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How does artificial intelligence promote renewable energy development? The role of climate finance

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ABSTRACT

Scholars, stakeholders, and the government have given significant attention to the development of renewable energy in recent times. However, previous research has failed to acknowledge the potential impact of artificial intelligence on advancing renewable energy development. Drawing insights from a global dataset encompassing 63 countries over the period 2000–2019, this paper provides significant observations regarding the influence of artificial intelligence on the progress of renewable energy, by using the Instrumental Variable Generalized Method of Moments model. We also explore their asymmetric nexus, and the potential mediation effect. Moreover, this study explores the moderating role of climate finance and highlights the following interesting findings. First, artificial intelligence contributes significantly to the enhanced development of renewable energy, and this primary finding holds after two robustness tests of changing independent and dependent variables. Second, artificial intelligence has an asymmetric effect on renewable energy development, and their nexus is closer in countries with lower levels of renewable energy development. Thid, artificial intelligence works on renewable energy development through technology effect and innovation effect. Fourth, climate finance also presents direct benefits to renewable energy development; simultaneously, climate finance plays an effective moderating role in the relationship between artificial intelligence and renewable energy development. These findings inspire us to propose policy implications to promote the enhanced development of renewable energy.

1. Introduction

The escalating levels of greenhouse gas emissions, particularly carbon emissions, have resulted in severe climate change and global warming (Khan et al., 2021; Zhao et al., 2022d). These phenomena have triggered catastrophic consequences for both ecosystems' sustainability and human beings (Bidwell and Sovacool, 2023; Zhao et al., 2022a). Furthermore, the deterioration of the climate system and the occurrence of climate-related disasters have hindered sustainable development on various fronts (Esperon-Rodriguez et al., 2022; Zhao et al., 2023b). For instance, extreme weather events such as hurricanes, floods, and droughts have inflicted immense damage on infrastructure, agriculture, and livelihoods (Halpern et al., 2022). Vulnerable communities, including those in low-lying coastal areas or arid regions, are particularly susceptible to the adverse effects of these climate hazards (Goodwin et al., 2023; Logan et al., 2023). Recognizing the critical importance of mitigating climate change, countries worldwide have increasingly acknowledged the need to address this pressing issue. One significant approach is the development of renewable energy (Naeem et al., 2023; Taghizadeh-Hesary et al., 2023). As mentioned in World Energy Outlook, in 2022, the share of power generation capacity from renewable energy sources was 41%, and the goal is to increase the proportion to 50% by 2030. Alongside this, there is also a target of achieving 500 gigawatts (GW) of renewable energy capacity by the year 2030.[1] Transitioning to renewable energy offers a pivotal solution for mitigating carbon emissions and promoting sustainable economic and social development (Zhao et al., 2023c). Thus, it is urgent and necessary to explore how to promote renewable energy development (RED).

As climate change continues to unfold, technological advancements are simultaneously progressing on a global scale. One significant

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[1] For details, please see https://www.iea.org/reports/world-energy-outlook-2023.

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development in this regard is the emergence of Industry 4.0, which has also propelled the growth of artificial intelligence (AI) (Lei et al., 2023). The Industry 4.0 revolution signifies a fundamental change in industrial processes, propelled by the incorporation of digital technologies into manufacturing and associated sectors (Olabi et al., 2023; Saheb et al., 2022). In particular, industrial robots play a pivotal role as a key enabling technology within industry 4.0 and the AI revolution, facilitating the intelligent and environmentally friendly transformation of traditional industries (Soori et al., 2023). The International Federation of Robotics (IFR) declares that industrial robots are versatile, reprogrammable machines that operate under automatic control, serving various purposes within industrial automation (IFR, 2023). World Robotics report reveals that in 2021, a record-breaking number of 517,385 new industrial robots were deployed in factories worldwide, marking a 31% surge from the previous year. As a result, the total number of operational robots worldwide has reached an unprecedented level of approximately 3.5 million units.[2] Moreover, industrial robots represent a distinct advancement in technology, setting them apart from early automation and conventional information and communication technologies (Li et al., 2023b; Sayed et al., 2023). Their extensive implementation in manufacturing and other domains has the potential to yield significant benefits for sustainable development (Yao et al., 2023; Delanoë et al., 2023). By leveraging automation, industrial robots contribute to reduced resource waste, shorter production cycles, and lower energy consumption (Entezari et al., 2023; Hossin et al., 2023). These outcomes hold immense significance in the pursuit of sustainable development goals.

Literatures have focused on the topic of AI and revealed its positive role in social, economic, and environmental improvement. Existing research has indicated that the development of AI technology, represented by industrial robots, helps to reduce inequality between developed and developing countries (Yang and Wang, 2023), improve the quality of trade products (Lin et al., 2022), promote green innovation (Lee et al., 2022b), and reduce carbon emissions (Li et al., 2022; Wang et al., 2023b; Yu et al., 2023). Furthermore, considering that AI is closely related to energy efficiency and innovation in renewable energy technology, it may also have the potential to accelerate RED. However, few studies have linked AI with sustainable energy development, which is also the objectivity of this study.

Since the adoption of the Kyoto Protocol in 1997, developed nations have provided financial support to developing countries to assist them in both mitigating and adapting to the impacts of climate change. Climate finance (CF) has emerged as a crucial mechanism for aiding developing countries in their efforts to tackle climate change, and has gained prominence in international climate negotiations (Anantharajah and Setyowati, 2022; Bhandary et al., 2021). The rationale behind the establishment of CF stems from the recognition that many developing countries face substantial challenges in addressing environmental sustainability issues due to limited resources and capacities (Carè and Weber, 2023; Stroebel and Wurgler, 2021). Consequently, CF is conceived as a crucial stride towards mitigating global emissions (Alharbi et al., 2023; Aquilas and Atemnkeng, 2022; Lee et al., 2022a; Sinha et al., 2023). It serves to assist developing nations in striking a delicate balance between sustaining economic growth and reducing GHG emissions, offering fresh incentives for the adoption of low-carbon pathways (Zhao et al., 2022c). Through CF, donor countries distribute versatile aid to recipient developing nations, enabling them to finance projects and programs focused on reducing emissions and safeguarding the environment (Alharbi et al., 2023; Biagini et al., 2014; Xu et al., 2023). In essence, CF acts as a catalyst for change by bridging the financial gap and supporting developing countries in their pursuit of sustainable development (Qi et al., 2023). It plays a pivotal role in facilitating the transition towards a low-carbon economy and enhancing climate resilience in vulnerable regions. By channeling financial resources towards initiatives such as renewable energy investments or initiatives aimed at combating deforestation (Tang and Zhou, 2023), CF contributes to global efforts aimed at tackling environmental degradation (Umar and Safi, 2023). Moreover, it fosters cooperation and partnership between developed and developing nations, recognizing the shared responsibility in addressing the climate crises and achieving collective climate goals (Yu et al., 2022). Scholars stress that in addition to CF's positive energy and environmental effects, it plays an important role in reducing economic risks (Zhao et al., 2022e), narrowing inequality (Kafle et al., 2022), and achieving the nationally determined contribution (NDC) target (Abi Suroso et al., 2022). In the nexus between AI and RED, it is also vital to consider the role of CF.

Based on the above background introduction, we are concerned with the following questions. (1) Can AI development facilitate RED? And will their nexus be asymmetric? (2) If AI leads to better RED, how does AI realize this positive RED effect? What are the impact mechanisms? (3) Will CF also have a positive impact on RED? And what is the role of CF in the AI-RED nexus? To this end, we utilize a global panel dataset of 63 countries for the period 2000–2019 to empirically investigate the impact of AI on RED by taking industrial robot installation as a proxy variable for AI. We also use the panel quantile regressions model to detect the asymmetric relationship between AI and RED. Also, we explore the impact mechanisms, as well as the mediation role of CF.

