates the links through which climate finance supports RNE.

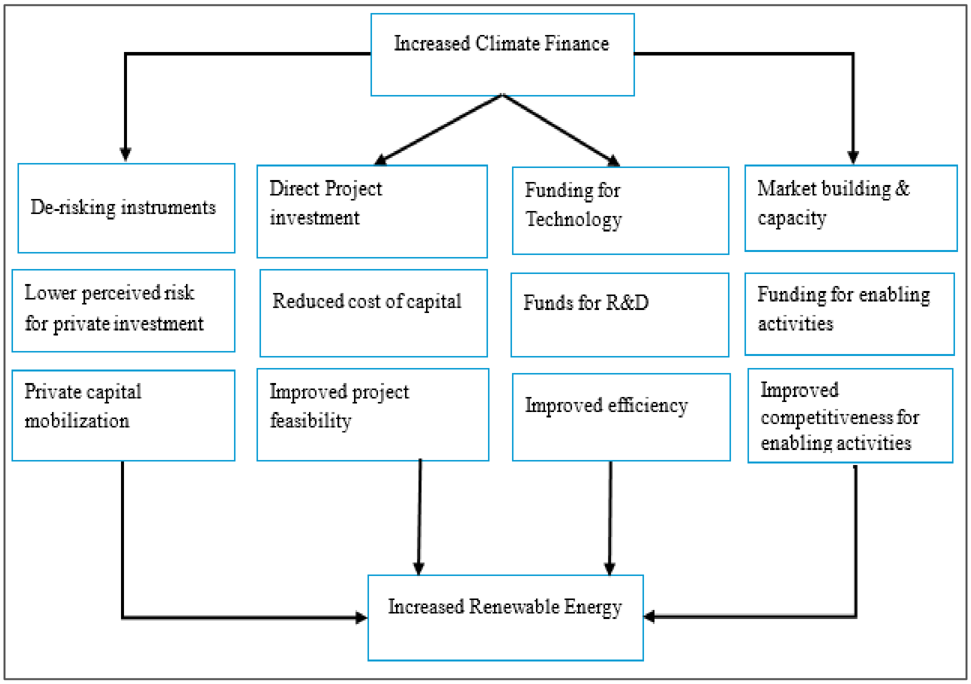

Figure 2: Renewable Energy Through Climate Finance

2.4 Conclusion, Research Gaps, and Contribution

Thus, AI plays a conducive role in the RNE; however, empirical literature is quite limited. The existing studies provide case studies in the context of a single country. Moreover, the empirical evidence is not conclusive. Most importantly, studies do not consider the role of climate finance, which is a crucial determinant of renewable energy. The present study extends empirical literature by examining the separate as well as simultaneous influences of AI and climate finance on RNE in high-income countries over the time period 2000-2020. Moreover, this study also considers the nonlinear effects of AI and climate finance depending on the existing level of RNE in high-income countries.

3. Methodology and Data

AI can effectively accelerate the adoption of renewable energy from technical operations and system maintenance to strategic planning and user engagement. This study develops a multivariate estimation model incorporating renewable energy and AI, along with various control variables, following (Zhao et al., 2024) and (Nepal et al., 2025). The specific model set up is as follows:

$$RNE_{it} = f(AI_{it}, GDP_{it}, FDI_{it}, IND_{it}, TRD_{it}, POP_{it}) \qquad \text{(A)}$$

Where RNE_{it} represents the renewable energy adoption, AI_{it} is the abbreviation for artificial intelligence. The other variables in the model ($GDP_{it}, FDI_{it}, TRD_{it}, IND_{it}, POP_{it}$) indicate gross domestic product, foreign direct investment, trade, industrial development, and population, and i and t in the subscripts, represent the sample country and time.

The dependent variable, RNE, is measured by renewable energy share (modern renewables) in final energy consumption that excludes traditional uses of bioenergy is taken as a renewable energy adoption proxy using data from the International Energy Agency (2025), and it also represents the sustainable energy target that tracks SDG 7.2.

AI, as one of the emerging technologies, is integrated across several industries and applications, making it difficult to access its actual level of development and scale. According to Wang et al. (2025), for analyzing AI through the lens of technological innovation (Ullah, 2021), AI-related patents serving can be used as a proxy indicator for AI advancement. Patent counts by the World Intellectual Property Organization (WIPO) for selected technology domains, including artificial intelligence technologies, are taken as a proxy for AI, and data is sourced from the Organization for Economic Cooperation and Development (OECD, 2025).

Regarding control variables, five key indicators following the study of (Zhao et al., 2024) are included: GDP, representing economic development; FDI, indicating the level of economic openness; TRD, indicating the level of trade activity; POP, capturing demographic trend; and IND, indicating industry development (value added of industry). The data of these variables is sourced from the World Bank (2025). In addition, AI and climate finance are also included due to their significant influence on renewable energy adoption. Climate finance plays a vital role in promoting global sustainable development, particularly by increasing climate-related expenditures, particularly in developed nations, in overcoming the issues created by climate change, and gaining access to necessary financial resources. We use climate-related public expenditure at the state and local government levels as a proxy for climate finance, and the data is sourced from the OECD (2025). This study covers 29 high-income countries over the period 2000–2020, depending on the data availability. Table 1 presents descriptive statistics.

