Artificial Intelligence and Renewable Energy Growth: Global Evidence from Panel Data

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Abstract

This research aims to provide improved and in-depth insight into the association between AI and RE. The indicators used for renewable energy include generation from solar, wind, hydroelectricity, geothermal, and biomass sources, whereas artificial intelligence is proxied by patent applications filed by residents. The analysis is conducted for 69 countries from 1990 to 2023 using the system generalized method of moments and panel quantile regression analysis to address endogeneity and distributional variance in artificial intelligence and renewable energy growth. The novelty of this study lies in the expanded empirical scope and methodological advancements as compared to the previous studies. This study incorporates system GMM and quantile regression techniques to offer a more nuanced understanding of the impacts of AI on RE. The results show that artificial intelligence has a significant positive impact on renewable energy. This emphasizes the need to integrate artificial intelligence into renewable energy systems to accelerate the energy transition to achieve sustainability.

Keywords: renewable energy, artificial intelligence, panel data analysis

Introduction

For decades, the world's progress has heavily relied on fossil fuels as its primary source of energy. Coal, oil, and gas have powered industries, fueled urbanization and made transportation faster. As fossil fuels are easily accessible and are widely available, this type of energy has brought unprecedented improvements in living standards. However, the reliance on non-renewable energy is a major cause of environmental issues for the planet and has brought severe unintended consequences, as a result affecting the environment as well as human beings.

The combustion of fossil fuels is known to emit greenhouse gases such as carbon dioxide (CO2), nitrous oxide (N2O) and methane (CH4). These emissions accumulate in the atmosphere and trap infrared radiation which causes a rise in the average global temperature. These emissions are known to have severe impacts on climate change and contribute to global warming [1][2]. Such emissions also cause a change in weather patterns, trap heat, and increase the risk of natural disasters. Around the world, countries are facing frequent extreme weather events such as floods, wildfires, droughts, and extreme heat, which cause immense damage to agriculture and livelihoods [3]. These growing threats sparked a debate on energy transition. Shifting to low-carbon energy has become a basic requirement for the secure future of the world. Many countries and international organizations have heavily invested in transitioning from fossil fuels to renewable energy. One pathway of this transition is renewable energy (RE), power that is generated from sources like the sun, wind, and water [4]. RE is known to create new opportunities for economic growth and reduce CO2 in the atmosphere [2]. It can create clean energy jobs, drive economic diversification and reduce dependence on fossil fuels. Many countries have introduced policies and set ambitious targets to increase RE capacity. Despite significant growth in many countries, the deployment of RE faces significant hurdles. Expanding RE sources is not that simple, and unlike fossil fuels, this form of energy is not constant. Thus, it is essential to explore the ways to promote RE development.

At the same time, intelligent technologies have emerged as transformative force in accelerating energy transition. Among them artificial intelligence (AI) is revolutionizing the world and is changing the way industries operate, particularly in industrial robots, which play a pivotal role as a key enabler of technology. These industrial robots are intelligent and facilitate environmentally friendly transformation [5][6]. These robots are versatile, learn from the data, and optimize faster than humans, serving different purposes within industrial automation [7][8]. The implementation of robots in industries, particularly in manufacturing, has the potential to bring significant benefits for sustainable development [9]. These machines can process a large volume of data, optimize workflows, reduce waste contribution to shorter production cycles, and lower energy consumption [10]. Companies can achieve greener production cycles and contribute substantially to sustainable development goals. Recent research highlights the transformative potential of AI in economic, social, and environmental improvement. The existing research suggests that AI technology helps in facilitating green innovation and energy-efficient solutions. It reduces social inequality between developing and developed countries and promotes inclusive growth, green innovation and helps in reducing carbon emissions [11] [12] [13] [14]. This signifies the potential of AI has the potential to accelerate RE development by increasing energy efficiency.

However, despite positive signs of AI in industry use, there are very few studies that link AI with RE development. The existing studies have focused on isolating technological and economic factors of AI but have not addressed AI’s integration into energy systems. Furthermore, there is limited information on how the impact of AI on RE varies based on countries’ development levels which potentially leads to asymmetric effects.