This paper makes several noteworthy contributions. First, unlike previous literature that has focused on the social and environmental impacts of AI, this study explores the relationship between AI and RED. Our empirical investigation is the first to examine the potential of AI in promoting RED, bridging a research gap and providing a fresh perspective on achieving RED through AI. Second, in terms of research design, we not only explore the linear nexus between AI and RED, but also document their nonlinear relationship, namely the asymmetric impact of AI on RED. Third, we meticulously examine the impact mechanisms of technology and innovation effects, considering energy efficiency and R&D as mediating variables. This contribution broadens the scope of research in this field. Fourth, we construct an integrated framework encompassing AI, CF, and RED, emphasize the positive influence of CF on RED, and further explore how CF amplifies the RED promotion effect of AI. Consequently, CF is identified as a moderating variable that synergistically works with AI to achieve enhanced RED outcomes.

In this study, we review the literature and summarize existing literature gaps. Afterward, we present the estimation model and data. Then, we deliver the estimation results and discuss further analysis. Finally, we conclude the paper and tender some policy suggestions.

2. Review of literature

2.1. Empirical studies on artificial intelligence and its nexus with energy

In recent decades, some scholars have investigated the development of AI, especially its effects on installing industrial robots and the consequent social-environmental implications. For example, Yang and Wang (2023) verify that industrial robot applications have positive effects enabling trapped countries to cross the middle-income trap, based on a dataset of 37 leapfrogged countries and 24 trapped economies during the period 1993–2019. The authors also maintain that technological innovation, industrial structure, and FDI are three mediators. Lin et al. (2022) find that industrial robot application also positively affects the quality of export trade because AI leads to higher labor productivity and human capital accumulation, and the role of AI is more effective in high-tech industries. Meanwhile, based on global panel data of 34 countries between 1993 and 2019, Lee et al. (2022b) show that industrial robot development has positive effects on green technology innovation, and environmental regulation can reinforce the technology

[2] For details, please see https://ec.europa.eu/newsroom/rtd/items/771175/en.

innovation promotion effect of AI. Thus, AI development is crucial for social, equal, and sustainable development.

In addition to AI's social impact, the literature also points out that it has positive environmental effects, such as promoting energy efficiency and inhibiting carbon emissions. For instance, Wang et al. (2023b) investigate the detailed relationship among industrial robot development, carbon emissions, and energy rebound. They declare that AI development induced by industrial robot applications can help reduce carbon emissions. Yu et al. (2023) also pay attention to the role of industrial robots in low-carbon city development in China and verify the carbon emissions mitigation effect of industrial robot application, and the impact mechanisms are energy efficiency and green technology. This conclusion is supported by Yao et al. (2023) who also find that AI in energy sector is helpful for enhancing energy efficiency. Li et al. (2022) find that industrial robot application drives the reduction of carbon intensity, and the carbon intensity reduction effect of AI is more prominent in some sectors such as manufacturing, electricity, and gas, which is similar to the conclusion of Olabi et al. (2023). Moreover, Liu et al. (2022) and Chen et al. (2021) also confirm the significance of AI in promoting energy efficiency. In addition, Li et al. (2023b) verify the positive effect of AI on energy and resource efficiency based on firm-level data in China between 2005 and 2014. And Sayed et al. (2023) show that AI can lead to the advancement and perfection of energy systems. The energy sustainable development effect of AI is also mentioned by Delanoë et al. (2023), Entezari et al. (2023), Hossin et al. (2023), and Lei et al. (2023).

2.2. Empirical studies on climate finance and its nexus with energy

In recent years, some studies have documented the impact of CF on RED. Specifically, Aquilas and Atemnkeng (2022) take the Congo basin as a case study to explore the role of CF for the period 2002–2020, and find that the enhancement in climate-related mitigation finance accelerates RED, which further leads to carbon emissions mitigation. Qi et al. (2023) also find that green finance projects are crucial for RED and realizing the zero emissions goal. In addition, based on the case of China, Tang and Zhou (2023) investigate the impact of CF on RED in China and show that CF can not only promote RED locally, but also has a positive effect on RED in neighboring regions. Lee et al. (2022a) investigate CF on carbon emissions between 2000 and 2018, and show that CF has a positive effect on carbon emissions mitigation. The finance of climate change mitigation and climate change adaptation both show significant effects. Moreover, they also reveal that compared to high-quality economies, small island countries benefit more from climate aid, which means that this effect is greater in developing countries. This conclusion is supported by Pinar (2023) who also shows the effectiveness of CF on carbon emissions mitigation. In addition, Umar and Safi (2023) take the budget spent on renewable energy public R&D as a proxy variable for climate-related development finance, and find that CF leads to lower trade-adjusted carbon emissions in OECD countries. Similarly, Yu et al. (2022) explore the nexus between CF and carbon emissions; based on the data from 60 countries around the world, they show that the amount of money spent on R&D for renewables can significantly reduce carbon emissions. Similar to CF, the role of finance on energy aid is stressed by Liu et al. (2023), who use 65 countries' data from 2002 to 2020 to find the impact of energy aid on carbon emissions. They conclude that energy aid finance is an effective means for mitigating carbon emissions. Moreover, technical and structural effects are the impact mechanisms. Chung et al. (2018) focus on the CF related to technology development, and find that CF has an insignificant impact on overall emissions reduction; however, they also mention that CF is effective in reducing carbon emissions in certain sectors such as electric power sector. Using the quantile regression model, Carfora et al. (2017) reveal that while climate financial support is crucial for curbing emissions, its influence varies depending on the distribution of fund allocation. The finding of the positive effect of CF on carbon emissions mitigation is also detected by Alharbi et al. (2023), Biagini et al. (2014), and Xu et al. (2023).

2.3. Literature gaps

While it is evident from the above discussions that the intersection of AI, CF, and RED has garnered significant attention from scholars, there remain noteworthy gaps in the existing literature. First, although prior studies have examined the social and environmental impacts of AI, including its pivotal role in elevating trade quality, fostering innovation, and propelling advancements in energy systems, a notable absence persists in connecting AI to RED. This signifies that the causal effect of AI on the advancement of renewable energy sources remains unverified.

Second, delving into the nuanced and potentially asymmetric impact of AI on RED, alongside the intricate underlying mechanisms at play, emerges as a crucial area for further exploration. Intriguingly, the literature landscape has seen scant investigation into the asymmetric effects of AI on RED and their pathways of influence, leaving a critical knowledge gap.

Third, while certain studies have shed light on the direct influence of CF on RED, there has been a notable dearth of scholarly attention directed towards probing whether CF wields a moderating influence in the intricate nexus between AI and RED. Consequently, the imperative arises for researchers to embark on the task of integrating AI, CF, and RED into a comprehensive analytical framework. This integrated framework will enable the estimation of CF's potentially pivotal moderating role, warranting a thorough and insightful discussion. In light of these considerations, it is imperative to conduct rigorous research endeavors that bridge these gaps.

3. Methodology and data

3.1. Econometric model

The research questions in the Introduction part drive us to construct a comprehensive framework to evaluate the causal relationship between AI and RED. To this end, we construct a multivariate estimation model that includes RED, AI, and a series of control variables.

$$RED_{it} = f(AI_{it}, GDP_{it}, FDI_{it}, TRADE_{it}, POP_{it}, IND_{it}) \tag{1}$$

where RED_{it} represents the development level of renewable energy, and AI_{it} shows the development level of artificial intelligence. The control variables GDP_{it}, FDI_{it}, $TRADE_{it}$, POP_{it}, and IND_{it} denote economic development, foreign direct investment, trade volume, population, and industrial development. In addition, i and t in the subscript represent the sample country and time.