Table 1: Descriptive Statistics

Variables	Observations	Mean	S.D	Minimum	Maximum
AI	609	2974.648	7069.692	5.7	48535.5
CF	609	358.5133	275.2719	25.37	1298.865
GDP	609	36607.61	22755.05	6336.383	112417.9
FDI	609	6290 million	38900	-292000	218000
IND	609	24.29013	5.289295	10.42672	40.81159
TRD	609	239,000 million	267000	4940	1410000
POP	609	.3479359	0.7853134	-3.847671	2.89096

Table 1 presents summary statistics. The maximum values of AI, CF, GDP, FDI, IND, TRD, and POP are taken by Japan, Luxembourg, Luxembourg, Japan, Norway, Germany, and Ireland, respectively. The minimum values of AI, CF, GDP, FDI, IND, TRD, and POP are taken by Lithuania, Lithuania, Latvia, the United Kingdom, Luxembourg, Iceland, and Croatia, respectively.

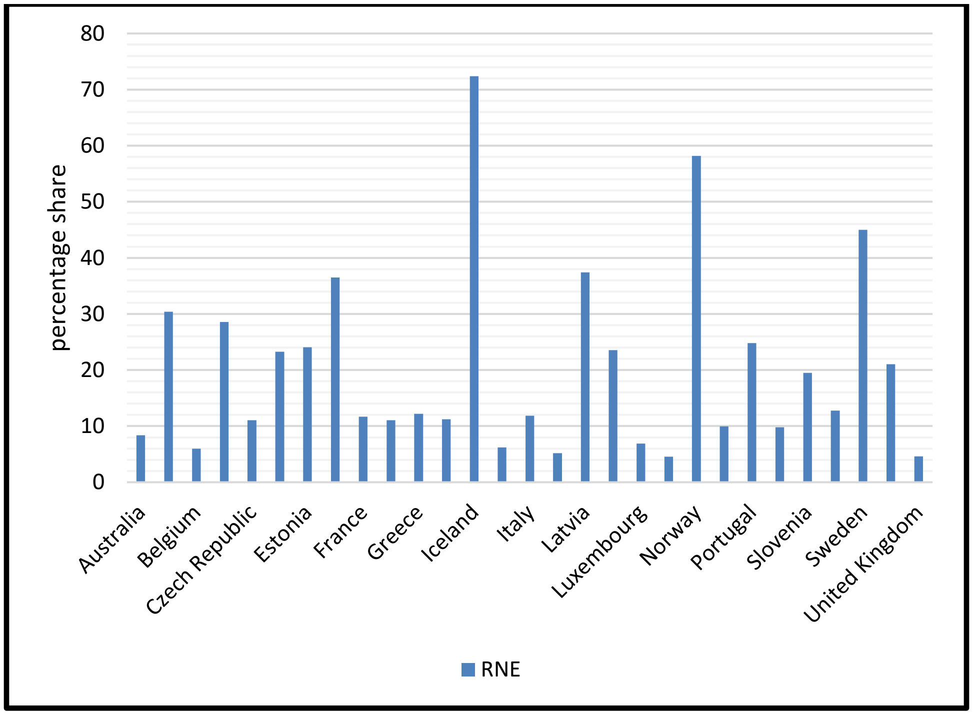

Figure 3: Renewable Share in Final Energy Consumption across High-Income Countries, 2020-2020

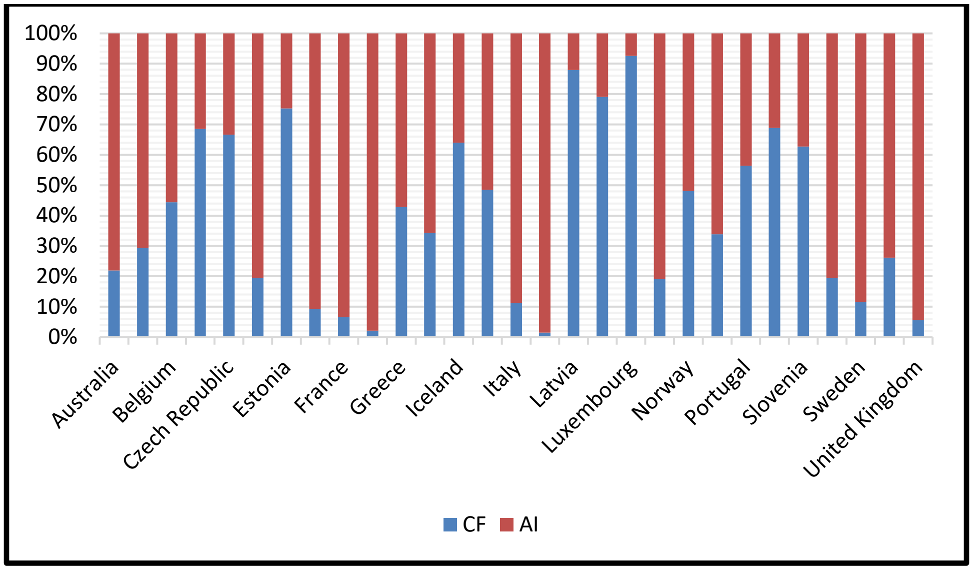

Figure 4: Artificial Intelligence Technology and Climate Finance Distribution in High- Income Countries, 2000-2020

Figure 3 shows the renewable share in final energy consumption in each high-income country from 2000-2020. Countries like Iceland, Norway, and Sweden lead in RNE, 40-70% while Japan, the Netherlands, Luxembourg, and the United Kingdom have the lowest 10% share of renewable energy in final energy consumption, while rest of the countries show moderating levels of renewable energy share in final energy consumption.