The objective of this study is to fill these gaps by investigating the role of AI on RE over a period of 33 years. The study addresses the following questions:

What are the impacts of AI on RE development across a diverse set of countries?

Are the impacts of AI consistent across varying levels of RE, indicating potential asymmetric impacts?

How do advanced methods, such as the system generalized method of moments (system GMM) and quantile regression, offer deeper insights into the heterogeneous impacts of AI on RE?

The novelty of this study lies in the expanded empirical scope and methodological advancements as compared to the previous studies. This study incorporates system GMM and quantile regression techniques to offer a more nuanced understanding of the impacts of AI on RE. The introduction of the GMM technique improves the robustness of causal inference by controlling dynamic panel bias, whereas the use of quantile regression reveals how the impact of AI varies across different levels of energy production and offers insights that are otherwise not attainable through mean-based approaches.

Literature Review

The rising environmental concerns and global efforts to mitigate the adverse effects of climate change emphasize transitioning from traditional fossil fuels to eco-friendly energy sources. This energy transition highly relies on deploying and progressing RE sources like solar, wind, hydro, biomass, and geothermal. In this ever-evolving technological paradigm, AI has played a pivotal role in accelerating RE adoption to meet the increasing energy demand. The employment of AI in grid management, forecasting resources, robotics, and increasing energy efficiency has eased the path to sustainable development.

Researchers in the past few years have tried to configure the effect of AI on environmental and social development and found it to be significant. A panel data study conducted by Lee et al. [11] in the manufacturing sector of 34 countries shows that employment of industrial robots helped achieve production accuracy, reduce resource wastage, and increase efficiency. These reduced costs aid in the expansion of green technology innovation. This effect strengthens in the presence of strict environmental regulations, thus promoting sustainable development. The nexus of AI, energy efficiency, and carbon emissions is further investigated by Yu et al. [13] for China. The study considered the role of industrial robots in the decarbonization of Chinese cities for the time period of 2010-2018. The application of industrial robots significantly reduced carbon emissions, specifically in the megacities of China, by promoting green technology.

A comprehensive review based on the incorporation of AI and data science in the RE sector, specifically in efficient management of the solar and wind energy systems, signifies AI’s transformative potential. The study proposed hybrid learning methods, investment in research and development (R&D), enhancing the skills of professionals through training and development of policies that balance the individual interests with the system [16].

Ukoba et al. [17] review the growing penetration of AI in RE systems and found it to be beneficial in increasing efficiency, reducing operational costs, and better forecasting. The ongoing technological advancement and effective policy measures will aid in achieving more resilient and sustainable systems. The findings of a study conducted by Zhao et al. [17] confirmed the positive contributory role of AI in the development of RE. The study employed a system GMM for panel data from 63 countries over the period 2000–2019. The influential role of AI was enhanced with the upgradation of technology and innovation and was more pronounced in countries that were in the initial stages of RE adoption. Moreover, climate finance was also seen as a potent variable in the expansion of RE through AI.

Technological innovation is also characterized by using patent data, as they are quantifiable and reflect technological progress over time. Patent data has indicated an increase in RE innovations supported by positive policy measures [18]. Esmaeilpour Moghadam & Karami [19] examined the role of green innovation proxied by green patents on RE advancement in the MENA region from 1985 to 2019. The study shows that green innovation positively influences RE development in the region and can be used as a tool for sustainable development.

A similar study conducted by Zhang et al. explored the role of AI in the development of RE for China by using wavelet analysis and found AI to be an integral component of energy transition [20]. The study suggested a mutual alliance between the government, businesses, and educational institutions to promote AI and RE development. Ametepey et al. used a Delphi approach to view experts' opinions about AI's role in the achievement of sustainability development goals (SDGs) [22]. The research strongly advocated the radical potential of AI in the attainment of all 17 goals. However, areas like peace, justice, and institutional framework show moderate effects that require strong strategic policies to ensure smooth integration of AI.

Majeed et al. examined the critical role played by AI in the adoption of RE by utilizing panel data from 29 high-income countries from 2000-2020 and found the strong positive influence of AI on RE development [23]. The study also highlighted the positive role of climate finance in supporting energy transition and advocated for policies that prioritize AI integration in RE systems. On the contrary, Zheng et al. used patent data for 56 less developed countries between 2007 and 2022 to examine the non-linear effect between AI and RE development [24]. The study revealed an inverted U-shaped association, indicating that AI initially drives RE growth, but the marginal gains diminish once it reaches the threshold. The study advocated strong institutional frameworks as a strengthening agent for AI-led growth.