We take the logarithmic form of the above variables to reduce the heteroscedasticity problem; thus, we generate the following equation.

$$\begin{aligned} lnRED_{it} = {} & \beta_0 + \beta_1 lnAI_{it} + \beta_2 lnGDP_{it} + \beta_3 lnFDI_{it} + \beta_4 lnTRADE_{it} \\ & + \beta_5 lnPOP_{it} + \beta_6 lnIND_{it} + \pi_i + \mu_t + \varepsilon_{it} \end{aligned} \tag{2}$$

In the above equation, the six parameters $\beta_1 - \beta_6$ measure the impacts of the independent variables on the dependent variable. On account that our research aim is to accurately evaluates the causal impact of AI on RED and we want to answer the question about the nexus between AI and RED, β_1 is the most important parameter that we concerned, which shows the elasticity relationship between AI and RED and we expect to be positive. We also consider two-way fixed effects, which can be found in π_i and μ_t. ε_{it} is the error term.

Regarding the estimation methodology, our primary choice is the IV-GMM approach. While this study incorporates various control variables related to the economy, trade, industrial development, and population, it is possible some variables that have impacts on RED are excluded, resulting in omitted variable bias. Additionally, reverse causality may exist because energy development may lead to economic improvement and induced technological advancements. Under such conditions, employing ordinary least squares (OLS), fixed effect (FE), random effect (RE), or feasible generalized least squares (FGLS) may not yield an effective and consistent estimation due to potential endogenous problems; although FGLS is reliable and feasible at dealing with unknown heteroscedasticity problems (Zhao et al., 2022b). In contrast, by utilizing orthogonal conditions, the IV-GMM technique can offer consistent and efficient estimators when addressing endogeneity concerns (Zhao et al., 2023a). Moreover, following Acheampong et al. (2020, 2021), we take the lag term of the independent variable (i.e., *AI*) as the IV in the IV-GMM model.

3.2. Variables and data

Our dependent variable, RED, is measured by the generation level of renewable energy (Zhao et al., 2023c). We obtain the data for renewable energy generation, including hydroelectricity, solar energy, wind energy, and geothermal energy generation, from the British Petroleum (BP) (BP, 2023) website. These data are then aggregated to obtain the total generation level of renewable energy, which serves as a proxy variable for RED. Fig. 1 presents the levels of RED in 2000, 2010, and 2019, respectively. The data in Fig. 1 illustrate a significant increasing trend in RED over the past two decades, despite the fact that developed countries generally have higher levels of RED than developing countries.

AI, being an emerging technology, is actively involved in various markets and applications, which complicates the task of accurately gauging its true development status and scale. Some studies measure AI from the perspective of technological innovation, for example, Wang et al. (2023a) track the number of AI-related patents. In addition, robot application is also adopted by scholars as a measurement of AI. For instance, Li et al. (2023b) employ the robot application data to investigate the impact of AI on resource efficiency. Moreover, Duan et al. (2023), Fu et al. (2021), Wu (2023), and Yang and Wang (2023) also document the topic of AI and focus on the development of industrial robots. Compared to technological innovations like patents, robot applications offer a more precise measure of AI development. This is because many technological patents often remain in the theoretical stage without practical application. In contrast, robots have already been integrated into industrial production, allowing them to provide a more accurate reflection of the current state of AI development, which means that robots embody AI technologies and their installation reflects the adoption and maturity of AI in automation. Hence, we use the industrial robot installation to represent the development of AI, which is our independent variable. The data of industrial robot installation in each country comes from the International Federation of Robotics (IFR, 2023). The federation also has data on industrial robot stock, which we will use as an alternative independent variable in the robustness tests. Notably, the data on industrial robots has only been updated to 2019; thus, the time span of this paper is 2000–2019.

Fig. 2 shows the box chart of industrial robot installations. On the one hand, the average installation of industrial robots exhibited an upward trend between 2000 and 2019, indicating an overall improvement in the global level of AI. On the other hand, although some countries had zero industrial robot installations, the number of countries without industrial robots is also decreasing steadily.

In terms of the control variables, we consider five variables: gross domestic product (i.e., *GDP*), which measures economic development; foreign direct investment (i.e., *FDI*), which reflects the openness level; imports of goods and services (i.e., *TRADE*), which helps us identify the trade volume; population (i.e., *POP*), which represents demographic growth; and value added of industry (i.e., *IND*), which denotes industry development. The data of all control variables are from the World Development Indicators (World Bank, 2023). Therefore, we have a global panel dataset of 63 countries for the period 2000–2019, and Table 1 shows descriptive statistics of the variables.

4. Estimation results and analysis

4.1. Baseline regression results

Table 2 presents the results of baseline regressions estimated by five models. On the one hand, these five models can be used for comparison to check the reliability of our primary result; on the other hand, IV-GMM is our preferred model, and we will analyze the result mainly in the last column. Before analyzing the coefficients estimated in the IV-GMM model, it is necessary to check its two tests, namely the LM test and the Wald test, which are used to verify the reliability of the IV. From the statistics of these two tests (see the last three rows in Table 2) we can see that our IV is neither under-identified nor weak.

AI has positive and significant coefficients in all the models, which indicates a robust positive nexus between AI and RED. Thus, developing AI is a feasible approach to promote RED. The coefficient of AI is 0.1187 in the IV-GMM model, implying that an increase in industrial robot installation by 1% can trigger an increase in RED of 0.1187%. The development of AI can bring several benefits to the development of renewable energy. By integrating robots into renewable energy operations, such as the production of solar panels or components for wind turbines, there can be a substantial enhancement in overall efficiency and productivity (Li et al., 2023b). This leads to increased output and reduced costs, making renewable energy technologies more economically viable. Aside from boosting productivity and efficiency, AI also plays a vital role in guaranteeing the quality control of renewable energy systems (Lee et al., 2022b; Wang et al., 2023b; Yu et al., 2023). More importantly, the installation and maintenance of renewable energy systems often involve working in challenging environments, such as offshore wind farms or solar power plants. Utilizing industrial robots can shield human workers from perilous environments and high-risk assignments. Robots are capable of executing tasks in hazardous or inaccessible areas, thereby diminishing the likelihood of accidents and injuries. This fosters a safer work environment and minimizes the risks associated with renewable energy development (Sayed et al., 2023; Wu et al., 2023).

Control variables also exert a significant impact on RED, except for FDI. Specifically, economy and population are positively related to RED, while trade and industry development are not beneficial for RED. As societies become more prosperous and populations expand, there is a greater need for energy to power industries, homes, transportation, and other sectors. Renewable energy sources offer a sustainable and environmentally friendly option to meet this growing energy demand. Moreover, as economies grow, investments in research and development increase, leading to technological innovations and improvements in renewable energy systems. This, in turn, promotes the adoption and utilization of renewable energy sources (Algarni et al., 2023; Wu and Wang, 2022; Xiao et al., 2022; Zhang et al., 2022). On the other hand, trade often involves the exchange of goods and resources, including fossil fuels. If countries rely heavily on traditional energy sources such as coal, oil, and natural gas for their industrial development, trade can contribute to increased non-renewable energy (Ivanovski and Churchill, 2020; Zafar et al., 2020). Moreover, industrial development often builds upon existing infrastructure and investments, which are based mainly on conventional energy systems and technologies. The cost and effort required to transition from traditional energy sources to renewable energy can be significant, potentially leading to continued reliance on non-renewable energy sources (Korczak et al., 2022; Wu et al., 2021).