Figure 4 shows the AI and climate finance distribution in high-income countries from 2000-2020. There seems to be a visible contrast between technology-led and environmental-led development approaches across high-income countries. It shows that AI is dominant in technologically advanced countries such as Japan, the United Kingdom, Germany, and France. While climate finance is higher in countries that focus on green investments, such as Luxembourg, Latvia, Iceland, and Lithuania.

4. Results and Discussion

4.1 Base Regression Results

The logarithmic form of Eq. (A) generates the following equation.

$$lnRNE_{i,t} = \beta_0 + \beta_1 lnAI_{i,t} + \beta_2 lnGDP_{i,t} + \beta_3 lnFDI_{i,t} + \beta_4 lnIND_{i,t} + \beta_5 lnTRD_{i,t} + \beta_6 POP_{i,t} + \pi_{i,t} + \varepsilon_{i,t} + \mu_{i,t} \quad (1)$$

In the above equation, the six coefficients present the effects of input variables on the outcome variable RNE. The main goal of this study is to assess the causal relationship between AI and the RNE. The study focuses on the coefficient associated with AI, as it captures the elasticity between AI and RNE. The anticipated relationship is positive. The model also incorporates two-way fixed effects, denoted by π_{it} and $\varepsilon_{it} + \mu_{it}$ indicates the combined error term.

The system generalized method of moments (GMM) is primarily employed estimation strategy. Although several economic control variables are included—such as FDI, TRD, IND and POP, there remains the possibility of omitting some relevant factors influencing RNE, thus leading to omitted variable bias. Furthermore, reverse causality may be present as advancements in energy infrastructure could stimulate economic growth and technological innovation. In such scenarios, conventional estimation techniques like ordinary least squares (OLS), fixed effects (FE), and random effects (RE) may produce inconsistent and biased results due to the presence of endogeneity. To overcome these issues, the system GMM method utilizes orthogonality conditions delivering consistent and efficient parameter estimates (Zhao et al., 2024).

Table 2: Baseline Regression Results

Variables	**POLS**	**FE**	**RE**	**System GMM**
Lag (RNE)				1.13282*** (0.03667)
AI	0.3580 *** (0.0433)	0.0807** (0.0799)	0.1731 *** (0.0717)	0.0617*** (0.0147)
GDP	0.2954 *** (0.1071)	1.0332 *** (0.3850)	0.5202*** (0.2112)	0.0603*** (0.0182)
FDI	-0.0298 (0.0487)	-0.0432 *** (0.0192)	-0.0456 *** (0.0228)	0.0079 (0.006)
IND	0.6350 *** (0.1637)	-1.2242*** (0.2023)	-1.7464 *** (0.1970)	-0.1520*** (0.0337)
TRD	-0.8553*** (0.0623)	1.3018*** (0.1477)	0.5604*** (0.1010)	-0.1481 *** (0.0331)
POP	0.0299 (0.0484)	0.0199 (0.0237)	0.0375*** (0.0279)	0.0096 (0.0069)
CONSTANT	17.880*** (2.4953)	-15.5624*** (2.2161)	-9.4096*** (2.45289)	-2.7860*** (0.7302)
Breusch Pagan Test	866.73***			
Hausman Test	32.75***			
Sargan Test				0.209
Hansen Test				0.080
AR(1)				0.000
AR(2)				0.212

Note 1: "Standard errors in the parentheses. * ** ***represents statistical significance at 10%, 5%, 1% respectively." **Note 2**: P-values for the Sargan Test, the Hansen Test, AR (1), and AR (2) are provided in the last column of Table 1.

Table 2 presents the baseline regression outcomes. The first column presents the list of variables used in the empirical analysis. The POLS, FE, RE, and system GMM are reported in columns 2-5. The system GMM model serves as the primary estimation model, whereas the other three models are included for comparison purposes to validate the robustness of our results.

The coefficient on AI is positively significant across all models, indicating a consistent and strong positive relationship between AI and RNE. This finding supports the idea that advancing AI technologies can effectively contribute to the renewable energy transition. The AI coefficients are 0.36, 0.08, and 0.17, while the coefficient for AI in the system GMM model is 0.0617. The size of the coefficient varies from 0.06 to 0.36; however, the direction of the effect remains the same across all estimation methods. Comparatively, POLS overestimates the influence of AI on RNE, while the FE model coefficient is closer to the system GMM estimate. The system GMM coefficient suggests that a 1% increase in AI-related patents will lead to a 0.0617% rise in renewable energy use. This result endorses the view that AI has significant potential to accelerate the renewable energy transition.