The literature also shows economic growth, industrialization, foreign direct investment and population as the influential factors of clean energy development [25][23]. This study also incorporated these variables to show how they can affect RE development across different countries.

Taken together, these studies highlight the significance of AI in the changing paradigm of energy systems. The integration of AI can speed up the process of energy transition and help achieve sustainability. The availability of limited literature on determining the impact of AI on RE development reflects the need to explore this area further.

From a theoretical standpoint, there are some distinct channels through which AI drives RE development. First, AI increases optimization and forecasting in energy systems. For instance, Algorithms of machine learning help to improve the accuracy of solar irradiance and wind speed predictions [17]. Second, AI lowers innovation and R&D costs by accelerating materials discovery. It simulates energy systems, and shortens the development cycle for RE technologies. Third, with the help of industrial automation and smart manufacturing, AI-driven robotics decreases production costs and waste [11]. Finally, AI powers demand-side flexibility and enables smart grid systems that integrate distributed renewable sources more efficiently.

The present study makes several notable contributions to the existing literature on AI and RE development. First, in contrast to the previous studies that either focused on a specific country or a region, this study takes a broader set of 69 countries covering 33 years, which aids in capturing technological evolution and policy shifts in the energy ecosystem. Second, the empirical methodologies of dynamic GMM and panel quantile regression estimate the nonlinear impact of AI on RE. The GMM approach handles endogeneity issues while panel quantile regression shows distributional heterogeneity across nations. Moreover, utilizing AI patents data as a proxy along with other macroeconomic indicators like GDP, inflation, and industrialization, the study offers deeper insights into how technological and economic factors jointly shape the RE growth globally.

Research Methodology

To reveal the impact of AI on RE based on the literature, we require a careful specification of the regression framework. There are numerous studies that have identified different determinants impacting RE, such as foreign direct investment (FDI), industry, and trade openness. Building on this notion, our model will incorporate artificial intelligence (AI) as an explanatory variable to quantify its contribution to RE. This empirical study will use the following regression model formulated after studying [17] and the literature on RE.

$$RE_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 X_{it} + v_i + \mu_t + \varepsilon_{it} \dots\dots (1)$$

In the above equation, RE is the renewable energy generation measured in terawatt-hours, where i shows the country and t represents the time period. β_0 is an intercept. AI is the artificial intelligence. β_1 is the slope coefficient, which will determine the effect of a change in the AI on the RE. The term X_{it} adds the row matrix that consists of all other variables with which the specific variables that can lead to the change of RE have been focused on, v_i is a country-specific unobservable effect, and μ_t is a time-specific factor. The error term ε_{it} represents the effect of all the omitted variables and unobserved heterogeneity. It controls the time-invariant characteristics such as geographic factors, institutional quality and policy frameworks.

$$RE_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 GDP_{it} + \beta_3 FDI_{it} + \beta_4 TO_{it} + \beta_5 IND_{it} + \beta_6 INF_{it} + \beta_7 POP_{it} + v_i + \mu_t + \varepsilon_{it} \dots\dots (2)$$

The above equation explicitly explains the term X_{it} which includes control variables used in the model. GDP represents the gross domestic product, FDI as foreign direct investment, TO as the trade activity, IND as the industrial development, INF as inflation, and POP as the total population. β_1 *to* β_7 are the parameters that denote the impact of the control variables on the dependent variable. $\beta_1$is the most significant parameter that demonstrates the nature of the relationship between the focused variable AI and the dependent variable RE.

The most commonly used proxy for technological innovation and capability is patent data. The empirical literature verifies its use in cross-country panel studies [19][24]. The selection of patents as a proxy of AI in this study is justified on the following basis. Firstly, patents are recorded systematically across countries and time periods which makes them well-suited for large panel datasets. Secondly, patent filings reflect intentional investment in innovation which signals the accumulation of technological knowledge and R&D capacity. Thirdly, resident patent applications also capture innovative capacity on the domestic level, which is more directly related to a country's ability to install and adapt AI in its own energy. Lastly, the broader innovation literature consistently treats patent counts as reliable indicators of the knowledge frontier within an economy [18].