4.2. Robustness checks

The baseline regressions results show a positive nexus between AI and RED, to test whether their positive nexus is robust or not, we have two robustness checks. First, we use the alternative independent variable, namely the volume of industrial robot stock, to represent AI development. The data on industrial robot stock also comes from the

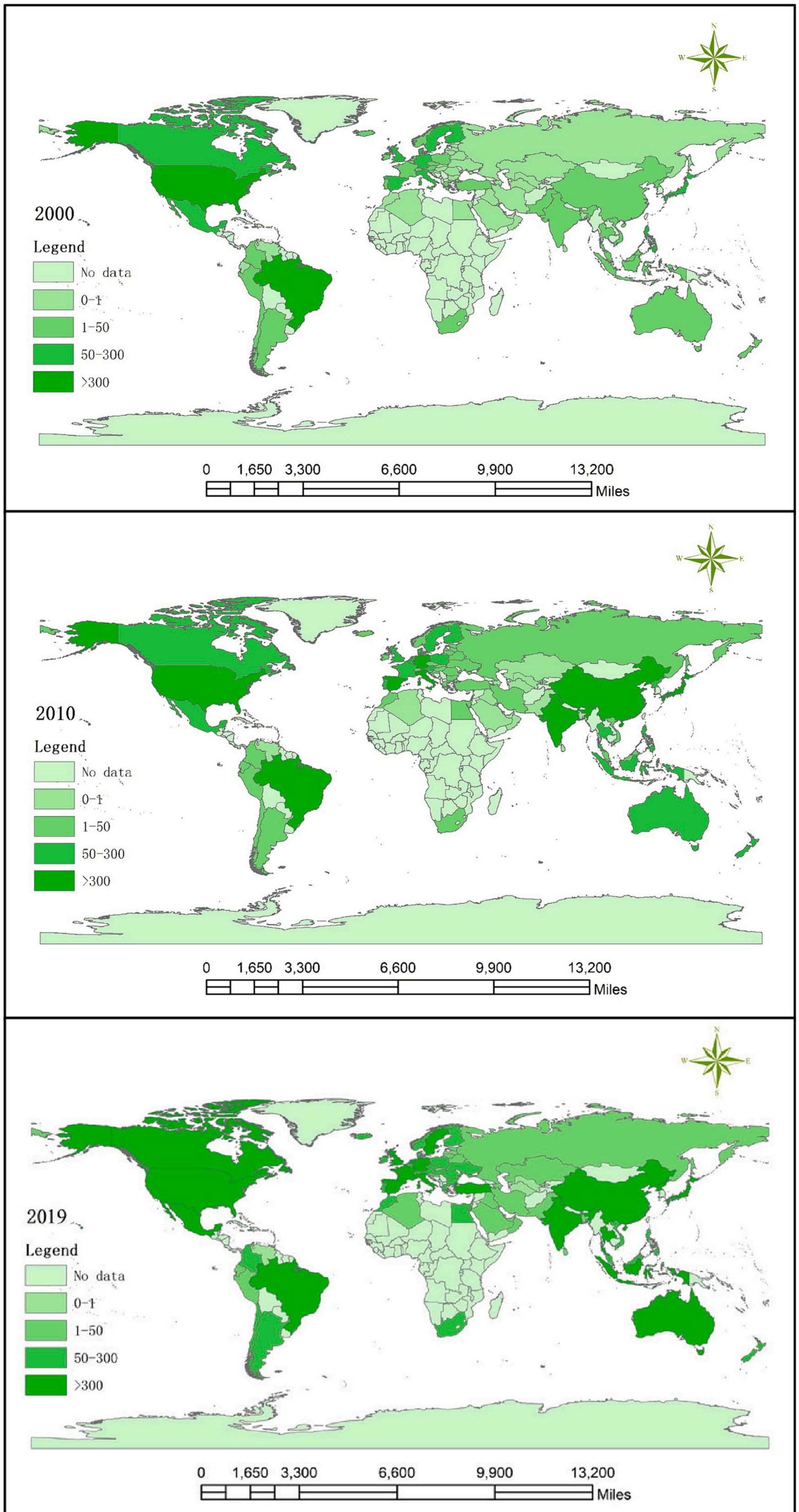

Fig. 1. Spatial distribution of renewable energy development for selected years.

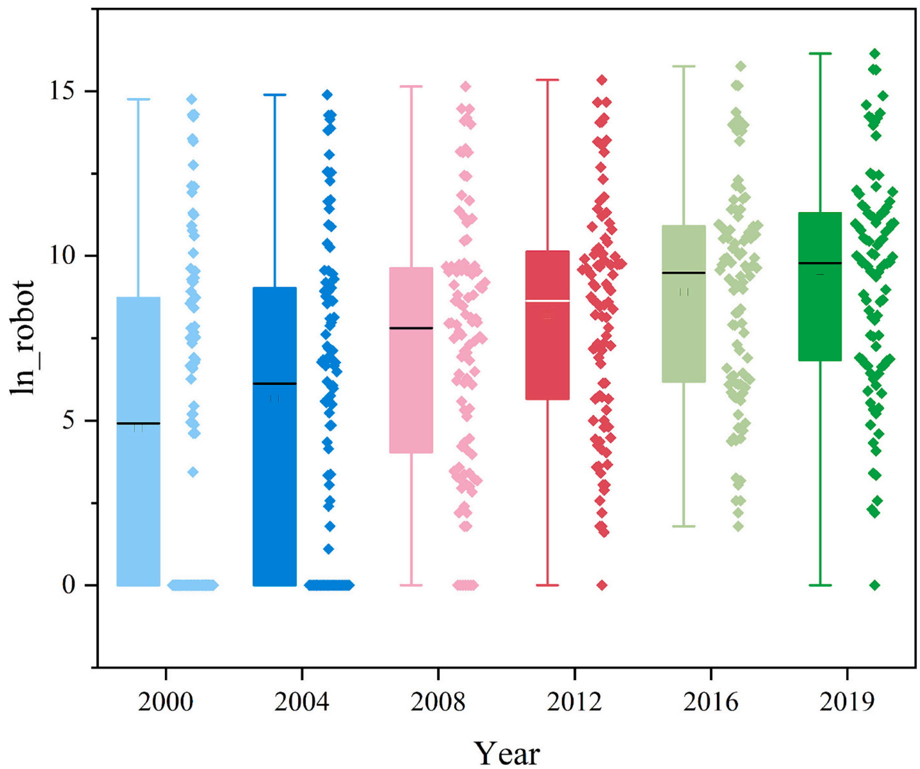

Fig. 2. Time trend box chart of international industrial robot installation.

Table 1
Descriptive statistics of the variables.

Variable	Mean	Std. Dev.	Min.	Median	Max.
lnRED	−1.9605	2.2062	−13.2355	−1.6561	2.9623
lnAI	7.0395	3.8850	0.0000	7.7928	14.8574
lnGDP	26.3249	1.5010	22.4627	26.2777	30.6960
lnFDI	1.2922	0.8210	−4.9021	1.2778	4.4727
lnTRADE	3.6369	0.5219	0.0000	3.5984	5.3439
lnPOP	16.9039	1.5939	12.5468	17.0202	21.0581
lnIND	3.3462	0.3023	2.6161	3.3015	4.3150

International Federation of Robotics (IFR, 2023). The results in Table 3 show the impact of industrial robot stock on RED. From Table 3 we can know that basically industrial robot stock has a positive and significant impact on RED; an increase of industrial robot stock by 1% can promote RED by 0.1282%, which is consistent with the elasticity relationship between industrial robot installation and RED.