Patent applications in AI technology, along with renewable energy technologies, can significantly accelerate the adoption of renewables through promoting innovation, supporting commercialization, and providing better policy guidance. An increase in AI patents signals that inventors are applying AI to address environmental challenges. These growing AI applications facilitate renewable energy initiatives.

AI-related patents are targeted at power grids, promoting smart features in physical grid systems. Such features foster renewable energy by providing supply-demand forecasting that helps to improve grid optimization. (Lee et al., 2022; Yu et al., 2022). The Sargan and Hansen test results indicate that the instruments used for the analysis are valid. The results from both tests suggest that the instruments are appropriately specified and are neither weak nor under-identified.

Our findings aligned with the literature, highlighting that AI significantly promotes RNE by increasing energy storage system efficiency (Kechida et al., 2024; Rajaperumal & Columbus, 2025), facilitating smart grid management and autonomous energy management (Ukoba et al., 2024), enhancing R&D investment, and labor productivity across nations (Wang et al., 2025). Although countries worldwide have increased efforts for renewable energy adoption following the Paris Agreement, concerns persist over the high costs and long payback periods, particularly in developing countries. However, advancements in AI offer solutions by improving energy efficiency and optimizing smart grids that potentially reduce costs and support an economically viable energy transition (Song et al., 2025). In another study, Senyapar et al. (2025) connect technological, behavioral, and ethical dimensions of AI that assist consumers in making complex energy decisions with increased assurance, awareness, effectiveness, and trust. Connecting these dimensions can resolve systematic challenges in the green energy transition by promoting sustainable behavioral change towards renewable energy adoption.

All control variables exhibit a significant influence on RNE, except FDI. Economic and population expansion have a positive association with RNE, whereas TRD and IND seem to hinder RNE progress. The energy demand across various sectors, such as industry, transportation, and households, rises as nations experience economic prosperity and population growth. In addressing energy demand for a rising population and economic growth, renewable energy is considered a sustainable and eco-friendly solution. Moreover, economic prosperity often leads to greater investment in R&D, driving innovation and technological improvements in renewable energy systems that further support their adoption (Algarni et al., 2023; Wu & Wang, 2022; Xiao et al., 2022; Zhang et al., 2022). A growing population requires more energy resources as existing resources become insufficient. In this situation, initiating investment in renewable energy sources becomes more attractive, and the energy transition escalates.

TRD and IND have a negative influence on RNE, indicating that trade mostly includes the imports and exports of traditional fuel resources, and in countries where industrial growth relies heavily on conventional energy sources, trade can support dependence on non-renewable energy (Ivanovski & Churchill, 2020; Zafar et al., 2020). Similarly, industrial growth that supports pre-existing energy infrastructure, generally based on traditional technologies, the financial and structural challenges of transitioning to renewable energy may result in prolonged reliance on fossil fuels (Korczak et al., 2022; Wu et al., 2021).

4.2 Quantile Regression Analysis

The study initially focused on examining the linear relationship between AI and RNE. The analysis is now extended to explore whether RNE differs from quantile to quantile. In this respect, different classes of quantiles (10th, 25th, 50th, 75th, and 95th) are used to analyze the effect of AI and CF across various segments (quantiles) of the sample. A method of moments panel quantile regression model is employed to capture the asymmetric influence of AI across different levels of RNE. This approach is particularly effective in assessing how the marginal impact of AI varies across the distribution of renewable energy adoption. Quantile regression shows considerable heterogeneity in estimated regression coefficients, while OLS regression may not provide an adequate summary of the joint distribution of RNE and AI.

The results reported in Table 3 show that AI demonstrates a consistently positive and statistically significant effect on RNE across all quantiles. This suggests that the positive relationship between AI and RNE holds across varying levels of RNE, reinforcing the robustness of baseline main findings. However, the marginal effect of AI tends to decline as the quantile level increases. For instance, at the 10th quantile, a 1% rise in AI is associated with a 0.38934% increase in RNE, whereas at the 95th quantile, the same increase in AI results in only a 0.3313% rise in RNE.

These results aligned with (Zhao et al., 2024), indicating that AI has a stronger impact on promoting renewable energy adoption in regions or contexts where RNE levels are relatively low. Therefore, in areas with limited renewable energy infrastructure, advancing AI technologies could serve as a more effective catalyst for accelerating the shift toward sustainable energy solutions.

Table 3: Quantile Regression Results

Variables	**Quantiles**				
	10th	**25th**	**50th**	**75th**	**95th**
AI	0.3893*** (0.1232)	0.3874*** (0.0520)	0.3539*** 0.0442	0.3439*** 0.0337	0.3313*** 0.0469
GDP	0.1319*** (0.3105)	0.2954*** (0.1319)	0.357*** (0.1118)	0.5029*** (0.0855)	0.68760*** (0.1190)
FDI	-0.1234*** (0.0359)	-0.029*** (0.0152)	-0.0162 (0.0137)	0.0156 (0.009)	0.05605 (0.0140)
IND	0.6659 (0.5012)	-0.6351*** (0.2117)	-0.8312*** (0.0568)	-0.6201*** (0.1372)	-0.6068*** (0.1908)
TRD	-1.0218*** (0.1583)	-0.855*** (0.0671)	-0.6306*** (0.1789)	-0.7745*** (0.0434)	-0.7025*** (0.0605)
POP	0.0656 (0.1353)	-0.029 (0.0572)	0.0438 (0.0484)	0.0764*** (0.0371)	0.1177 (0.0516)
Constant	27.851*** (5.872)	17.880*** (2.5007)	16.437*** (2.1232)	13.040*** (1.620)	8.731*** (2.253)

Note: "Standard errors in the parentheses. * ** ***represents statistical significance at 10%, 5%, 1% respectively."