Econometric methodology

This study employs a panel data set that includes a sample of 69 economies from 1990 to 2023 based on the data of British Petroleum (BP) (BP, 2025) and the World Bank (2025). These are reliable and provide consistent data on energy production and economic indicators. The sample data consists of 69 economies because of the data constraints and aims to balance broad geographical representation.

To estimate the regression parameters and capture the relationship between AI and RE, we have used pooled OLS (POLS), serving as a baseline estimator. To address any potential biases, fixed effects (FE) is employed. Whereas random effects (RE) is used for comparison assuming cross-sectional effects in the assessment of the nexus between AI on RE. Another critical challenge in the analysis is the endogeneity problem which is addressed using system GMM, and Quantile regression analyzes the relationships of all the distributions of a dependent variable, giving a more complete picture compared to traditional regression. Quantile regression is a statistical technique that allows researchers to study how the association between variables varies across different points of a distribution, rather than only focusing on the average effect like ordinary least squares (OLS). Instead of estimating how independent variables affect the mean of the dependent variable, quantile regression estimates their impact at various quantiles that are 10th, 50th, or 90th percentiles. Table 1 describes the data applied for empirical analysis.

Table 1: *Variable Description, Transformation and Data Source*

Var.	Description	Definition of Variables	Source
		Dependent Variable	
RE	Generation from Solar, Wind, Hydroelectricity, Geo-thermal, and Biomass Sources (TWH)	"A ratio of the total electricity produced using solar, wind, hydroelectricity, geothermal, and biomass, in terawatt-hours (TWh). It shows the total contribution of renewable sources to total energy generation."	BP (2025)
		Independent Variables (Control Variables)	
GDP	GDP per capita (constant 2015 US$)	"The gross domestic product is the total value of goods and services produced in a country divided by its population adjusted to the prices in 2015. It is a ratio of the average real income per capita."	WDI (2025)
FDI	Foreign direct investment, net inflows (% of GDP)	"Net inflows of foreign investment in the domestic enterprises with the view of long-term ownership (10% or more). It comprises equity and reinvested earning and the capital flows in the total of GDP."	WDI (2025)
TO	Trade (% of GDP)	"The percentage change of the total exports and imports of goods and services to the GDP which shoes the extent to which an economy is integrated with the global markets."	WDI (2025)
IND	Industry, including construction, value added (constant 2015 US$)	"The sum of the contribution of industries, the mining industry, the manufacturing industry, the construction industry, the electricity industry, the water industry, and the gas industry to the economy calculated as the output less the intermediate inputs. It is inflated based on 2015."	WDI (2025)
INF	Inflation, consumer prices (annual % growth)	"The change in the average cost of a fixed quantity of goods and services (expressed in US dollars) in a fixed list of goods and services per year as a percentage of the yearly customer purchasing power, valued at constant 2015 prices."	WDI (2025)
POP	Population (total)	"The de facto population definition is the mid-year number of all the individuals residing in a nation, with or without citizenship or legal	WDI (2025)

		status.”	
		Focus Variable	
AI	Patent applications, residents	“The total patent applications made in the world to either new or to enhance products or processes, where national offices or the patent cooperation treaty are used to make the application and exclusive rights are usually granted, usually over 20 years.”	WDI (2025)

Descriptive Statistics

Table 2 presents the outcomes of descriptive statistics.

Table 2: *Descriptive Statistics*

Variables	Obs	Mean	Std. Dev	Min	Max
RE	2482	.159	1.265	-.278	18.691
AI	3191	2.342	1.191	0	6.154
GDP	6875	3.723	.651	2.222	5.351
FDI	5855	.349	.696	-6.505	3.233
TO	5857	1.866	.251	-1.678	2.936
IND	5772	9.812	1.08	6.412	12.821
INF	5428	.66	.568	-2.203	4.376
POP	7378	6.441	1.018	3.917	9.158