Second, we also change our dependent variable, and we use the volume of renewable energy consumption, instead of renewable energy generation, to gauge RED. BP provides us with data on hydroelectricity consumption, solar consumption, wind consumption, and geothermal consumption (BP, 2023), and we aggregate these kinds of renewable consumption data to obtain the total renewable energy consumption. Renewable energy consumption is then applied as the dependent variable to get results in Table 4. Notably, the coefficients of AI are all significant and positive in five models, and the last column shows that for a 1% increase in industrial robot installation, renewable energy consumption will be significantly enhanced by 0.1192%. Thus, we can confirm that the positive effect of AI on RED is robust and reliable.

Table 2
Baseline regression result.

Variable	OLS	FE	RE	FGLS	IV-GMM
lnAI	0.1124***	0.0430***	0.0472***	0.1124***	0.1187***
	(5.4579)	(3.7023)	(4.0929)	(5.4736)	(3.9801)
lnGDP	0.2247***	0.2689***	0.3009***	0.2247***	0.2077**
	(3.4572)	(4.9158)	(5.7465)	(3.4671)	(2.1561)
lnFDI	0.0603	−0.0596**	−0.0534**	0.0603	0.0645
	(0.9635)	(−2.3036)	(−2.0601)	(0.9663)	(1.0550)
lnTRADE	−1.2761***	0.5075***	0.4201***	−1.2761***	−1.2691***
	(−9.8126)	(4.0610)	(3.4262)	(−9.8410)	(−9.4343)
lnPOP	0.3343***	1.4695***	0.8212***	0.3343***	0.3448***
	(7.3243)	(4.7269)	(6.1652)	(7.3455)	(5.2304)
lnIND	−1.5553***	−1.4364***	−1.6424***	−1.5553***	−1.6456***
	(−8.4623)	(−7.0398)	(−8.4202)	(−8.4868)	(−5.1224)
Constant	−4.6403***	−31.2881***	−20.3200***	−4.6403***	−4.1494*
	(−2.7846)	(−6.0798)	(−8.3067)	(−2.7927)	(−1.7069)
KP LM (statistic)					154.587
KP LM (Pvalue)					0.000
KP Wald F					1693.916

Notes: *** 0.01 ** 0.05 * 0.1.

Table 3
Robustness tests I: using alternative independent variable.

Variable	OLS	FE	RE	FGLS	IV-GMM
lnAI_alter	0.1179***	−0.0262***	−0.0246***	0.1179***	0.1282***
	(6.5337)	(−2.8790)	(−2.6984)	(6.5526)	(5.5751)
lnGDP	0.2506***	0.4362***	0.4825***	0.2506***	0.2213***
	(4.4647)	(9.3906)	(11.5029)	(4.4776)	(2.8607)
lnFDI	0.0361	−0.0571**	−0.0501*	0.0361	0.0411
	(0.5835)	(−2.1997)	(−1.9193)	(0.5852)	(0.6754)
lnTRADE	−1.2914***	0.6530***	0.5676***	−1.2914***	−1.3085***
	(−10.1883)	(5.2966)	(4.6930)	(−10.2177)	(−10.0893)
lnPOP	0.2905***	1.5194***	0.7957***	0.2905***	0.2985***
	(6.4731)	(4.8875)	(6.1704)	(6.4918)	(4.8798)
lnIND	−1.5852***	−1.5059***	−1.7559***	−1.5852***	−1.6727***
	(−8.7733)	(−7.4189)	(−9.0804)	(−8.7987)	(−5.1195)
Constant	−4.1685***	−36.4035***	−24.3803***	−4.1685***	−3.2340
	(−2.6175)	(−7.3121)	(−10.6840)	(−2.6250)	(−1.4438)
KP LM (statistic)					278.769
KP LM (Pvalue)					0.000
KP Wald F					2872.709

Notes: *** 0.01 ** 0.05 * 0.1.

Table 4
Robustness tests II: using alternative dependent variable.

Variable	OLS	FE	RE	FGLS	IV-GMM
lnAI	0.1129***	0.0454***	0.0504***	0.1129***	0.1192***
	(5.4657)	(3.9068)	(4.3591)	(5.4815)	(4.0029)
lnGDP	0.2265***	0.2918***	0.3295***	0.2265***	0.2082**
	(3.4734)	(5.3234)	(6.2771)	(3.4835)	(2.1633)
lnFDI	0.0470	−0.0633**	−0.0569**	0.0470	0.0522
	(0.7487)	(−2.4403)	(−2.1895)	(0.7508)	(0.8486)
lnTRADE	−1.2906***	0.5524***	0.4630***	−1.2906***	−1.2867***
	(−9.8932)	(4.4114)	(3.7649)	(−9.9217)	(−9.5245)
lnPOP	0.3324***	1.6278***	0.8423***	0.3324***	0.3433***
	(7.2590)	(5.2257)	(6.3076)	(7.2800)	(5.2061)
lnIND	−1.5390***	−1.5139***	−1.7315***	−1.5390***	−1.6294***
	(−8.3474)	(−7.4051)	(−8.8527)	(−8.3715)	(−5.0891)
Constant	−0.0574	−29.9112***	−16.7237***	−0.0574	0.4711
	(−0.0343)	(−5.8008)	(−6.8188)	(−0.0344)	(0.1939)
KP LM (statistic)					154.587
KP LM (Pvalue)					0.000
KP Wald F					1693.916

Notes: *** 0.01 ** 0.05 * 0.1.

4.3. Asymmetric nexus analysis

We have investigated the linear relationship between AI and RED, now we wonder whether the non-linear relationship also exists. To this end, we employ the panel quantile regression model to test the asymmetric impact of AI on RED. This model is helpful in identifying the marginal impact of AI on different quantiles of RED.

Table 5 shows the panel quantile regressions results. AI exerts a positive and significant impact on RED from the 10th quantile to the 90th quantile, implying that a positive AI-RED nexus exists at all quantiles of RED, which once again shows the robustness of our primary finding. On the other hand, as the quantile levels of RED increase, the

Table 5
Panel quantile regression result.

Variable	Quantiles				
	10th	25th	50th	75th	90th
lnAI	0.2861***	0.1420***	0.0646***	0.0467***	0.0759***
	(7.0401)	(4.6508)	(5.0755)	(4.0614)	(2.7765)
lnGDP	−0.0607	0.1540	0.4197***	0.5420***	0.4717***
	(−0.4798)	(1.6209)	(10.6033)	(15.1324)	(5.5460)
lnIND	0.1357	−0.0285	−0.0345	−0.0532	0.0217
	(0.9724)	(−0.2718)	(−0.7900)	(−1.3473)	(0.2310)
lnTRADE	−1.0870***	−1.0649***	−1.3602***	−1.5027***	−1.4013***
	(−3.8064)	(−4.9637)	(−15.2208)	(−18.5814)	(−7.2975)
lnPOP	0.7469***	0.4530***	0.0341	−0.0718**	−0.0783
	(7.3879)	(5.9639)	(1.0788)	(−2.5067)	(−1.1519)
lnIND	−3.4531***	−1.3939***	0.0103	0.6705***	0.9636***
	(−8.4829)	(−4.5580)	(0.0809)	(5.8165)	(3.5201)
Constant	−1.2030	−6.5106**	−8.6167***	−11.0479***	−10.2297***
	(−0.3353)	(−2.4153)	(−7.6741)	(−10.8731)	(−4.2400)

Notes: *** 0.01 ** 0.05 * 0.1.

marginal impact of AI on RED shows a decreasing trend. For example, at the 10th quantile, a 1% increase in AI will result in a 0.2861% increase in RED; while at the 90th quantile, for a 1% increase in AI, RED can only be increased by 0.0759%. That is to say, the positive RED effect of AI is more prominent in lower quantiles of RED. Thus, in areas with lower levels of RED, the development of AI can be a more effective means for stimulating RED. Moreover, Fig. 3 also vividly shows the asymmetric effect of AI on RED.