Nations with lower levels of RNE often remain dependent on conventional energy sources. In such contexts, the AI can play a transformative role by helping to overcome existing barriers and facilitating the deployment of renewable energy technologies. These countries typically lack well-developed renewable energy infrastructure and the application of AI is more impactful in accelerating progress toward clean energy.

Conversely, in countries where renewable energy systems are already well-established, the economic benefits of incorporating AI may have a relatively low impact. These higher-quantile nations have often already invested heavily in renewable technologies, so the additional efficiency or cost savings achieved through AI integration tend to be marginal compared to those in less advanced RNE countries.

The coefficient on GDP also shows a positive and significant influence across all quantiles. The marginal effects gradually increase from lower quantiles to higher quantiles. This finding suggests that countries with existing higher levels of renewable energy are in better positions to take advantage of AI applications by devoting more resources toward AI integration into the renewable energy sector. The effect of FDI is only significant in the 10th and 25th quantiles, while in all remaining quantiles, FDI does not exert any significant influence on RNE. The effect of IND is negatively significant across all quantiles except the bottom quantile. Similarly, the effect of trade is also negatively significant across all quantiles. These findings are in line with baseline findings. The effect of population growth, however, becomes insignificant except 75th quantile, implying that population growth significantly influences RNE only in countries where the existing level of renewable energy is higher.

4.3 Climate Finance and Renewable Energy

4.3.1 The Direct Influence of Climate Finance on RNE

$$lnRNE_{i,t} = \beta_0 + \beta_1 lnCF_{i,t} + \beta_2 lnGDP_{i,t} + \beta_3 lnFDI_{i,t} + \beta_4 lnIND_{i,t} + \beta_5 lnTRD_{i,t} + \beta_6 POP_{i,t} + \pi_{i,t} + \varepsilon_{i,t} + \mu_{i,t} \tag{2}$$

Beyond AI, climate plays a significant role in influencing RNE. Climate finance is vital for promoting sustainable development globally, particularly by increasing climate-related expenditures to address the severe climate challenges that require financial resources needed to tackle these issues (Majeed & Mazhar, 2019). Our analysis begins by assessing the direct effect of climate finance, treating it as a key independent variable. Following the approach used in the baseline regressions, we employ four estimation methods— (OLS, FE, RE, GMM) and the results are summarized in Table 4.

Table 4: Estimates of the Direct Impact of Clean Finance on Renewable Energy Adoption

Variables	POLS	FE	RE	System GMM
Lag (RNE)				1.3084*** (0.0769)
CF	0.0329 (0.1282)	0.0482*** (0.0916)	0.1330 (0.0997)	0.0094* (0.0179)
GDP	0.6207*** (0.2116)	0.6611*** (0.5678)	0.6815*** (0.3169)	0.2297*** (0.0498)
FDI	-0.1696*** (0.0545)	0.0003 (0.0176)	0.0043 (0.0206)	0.0236*** (0.0101)
IND	-0.9916*** (0.2512)	-1.4989*** (0.3048)	-1.7191*** (0.3073)	-0.3759*** (0.0904)
TRD	-0.2227*** (0.0979)	-1.3142*** (0.2239)	-0.3119*** (0.1309)	-0.1039*** (0.0286)
POP	0.0418 (0.0778)	0.0464 (0.0329)	-0.0287 (0.0375)	0.0309*** (0.0120)
CONSTANT	2.3142*** (3.1887)	19.491*** (3.5374)	7.8811*** (3.4810)	3.9989*** (2.5153)
Breusch Pagan Test	633.66***			
Hausman Test	267.25***			
Sargan Test				0.179
Hansen Test				0.277
AR (1)				0.016
AR (2)				0.947

Note 1: "Standard errors in the parentheses. * ** ***represents statistical significance at 10%, 5%, 1% respectively." **Note 2**: P-values for the Sargan Test, the Hansen Test, AR (1), and AR (2) are provided in the last column of Table 1.

Table 4 presents the effects of climate finance on RNE, indicating an overall significant positive impact, although the coefficients in the first and third columns are not statistically significant. The results from the system GMM model, displayed in the final column, reveal that a 1% increase in climate finance corresponds to a 0.0094% rise in RNE, highlighting climate finance's supportive role in advancing renewable energy projects. Climate finance supplies the essential funding needed to initiate and expand renewable energy projects

(Aquilas and Atemnkeng, 2022), helping to alleviate the high initial costs associated with these investments in renewable energy projects. By boosting climate-related expenditures, climate finance reduces financial obstacles, making renewable energy ventures more economically feasible and appealing to investors (Lee et al., 2022; Qi et al., 2023). Furthermore, climate finance instruments such as guarantees and insurance schemes contribute to lowering investment risks tied to renewable energy initiatives (Yu et al., 2022). Climate finance promotes renewable energy projects by providing concessional loans and guarantees that reduce the cost of capital for renewable energy projects (Briera & Lefèvre, 2024). This finding is consistent with (Borojo et al.,2024) who found favorable effects of climate finance on RNE in middle-income countries (Borojo et al.,2024).