Table 2 shows the descriptive statistics of the variables used in the study. The minimum value of RE is -0.278 for Algeria, and the maximum value is 18.691 for China. The minimum and maximum values of AI are 0 and 6.154 for China, respectively. Moreover, the minimum and maximum values for GDP are 2.222 for Belarus and 5.351 for Monaco. Similarly, the minimum and maximum values for FDI are -6.505 for Turkmenistan and 3.233 for Australia, respectively. The minimum and maximum values TO are -1.678 for the Congo, Rep. and 2.936 for Thailand, respectively. The IND is recorded as the minimum and maximum values are 6.412 for Indonesia, Tuvalu, and 12.821 for Iran, Islamic Republic. Moreover, the minimum and maximum values for inflation are -2.203 for Dominica and 4.376 for Congo, Dem. Republic. Likewise, the minimum and maximum values for POP are 3.917 for Croatia and 9.158 for Madagascar, respectively.

Correlation Matrix

Table 3 Represents the variables used for empirical analysis. The indicator of AI has a positive correlation with RE.

Table 3: *Correlation Matrix*

Variables	RE	AI	GDP	FDI	TO	IND	INF	POP
RE	1.000							
AI	0.484	1.000						
GDP	0.133	0.288	1.000					
FDI	-0.028	-0.069	0.286	1.000				
TO	-0.178	-0.189	0.354	0.524	1.000			
IND	0.477	0.755	0.216	-0.142	-0.339	1.000		
INF	-0.161	-0.095	-0.495	-0.234	-0.261	-0.170	1.000	
POP	0.134	0.039	-0.023	0.029	-0.082	0.153	-0.022	1.000

Results & Discussions

Results of Panel Regression

Table 4 reports the results using POLS, FE, RE, and GMM methods.

Table 4: *Results of Panel Data Regression*

	OLS	FE	RE	GMM
Variables	**(RE)**	**(RE)**	**(RE)**	**(RE)**
AI	0.365***	0.640***	0.517***	0.365***
	(0.0366)	(0.0731)	(0.0658)	(0.0492)
GDP	-0.0872*	4.645***	0.713***	-0.116***
	(0.0504)	(0.464)	(0.161)	(0.0439)
FDI	0.0849*	-0.124***	-0.119***	0.0538
	(0.0446)	(0.0455)	(0.0460)	(0.0357)
TO	-0.377***	0.560**	0.398**	-0.282***
	(0.116)	(0.233)	(0.202)	(0.0854)
IND	0.270***	-2.346***	0.460***	0.257***
	(0.0556)	(0.379)	(0.140)	(0.0285)
INF	-0.233***	0.00112	-0.0917**	-0.280***

	(0.0440)	(0.0430)	(0.0434)	(0.0396)
POP	0.0762***	-0.0312	-0.0113	0.0859***
	(0.0205)	(0.0335)	(0.0327)	(0.0149)
Constant	-3.192***	4.239*	-9.715***	-3.169***
	(0.638)	(2.471)	(1.280)	(0.356)
F State	90.72 0.0000	1,587		
Adj R-squared	0.2837			
Observations	1,587	1,587	1,587	1,375
R-squared	0.287	0.229		0.287
VIF	1.81			
BPG Test	3888.77 (0.0000)			
Wald Test			358.29 0.0000	
BPLM Test			1505.06 0.0000	
Hausman Test			121.61 0.0000	
Hansen's J				7.93284 (0.2431)
Number of id		169		

Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

All the models have positive and significant coefficients for AI, which shows that AI and RE have a positive linkage. Therefore, advancement in AI facilitates RE. The POLS coefficient of AI is 0.365, which shows that an increase in AI by one unit leads to an increase in RE by 36.5%. The results indicate that the development of AI contributes to the progression of RE in the nation. The incorporation of AI into RE significantly increases the overall efficiency and productivity. It results in the maximization of production and the minimization of expenses, which makes RE technologies more cost-effective. Besides increasing productivity and efficiency, AI ensures more resilient and high-performance RE infrastructure [11] [15] [13].

More precisely, installation and maintenance of RE systems deal with difficult conditions in many cases, e.g., offshore wind farms or solar power plants. The application of AI can protect human laborers against unfriendly conditions and dangerous tasks, thus reducing the risk of accidents and injuries. It supports a more secure workplace and mitigates the challenges accompanying RE development [26][27].