Countries with lower levels of RED tend to rely more on traditional energy sources. Introducing AI and industrial robots can facilitate the adoption of renewable energy technologies by overcoming barriers. These countries may have less established renewable energy infrastructure, making AI more impactful for driving RED. Conversely, in countries with well-established renewable energy generation, transitioning to AI-integrated systems may not yield significant economic benefits compared to their existing infrastructure. These countries may have already made substantial investments in renewable energy technologies, and introducing AI and industrial robots may not lead to substantial additional gains or cost savings. Wang et al. (2023b) also find that industrial robot development has a more powerful effect on reducing carbon emissions in less developed and industrialized regions in China, which is consistent with our finding that AI is more useful for promoting RED in low RED countries.

4.4. Mediation effect model

We further analyze how AI affects RED, which means that we will answer the question of through what mechanisms can AI works on RED. The development of AI has the potential to promote more efficient production and innovation. Yu et al. (2023) consider technology effect when studying industrial robot development and cities' decarbonization, and energy efficiency is also used as a mediation variable in their study. Also, Li et al. (2022) reveal the positive role of AI in improving energy efficiency. Thus, we tend to explore the mechanisms of the technology effect and the innovation effect. Specifically, we use the following equations to conduct mediation effect regressions.

$$\begin{cases} lnEE_{it} = \delta_0 + \delta_1 lnAI + \sum_{k=2}^{6} \delta_k lnControl_{it} + \pi_i + \mu_t + \varepsilon_{it} \\ lnRED_{it} = \lambda_0 + \lambda_1 lnEE_{it} + \lambda_2 lnAI_{it} + \sum_{k=3}^{7} \lambda_k lnControl_{it} + \pi_i + \mu_t + \varepsilon_{it} \end{cases} \tag{3}$$

$$\begin{cases} lnR\&D_{it} = \varphi_0 + \varphi_1 lnAI_{it} + \sum_{k=2}^{6} \varphi_k lnControl_{it} + \pi_i + \mu_t + \varepsilon_{it} \\ lnRED_{it} = \chi_0 + \chi_1 lnR\&D_{it} + \chi_2 lnAI_{it} + \sum_{k=3}^{7} \chi_k lnControl_{it} + \pi_i + \mu_t + \varepsilon_{it} \end{cases} \tag{4}$$

where *EE* is energy efficiency which is measured by the ratio of GDP to energy consumption, and *R&D* is spending on research and development. They are two mediating variables denoting the technology effect and innovation effect. Thus, Eq. (3) shows the technology effect, which corresponds to the first two columns in Table 6, and Eq. (4) shows the innovation effect, which corresponds to the last two columns in Table 6.

According to Table 6, first, AI is positively linked to energy efficiency. From the first column, we know that an increase in AI by 1% can

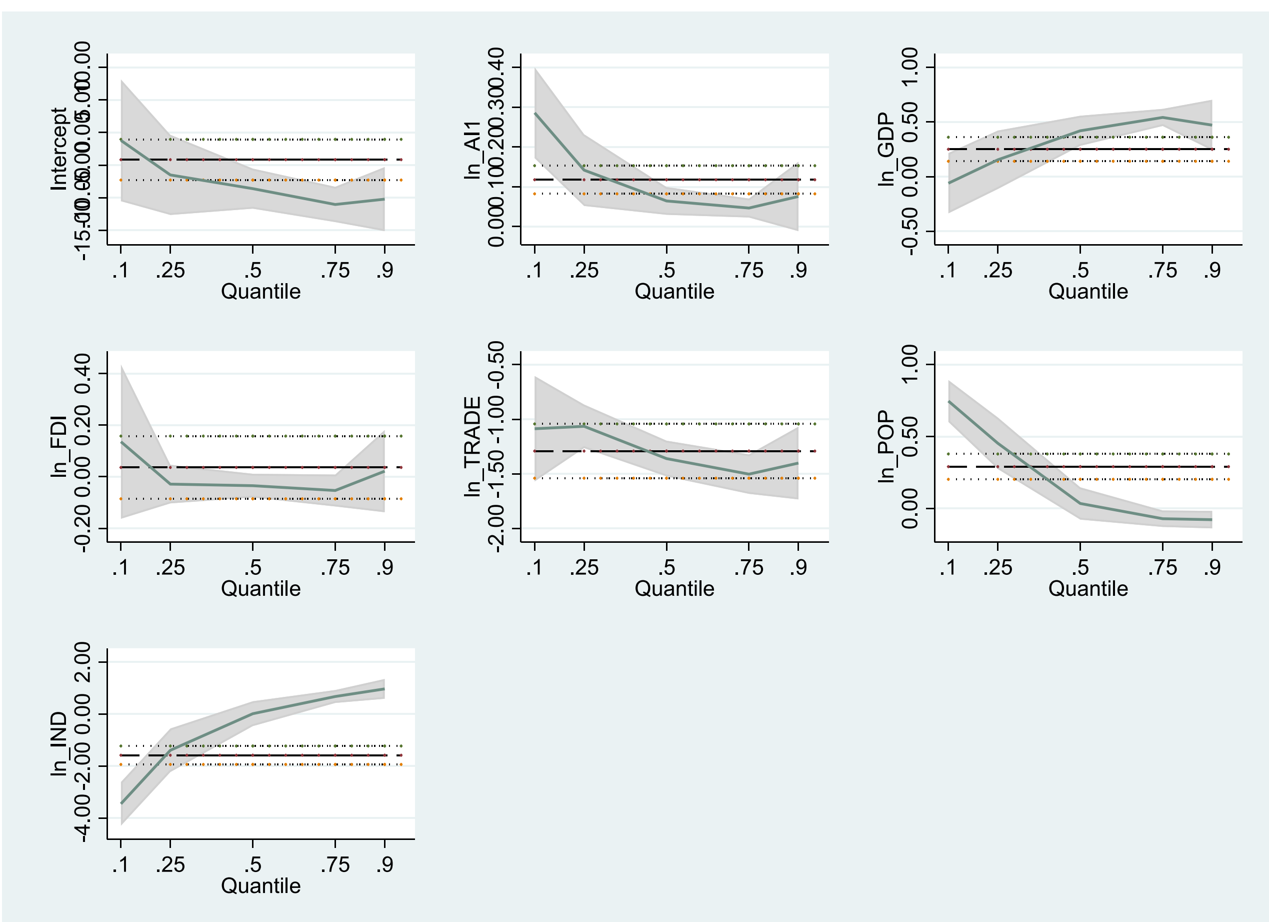

Fig. 3. Figure of panel quantile regression result.

Table 6
Mediation effect results.