We also examined the nonlinear influence of climate finance on RNE using quantile regression, with the findings presented in Table 5.

Table 5: Quantile Regression Results

Variables	Quantiles				
	10th	**25th**	**50th**	**75th**	**95th**
CF	0.1288* (0.2839)	0.07309* (0.1877)	0.0168* (0.1068)	0.0121** (0.0879)	0.0435* (0.1018)
GDP	0.3145*** (0.4424)	0.4926*** (0.2925)	0.6723*** (0.1666)	0.7647*** (0.1369)	0.8649*** (0.1589)
FDI	-0.3356*** (0.1150)	-0.2391*** (0.0761)	-0.1416*** (0.0435)	-0.0915*** (0.0355)	-0.0372*** (0.0416)
IND	1.1299*** (0.618)	-1.0495*** (0.4087)	-0.9682*** (0.2325)	-0.9265*** (0.1915)	-0.8811*** (0.2216)
TRD	-0.1171*** (0.2172)	-0.1785 (0.1436)1	-0.2405*** (0.0817)	-0.2723*** (0.0673)	-0.306*** (0.0779)
POP	0.0488 (0.1636)	0.0447 (0.1082)	0.0406 (0.0615)	0.0385 (0.0507)	0.0362 (0.0586)
Constant	4.2772*** (6.7424)	3.1358*** (4.4584)	1.9835*** (2.5369)	1.3912*** (2.0893)	2.749*** (2.4182)

Note: "Standard errors in the parentheses. * ** ***represents statistical significance at 10%, 5%, 1% respectively."

Table 5 presents the results of the panel quantile regression analysis. Climate finance has a positive and statistically significant effect on RNE across all quantiles, from the 10th to the 95th percentile, indicating a positive nexus between climate finance and RNE exists across all quantiles, and this consistent relationship reinforces the robustness of our main findings. However, the marginal influence of Climate finance decreases as the level of RNE rises. For instance, at the 10th quantile, a 1% increase in climate finance corresponds to a 0.12884% increase in renewable energy adoption, whereas at the 95th quantile, the same increase in climate finance is associated with only a 0.0435% rise. This suggests that the impact of climate finance is stronger in regions with lower levels of renewable energy adoption. Therefore, boosting climate-related expenditures may be particularly effective in promoting renewable energy adoption in areas where adoption rates are currently low.

4.3.2 The Moderating Role of Climate Finance

After detecting the direct impact of climate finance, the study now explores how climate finance acts as a moderating factor in the AI and RNE nexus. Firstly, we have added both AI and climate finance into the estimation model (Eq. 3) to see the individual effect of AI and climate finance on renewable energy.

$$lnRNE_{i,t} = \beta_0 + \beta_1 lnAI_{i,t} + \beta_2 lnCF_{i,t} + \beta_3 lnGDP_{i,t} + \beta_4 lnFDI_{i,t} + \beta_5 lnIND_{i,t} + \beta_6 lnTRD_{i,t} + \beta_7 POP_{i,t} + \pi_{i,t} + \varepsilon_{i,t} + \mu_{i,t} \quad (3)$$

Secondly, to explore the moderating role of climate finance in the AI and RNE nexus, we have added interaction AI*CF along with AI and CF into the estimation model (Eq. 4) to see the specific and joint effect of AI, CF, and AI*CF on RNE, respectively.

$$\begin{aligned} lnRNE_{i,t} = \beta_0 &+ \beta_1 lnAI_{i,t} + \beta_2 lnCF_{i,t} + \beta_3 lnAI_{i,t} * lnCF_{i,t} \\ &+ \beta_4 lnGDP_{i,t} + \beta_5 lnFDI_{i,t} + \beta_6 lnIND_{i,t} + \beta_7 lnTRD_{i,t} \\ &+ \beta_8 POP_{i,t} + \pi_{i,t} + \varepsilon_{i,t} + \mu_{i,t} \quad (4) \end{aligned}$$

Table 6: Results of the Moderating Role of Climate Finance

Variables	**POLS**	**FE**	**RE**	**System GMM**	**System GMM**
Lag (RNE)				1.3299*** (0.0797)	1.1518 *** (0.0440)
AI	0.5756*** (0.0709)	0.11499 (0.1171))	0.13756 (0.1004)	0.1876*** (0.0460)	0.0298*** (0.0259)
CF	0.3940 *** (0.1224)	0.0593 (0.0923)	0.1417 (0.0998)	0.1048*** (0.0353)	0.0757*** (0.0309)
GDP	0.0251*** (0.2042)	0.6643*** (0.5679)	0.6725*** (0.3139)	0.0662*** (0.0331)	0.0584*** (0.0194)
FDI	-0.1557 *** (0.0485)	-0.0012 (0.0176)	-0.0033 (0.0206)	0.0211*** (0.0098)	0.0087*** (0.0067)
IND	-0.4287*** (0.2339)	-1.4443*** (0.3099)	-1.7192*** (0.3071)	-0.2274*** (0.0585)	-0.1711*** (0.0392)
TRD	-1.1220*** (0.1409)	-1.2604*** (0.2304)	-0.4228*** (0.1580)	-0.4019*** (0.0977)	-0.1749*** 0.0438
POP	0.1534*** (0.0732)	0.0389 (0.0337	0.0408 (0.0387)	0.0159 (0.0145)	0.0109 (0.0071)
AI*CF					0.0174*** (0.0059)
CONSTANT	27.939*** (4.2409)	18.954*** (3.5797)	9.8121*** (3.8346)	8.3730*** (2.2594)	3.8662*** (2.0792)
Breusch Pagan Test	367.16***				
Hausman Test	238.23***				
Sargan Test				0.619	0.222
Hansen Test				0.291	0.238
AR (1)				0.025	0.000
AR (2)				0.815	0.232