Based on system GMM results, all control variables significantly affect RE except FDI. GDP, TO, and INF show a negative relationship with RE, whereas IND and POP depict a positive association with RE. An increase in GDP causes RE progression to slow down, which shows that the increase in demand due to economic growth is met by production using traditional fuel sources rather than exploiting RE sources. The negative influence of TO on RE development depicts that the country still imports or employs carbon-intensive fuels, which slows the rate of energy transition [28][29] Similarly, energy diversity harms inflation. This finding suggests the disinflationary impact of energy diversity when the sources of energy are not linked to a single source. In contrast, IND shows a positive association with RE, implying that the expanding manufacturing sector demands diversified energy sources, which leads to the adoption of RE sources. More time and money will be needed to switch from traditional industrial infrastructure utilizing fossil fuels to RE, which may result in the further use of non-RE sources [30][31]. Similarly, POP positively influences RE development in nations due to the rising energy needs of a growing population. This puts pressure on the government to invest in clean and environmentally friendly resources to meet the ever-increasing energy demand. This encourages the use and implementation of renewable energy sources [32][28][33][21]. FDI shows a positive but statistically insignificant relationship with RE, which indicates that foreign funding has the potential to enhance RE systems, but is presently not being utilized for RE development, rather directed towards other carbon-intensive sectors.

Results of Quantile Regression

To explore the asymmetric relationship between AI and RE, panel quantile regression is employed. This approach aids in assessing the variation in the marginal impact of AI on RE development. The results strongly support the positive influence of AI on RE across all quantiles. The development and progression of AI technologies have a magnifying effect on RE adoption, increasing from 0.546% in the first quantile to 22.5% in the last quantile. These results align with the findings of Li et al. (2023b).

Table 5: *Results of Quantile Regression*

VARIABLES	q10	q25	q75
AI	0.00546***	0.0160***	0.225***
	(0.00190)	(0.00322)	(0.0254)
GDP	0.00702***	0.0210***	0.124***

	(0.00247)	(0.00343)	(0.0386)
FDI	0.00131	0.0117***	0.0266
	(0.00125)	(0.00230)	(0.0211)
TO	-0.00144	-0.0312***	-0.337***
	(0.00496)	(0.00843)	(0.0685)
IND	0.00278	0.0258***	0.127***
	(0.00191)	(0.00448)	(0.0248)
INF	-0.00600***	-0.0194***	-0.0729**
	(0.00198)	(0.00429)	(0.0285)
POP	0.00114*	0.000907	0.0961***
	(0.000629)	(0.00184)	(0.0190)
Constant	-0.348***	-0.595***	-2.283***
	(0.0301)	(0.0520)	(0.289)
Observations	1,587	1,587	1,587

Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Conclusion & Policy Implications

This study explores the underlying factors influencing RE development, specifically focusing on AI, using a panel dataset of 69 countries from 1990 to 2023. The empirical analysis through system GMM and panel quantile regression reveals a statistically significant positive relationship between AI and RE. The findings highlight that AI is a significant contributor to RE development. It drives technological progress and innovation, which enhances energy efficiency, forecasting, and grid management, thus promoting regional RE development.

The research findings of this study imply several policy measures to encourage RE development. As AI is a significant contributor to RE, the governments should support AI development by financing research and development, establishing AI infrastructure, and collaborating between industries, educational and energy institutions. In developing countries, trade policies should be revised to import technologies that aid in establishing RE infrastructure to phase out old technologies dependent on fossil fuels and accelerate the energy transition. Moreover, industrial expansion and rising population emphasize the need to equip humans with the necessary skills to utilize, upgrade, and integrate AI innovations into the existing system. Therefore, policymakers should make policies to introduce such skill development programs and training specifically in developing nations, which could improve human capabilities to leverage digital technologies.

The study highlights significant contributors to RE development, yet it has certain limitations. First, data availability remains a significant concern; the sample data comprises only those nations that had data regarding all variables, specifically AI. Second, AI is measured through patent data, which only reflects AI's potential and ignores its practical implementation in the region. Third, the panel data techniques may overlook the institutional differences across countries, which can subsequently affect RE development in an area. Future studies can consider these limitations to provide a more comprehensive analysis.

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