Explained variables: *lnRED* in (2) and (4); while *lnEE* in (1), and *lnR&D* in (3)				
Variable	(1)	(2)	(3)	(4)
lnAI	0.0125***	0.0956***	0.0728***	0.1043***
	(4.1199)	(3.4486)	(7.8216)	(3.4799)
lnEE		2.1016***		
		(16.2854)		
lnR&D				0.2306*
				(1.8405)
lnGDP	−0.0135	0.2256**	0.3346***	0.1222
	(−1.4242)	(2.5113)	(12.7298)	(1.1282)
lnFDI	−0.0078	0.0903	0.0124	0.0647
	(−0.5995)	(1.5712)	(0.6008)	(1.0735)
lnTRADE	−0.0789***	−1.0828***	0.1896***	−1.3010***
	(−2.9077)	(−8.5704)	(4.1109)	(−9.8489)
lnPOP	−0.0846***	0.5413***	−0.3156***	0.4279***
	(−7.8042)	(8.5270)	(−16.2211)	(5.0762)
lnIND	−0.2515***	−1.2170***	−1.1852***	−1.4298***
	(−9.3135)	(−3.9076)	(−15.3907)	(−5.0117)
Constant	2.0343***	−8.2516***	−0.9204	−3.7712
	(4.9269)	(−3.6550)	(−1.3803)	(−1.5582)
KP LM (statistic)	175.523	152.036	175.523	169.792
KP LM (Pvalue)	0.000	0.000	0.000	0.000
KP Wald F	1924.626	1657.790	1924.626	1121.967

Notes: *** 0.01 ** 0.05 * 0.1.

trigger energy efficiency to increase by about 0.0125%. Then, energy efficiency also has a positive impact on RED, as every additional increase in energy efficiency results in an increase of 2.1016% in RED. Thus, it is feasible to conclude that AI can indirectly affect RED by increasing energy efficiency. AI can optimize manufacturing processes to maximize energy efficiency (Liu et al., 2022). It can be programmed to analyze data and make real-time adjustments to optimize energy usage (Li et al., 2023b). For example, robots can determine the optimal speed, temperature, and pressure for specific manufacturing tasks, leading to energy savings. By continuously monitoring and adjusting production parameters, robots help minimize energy waste and improve energy efficiency. Moreover, by continuously optimizing processes and making adjustments based on evolving data, AI development contributes to ongoing energy efficiency improvements (Chen et al., 2021; Hossin et al., 2023). When energy efficiency is enhanced, the demand for conventional energy sources is decreased, and energy efficiency creates space and opportunity for the adoption and development of renewable energy sources.

As for the second mechanism, the result in the third column tells us that AI leads to a higher level of R&D; if AI is increased by 1%, R&D can be enhanced by 0.0728%. Also, the nexus between R&D and RED is positive, and a 1% increase in R&D will result in a 0.2306% increase in RED. Hence, we also confirm the second impact mechanism of the innovation effect. By handling routine activities, robots free up valuable human resources and time, enabling researchers to dedicate their efforts to innovation, experimentation, and problem-solving. Thus, AI is conducive to increasing R&D (Bahoo et al., 2023; Khan et al., 2023). In addition, the development of AI has led to advancements in manufacturing techniques, such as additive manufacturing (3D printing) and precision machining, which are also crucial for R&D development (Li et al., 2023a; Rammer et al., 2022). Further, R&D and innovation contribute to the continuous improvement of renewable energy technology performance, and also lead to cost reductions in renewable energy production and generation.

5. Further discussion: the role of climate finance

5.1. The direct role of climate finance

In addition to AI, the role of CF in affecting RED cannot be ignored. CF is crucial for global sustainable development, because it is important in helping developing countries, which often face the greatest challenges posed by CF, to access the resources necessary to address climate-related issues. We use the aid commitments to countries and regions as the proxy variable for CF, and find the data on aid commitments to countries and regions from the website of the Organization for Economic Cooperation and Development (OECD, 2023). Thus, we will examine the direct impact of CF. Specifically, CF is the key independent variable, and then we follow the practice in baseline regressions, and use five models (i.e., OLS, FE, RE, FGLS, IV-GMM) to estimate the results (see Table 7).

Generally speaking, the impact of CF on RED is significantly positive, despite the fact that its coefficients in the second and third columns are insignificant. The result in the last column estimated by IV-GMM indicates that a 1% increase in CF can accelerate RED by 0.3810%. Thus, CF plays a positive role in accelerating RED. CF provides the necessary financial resources to support the deployment and scaling up of renewable energy projects (Aquilas and Atemnkeng, 2022), and helps overcome the initial investment costs of renewable energy. By providing grants and loans, CF reduces financial barriers and makes renewable energy projects more economically viable and attractive to investors (Lee et al., 2022a; Qi et al., 2023). Moreover, CF instruments, such as guarantees and insurance mechanisms, can help mitigate the risks associated with renewable energy investments (Yu et al., 2022).

5.2. The moderating role of climate finance

Having detected the direct impact of CF, we then explore the moderating role of CF in the AI-RED nexus. Specifically, first, we add both AI and CF into the estimation model (see Eq. (5)); second, we generate an interaction term by interacting AI with CF, and then estimate the impact of this interaction term on RED (see Eq. (6)); third, we add both the interaction term and CF into the estimation model (see Eq. (7)).

$$lnRED_{it} = \alpha_0 + \alpha_1 lnAI_{it} + \alpha_2 lnCF_{it} + \alpha_3 lnGDP_{it} + \alpha_4 lnFDI_{it} + \alpha_5 lnTRADE_{it} + \alpha_6 lnPOP_{it} + \alpha_7 lnIND_{it} + \pi_i + \mu_t + \varepsilon_{it} \tag{5}$$

$$lnRED_{it} = \eta_0 + \eta_1 lnAI_{it} \cdot CF_{it} + \eta_2 lnGDP_{it} + \eta_3 lnFDI_{it} + \eta_4 lnTRADE_{it} + \eta_5 lnPOP_{it} + \eta_6 lnIND_{it} + \pi_i + \mu_t + \varepsilon_{it} \tag{6}$$

$$lnRED_{it} = \rho_0 + \rho_1 lnAI_{it} + \rho_2 lnAI_{it} \cdot CF_{it} + \rho_3 lnGDP_{it} + \rho_4 lnFDI_{it} + \rho_5 lnTRADE_{it} + \rho_6 lnPOP_{it} + \rho_7 lnIND_{it} + \pi_i + \mu_t + \varepsilon_{it} \tag{7}$$

Table 8 presents the moderation effect results, and the three columns in Table 8 correspond to the above three equations. From the first column we can find that both AI and CF exert positive effects on RED, which is consistent with previous findings. The interaction term in the second column is significantly positive, and also remains positive in the third column, which indicates that AI development can facilitate RED, and the interaction of AI and CF can strengthen this effect. CF emphasizes technology transfer to developing countries. Renewable energy technologies, such as solar panels or wind turbines, can be expensive for developing nations to adopt and deploy (Gu et al., 2022). CF can support technology transfer by facilitating the acquisition of renewable energy technologies, knowledge, and expertise from developed countries (Tawney and Weischer, 2021). This transfer of technology enables developing countries to access and deploy renewable energy solutions more effectively (Arezki, 2021). In this circumstance, with the help of CF, AI can also be promoted, especially in developing countries. That is to say, the interaction of AI and CF can be more effective in accelerating RED. Fig. 4 summarizes the intricate nexuses among AI, RED, CF, and the impact channels.

6. Conclusions and policy implications

6.1. Conclusions

Based on a panel dataset of 63 countries between 2000 and 2019, this

Table 7
Result of the direct impact of climate finance on renewable energy development.

Variable	OLS	FE	RE	FGLS	IV-GMM
lnCF	0.2848***	−0.0193	−0.0170	0.2848***	0.3810***
	(3.3290)	(−0.4236)	(−0.3720)	(3.3547)	(3.0793)
lnGDP	0.5845***	0.0792	0.1857***	0.5845***	0.6350***
	(5.5669)	(1.2089)	(3.3992)	(5.6099)	(6.5115)
lnFDI	0.2565*	−0.0428	−0.0381	0.2565*	0.1724
	(1.7638)	(−0.7935)	(−0.7004)	(1.7774)	(0.8847)
lnTRADE	−0.9895***	−0.0838	−0.0345	−0.9895***	−1.0087***
	(−5.0977)	(−0.5527)	(−0.2296)	(−5.1370)	(−5.4917)
lnPOP	0.0493	2.5373***	1.4199***	0.0493	−0.0703
	(0.3629)	(5.6764)	(5.4351)	(0.3657)	(−0.4873)
lnIND	−2.1817***	−0.7893***	−0.9910***	−2.1817***	−2.1363***
	(−6.7240)	(−2.9783)	(−3.7848)	(−6.7759)	(−5.3727)
Constant	−9.2277***	−45.7663***	−28.5439***	−9.2277***	−8.9885***
	(−4.1457)	(−6.6279)	(−6.8031)	(−4.1776)	(−4.0639)
KP LM (*statistic*)					180.146
KP LM (*Pvalue*)					0.000
KP Wald F					632.118

Notes: *** 0.01 ** 0.05 * 0.1.