Note 1: "Standard errors in the parentheses. * ** ***represents statistical significance at 10%, 5%, 1% respectively." **Note 2**: P-values for the Sargan Test, the Hansen Test, AR (1), and AR (2) are provided in the last column of Table 1.

Table 6 presents the moderation effect results, and it can be seen that although the coefficients of AI and climate finance are insignificant in the second and third columns, but have a positive impact on RNE. The GMM estimates in the fourth column show that a 1% increase in AI increases RNE by 0.1876% and 1% increase in climate finance increases RNE by 0.1048%. The interactive term AI*CF in the fifth column also shows a significant and positive impact on RNE. This finding suggests that climate finance strengthens the effect of AI on RNE (Arezki, 2021). The results aligned with (Zhao et al., 2024), supporting that increasing AI patents are a clear signal that inventors are applying AI to address environmental challenges, which, along with climate finance, is crucial for promoting RNE. The quantile regression results for eq. (3) are represented in Table 7.

Table 7: Quantile Regression Results of the Climate Finance

Variables	**Quantiles**				
	10th	**25th**	**50th**	**75th**	**95th**
AI	0.8267^{***} (0.1873)	0.6832^{***} (0.1269)	0.51795^{***} (0.0641)	0.4512^{***} (0.0510)	0.3768^{***} (0.0570)
CF	0.5693^{***} (0.3050)	0.4691^{***} (0.2041)	0.3538^{***} (0.1037)	0.3073^{***} (0.083)	0.2553^{***} (0.0935)
GDP	0.2569^{***} (0.5065)	0.1243^{***} (0.3385)	0.0282^{***} (0.1721)	0.0897^{***} (0.1390)	0.1582^{***} (0.1554)
FDI	-0.3262^{***} (0.1086)	-0.2287^{***} (0.0739)	-0.1165^{***} (0.0372)	-0.0719^{***} (0.0295)	-0.0208 (0.0330)
IND	-0.0169 (0.6124)	-0.237^{***} (0.4105)	-0.5311 (0.2084)	-0.6493^{***} (0.1678)	-0.7813^{***} (0.1877)
TRD	-1.3951^{***} (0.3520)	-1.239^{***} (0.2361)	-1.0592^{***} (0.1198)	-0.9868^{***} (0.0964)	-0.9058^{***} (0.1078)
POP	0.3391^{***} (0.1895)	0.2328^{***} (0.1275)	0.1107^{***} (0.0646)	0.0614 (0.0518)	0.0064^{***} (0.0584)
Constant	38.984^{***} (10.666)	32.667^{***} (7.1845)	25.401^{***} (3.6400)	22.471^{***} (2.9151)	19.199^{***} (3.260)

Note: "Standard errors in the parentheses. * ** ***represents statistical significance at 10%, 5%, 1% respectively."

Table 7 presents the results of the panel quantile regression analysis. Both AI and climate finance have a positive and statistically significant effect on RNE across all quantiles, from the 10th to the 95th percentile. Moreover, the interaction AI*CF reported in Table 8 also has a positive and statistically significant effect on RNE across all quantiles, from the 10th to the 95th percentile. This demonstrates a consistent positive relationship between AI, CF, and RNE throughout different levels of renewable energy adoption. However, the marginal effects of AI and climate finance tend to diminish as the quantile levels of RNE increase. This suggests that the influence of AI and climate finance on promoting renewable energy adoption is stronger in regions with lower RNE levels. Therefore, increasing AI-related patent activity and climate finance expenditures could be particularly effective strategies for enhancing renewable energy adoption in areas where it is currently less developed.