Table 8
Result of the moderating role of climate finance.

Variable	(1)	(2)	(3)
lnAI	0.0896***		
	(2.6949)		
lnCF	0.3664***		0.2072**
	(3.0965)		(2.3463)
*lnAI*CF*		0.0108**	0.0091*
		(2.0190)	(1.6735)
lnGDP	0.3651***	0.2894*	0.4230***
	(2.6841)	(1.9375)	(2.8800)
lnFDI	0.2312	0.3126*	0.2538
	(1.1901)	(1.6882)	(1.2708)
lnTRADE	−1.3335***	−1.1365***	−1.1650***
	(−6.8404)	(−5.7223)	(−5.4981)
lnPOP	0.0039	0.3624***	0.1101
	(0.0292)	(4.5081)	(0.9205)
lnIND	−1.8660***	−2.4263***	−2.2822***
	(−5.2208)	(−5.4921)	(−5.6914)
Constant	−3.5535	−4.5077	−5.0198
	(−1.0372)	(−1.1380)	(−1.2662)
KP LM (*statistic*)	179.321	78.961	66.835
KP LM (*Pvalue*)	0.000	0.000	0.000
KP Wald F	317.384	595.332	252.187

Notes: *** 0.01 ** 0.05 * 0.1.

paper empirically investigates the impact of AI on RED, and examines their asymmetric nexus. Moreover, we explore the impact mechanisms through which AI affects RED, and consider the role of CF. We arrive at some significant conclusions. On the one hand, this paper reveals a direct connection between AI and RED: Primary finding provides strong evidence of the positive impact of AI on RED; by implication, the development of AI contributes significantly to RED. Furthermore, the RED promotion effect of AI is asymmetric, and AI is more effective in stimulating RED in countries with lower levels of RED. On the other hand, mechanisms for the impact are also summarized: AI indirectly affects RED by promoting energy efficiency and R&D, which reveals the importance of technology effect and innovation effect. Moreover, CF also plays a significant role in promoting RED. At the same time, CF is a moderating variable in the AI-RED nexus, which suggests that the synergy of AI and CF is an important means of accelerating RED.

6.2. Policy implications

Our conclusions lead to the following policy implications, which can be grouped into two aspects.

The first aspect involves AI-related policy recommendations. It is feasible for countries to allocate funding specifically for AI research in the field of renewable energy. This support could aid in the development of AI algorithms and models that optimize energy generation, storage, and distribution systems, ultimately leading to more efficient and cost-effective renewable energy solutions. Additionally, governments can

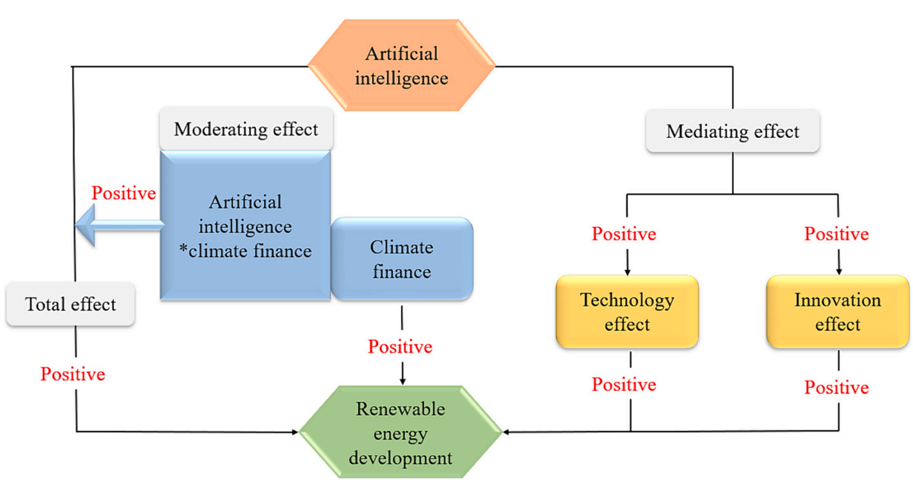

Fig. 4. The relationship among renewable energy development, artificial intelligence, and climate finance.

provide financial incentives, such as tax credits or subsidies, to encourage the implementation of AI technologies in renewable energy projects. This could attract private sector investment and expedite the adoption of AI solutions, ultimately enhancing the performance and reliability of renewable energy systems. Furthermore, the promotion effect of AI on RED is asymmetric, with AI proving more effective in countries with lower levels of RED. Thus, for developing countries, the development of AI and CF is more urgent compared to developed countries. In such cases, governments can contribute to international CF mechanisms, such as the green climate fund, to support renewable energy projects in developing countries. These actions offer financial assistance and technical support to help developing countries transition to renewable energy and adapt to climate change. By mobilizing resources at a global level, these practices can accelerate the deployment of renewable energy technologies worldwide.

The second aspect focuses on the role of CF. Considering that CF is also an essential driver of RED, it is important to utilize CF to achieve better RED. The results regarding the direct impact of CF on RED suggest a consistent and steady provision of financial resources for climate-related development. Furthermore, it recommends the establishment of a monitoring system for climate funds to ensure their efficient utilization in the generation of renewable energy sources, including solar, hydroelectric, biomass, wind, and geothermal energy. Governments can establish or support the issuance of green bonds, specifically designated for financing renewable energy projects. Green bonds provide investors with an opportunity to support sustainable projects while earning a return on their investment. Governments can also contribute to climate funds that pool resources to support renewable energy initiatives, particularly in developing countries. Moreover, governments can allocate a greater portion of their budgets towards funding renewable energy initiatives. This includes investments in research and development, infrastructure development, and subsidies or grants for renewable energy projects. Increased public funding can attract private sector investments and provide financial support for the development and deployment of renewable energy technologies.

This paper addresses a gap in the current literature concerning the nexus of AI, RED, and CF. Nonetheless, it comes with certain limitations that lay the groundwork for future research. First, this study employs the IV-GMM static panel model to estimate their relationship. However, it does not account for the dynamic relationship and potential spatial networks. Future studies can expand on this static relationship by examining the hysteresis and spatial autocorrelation features of AI and RED. Second, this study delves into two mechanisms, focusing on the effects of technology and innovation. Yet, there may be additional impact channels that we may not have considered. Providing further insight into these potential impact channels between AI and RED is also of significance.

Inclusion and diversity

We carefully sought to achieve gender parity in our reference list while still citing sources that were scientifically pertinent to this work. The contributors from the research site who took part in the data collection, design, analysis, and/or interpretation of the study are listed as authors in this paper.

CRediT authorship contribution statement

Congyu Zhao: Writing – original draft, Software, Methodology, Data curation. **Kangyin Dong:** Writing – review & editing, Funding acquisition, Conceptualization. **Kun Wang:** Writing – review & editing, Methodology. **Rabindra Nepal:** Writing – review & editing, Validation, Supervision, Conceptualization.

Declaration of competing interest

No potential conflict of interest was reported by the authors.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Appendix A. Supplementary data

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