Table 8: Quantile Regression Results of the Moderating Effect of Climate Finance

Variables	Quantiles				
	10th	**25th**	**50th**	**75th**	**95th**
AI	0.3375 (0.4939)	0.3242 (0.3269)	0.1354** (0.2007)	0.0300* (0.1257)	0.0784*** (0.2221)
CF	0.5227 (0.4911)	0.4712 (0.4652)	0.2745** (0.1996)	0.1450* (0.1251)	0.0118*** (0.2209)
AI*CF	0.12457*** (0.0817)	0.1138*** (0.0097)	0.0905*** (0.0332)	0.0726*** (0.0208)	0.0543*** (0.0367)
GDP	0.1195*** (0.3437)	0.2012*** (0.1333)	0.2320*** (0.1396)	0.2906*** (0.0875)	0.3510*** (0.1545)
FDI	-0.0783* (0.0326)	-0.0681* (0.0154)	-0.0261*** (0.0134)	-0.0011 (0.0084)	-0.0291 (0.0148)
IND	-0.7122*** (0.4974)	-0.6125*** (0.2954)	-0.6559*** (0.2019)	-0.6265*** (0.1265)	-0.5962*** (0.2235)
TRD	-1.0079*** (0.2127)	-1.0006** (0.0221)	-0.9531*** (0.0864)	-0.9246*** (0.0541)	-0.8952*** (0.0956)
POP	0.0090 (0.1383)	0.0495 (0.0353)	0.0503*** (0.0562)	0.0718*** (0.0352)	0.0939*** (0.0621)
Constant	26.986*** 6.9304	24.6523*** (2.2985)	22.4048*** 2.8219	20.014*** 1.7690	17.5556*** 3.1213

Note 1: "Standard errors in the parentheses. * ** ***represents statistical significance at 10%, 5%, 1% respectively." **Note 2**: P-values for the Sargan Test, the Hansen Test, AR (1), and AR (2) are provided in the last column of Table 1.

5. Conclusion

This research examined the drivers of renewable energy adoption with a particular focus on AI and climate finance using panel data from 31 high-income countries over the period 2000-2020. The empirical results are estimated using conventional panel data techniques, such as pooled ordinary least squares, fixed and random effects models, along with system generalized method of moments. Moreover, the method of moments quantile regression model is employed to explore the nonlinear effects across economies.

The empirical outcomes indicate that AI exerts a positive and significant influence on renewable energy. This finding implies that AI initiatives can trigger efforts toward the renewable energy transition. Moreover, the results demonstrate that the marginal effects of AI on RNE vary across different levels of AI. Similarly, climate finance also positively and significantly contributes to renewable energy. Finally, the results show that climate finance moderates the role of AI in RNE.

5.1 Research Contribution

This study contributes to the extant literature in the following distinct ways. First, the existing research on the role of AI in renewable energy has mainly focused on country-specific case studies, which provide a limited understanding. In contrast, this study focuses on high-income countries and provides broader findings that are not only useful for technologically advanced economies but also provide insights for the rest of the world. Second, this study allows heterogeneous experiences of sampled economies by allowing non-linear effects of AI on renewable energy, depending upon the diverse exposure of economies to RNE. Third, unlike prior studies, which consider the role of financial development in renewable energy, the present research considers the role of climate finance, which is a more direct and accurate measure of the role of finance in supporting renewables.

5.2 Theoretical and Policy Implications

This research aligns with innovation diffusion theory. This theory postulates that technological innovations penetrate societies depending upon factors such as perceived benefits, compatibility, and complexity. AI technology supports renewable energy by optimizing grid management, forecasting demand, and improving efficiency. Meanwhile, climate finance makes RNE more feasible by reducing perceived risks and cost hurdles. The findings can be linked with the later part of the environmental Kuznets curve (Majeed & Mazhar, 2020), where high-income countries prioritize environmental quality and transition toward sustainability by integrating AI into sustainability and providing climate finance. Moreover, the resource-based view suggests that firms acquire a competitive advantage through unique resources and capabilities. In high-income countries, firms using AI and having climate finance support are in a better position to adopt a renewable energy transition.

Following the research outcome of the study, policy implications are as follows: Policy makers of the selected economies can cultivate the culture of AI integration in renewable energy adoption by supporting basic research in AI, technological innovation, talent development, and international cooperation. Moreover, investment in an AI-optimized grid needs to be increased to best manage the increased and volatile power load. Since AI flourishes on data availability, strategies to enhance data availability, reliability, and efficiency can enhance the role of AI in renewable energy adoption. The availability of AI infrastructure is another powerful driver of AI progress. In this way, funding for the use of renewable energy sources can be combined with the creation of AI infrastructure. In a similar vein, human skill sets are crucial for advancing AI development and application. In this way, training, grants, and scholarships for AI projects can be improved.

5.3 Research Limitations and Future Research

The present research study has confronted certain limitations. The data availability remained a major challenge in conducting the empirical analysis for this research. The data for all selected economies was not available. The final sample includes only those economies that have data on both focused variables, namely AI and climate finance. The results of the study offer useful implications for high-income countries; however, these outcomes cannot be generalized for the rest of the world. The study used a single indicator of AI applications. Future research may consider alternative indicators to provide a more comprehensive analysis. This research assumes a symmetrical association between AI and RNE. Future research can consider the asymmetric effects of AI on RNE across different income groups.

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Appendix

Table A1: List of Sampled Economies

1	Australia	9	France	17	Latvia	27	Slovenia
2	Austria	10	Germany	18	Lithuania	28	Spain
3	Belgium	11	Greece	19	Luxembourg	29	Sweden
4	Croatia	12	Hungary	20	Netherland	30	Switzerland
5	Czech Republic	13	Iceland	21	Norway	31	United Kingdom
6	Denmark	14	Ireland	22	Poland		
7	Estonia	15	Italy	23	Portugal		
8	Finland	16	Japan	24	Slovak Republic		