The role of artificial intelligence and green technological innovation in shaping greener and nuclear energy efficiency: Evidence from developed and developing countries using a panel time-varying approach

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ABSTRACT

Artificial intelligence (AI) and green technological innovation have become central to improving the efficiency of renewable and nuclear energy systems, particularly following the rapid acceleration of AI deployment since 2022. This study investigates the dynamic and heterogeneous effects of AI and green technological innovation, proxied by green patents, on the efficiency of renewable and nuclear energy across advanced and developing countries over the period 2000–2024. Employing a Time-Varying Interactive Fixed Effects (TV-IFE) model alongside Bootstrap Quantile Regression (BSQR), the analysis captures structural changes, cross-country heterogeneity, and distribution-specific responses that are not observable using conventional static panel approaches. The results reveal a pronounced strengthening of AI's contribution to energy efficiency in the post-2022 period, reflecting the maturation of AI-driven optimization, automation, and intelligent energy management systems. While green technological innovation initially exhibits a weak or negative effect, its impact becomes significantly positive as AI adoption deepens, indicating a strong complementary relationship between digital intelligence and green innovation. Importantly, the findings uncover substantial heterogeneity across development levels: advanced economies experience immediate and persistent efficiency gains from AI, whereas developing economies display delayed but accelerating benefits once technological and institutional thresholds are reached. The findings offer a forward-looking framework for future research, encouraging scholars to adopt time-varying methodologies, post-AI-boom datasets, and development-specific analyses when assessing the role of emerging digital technologies in energy transitions.

1. Introduction

Climate change is arguably one of the most pressing challenges of our time, necessitating transformative changes to global energy systems with unprecedented urgency. Across the globe, nations face growing challenges in decarbonizing their economies and implementing sustainable energy plans to achieve climate change and net-zero carbon targets [1,2]. Depletion of fossil fuels has led to environmental degradation and climate change, threatening sustainable global economic growth and exacerbating severe weather phenomena and natural disasters [3]. Reducing greenhouse gas (GHG) emissions and decreasing reliance on depletable fossil fuels are crucial for mitigating these impacts and achieving sustainable development [4,5]. Consequently, transitioning to RENE is widely recognized as a crucial step toward achieving sustainable growth worldwide [6]. However, the high cost of RENE compared to fossil fuels poses a challenge, highlighting the need for rapid technological advancements in AI and Green Technological Innovation (GTI) [7,8]. Progress in GTI can lower the cost of RENE

deployment, promote its development, and help mitigate climate change and enhance macroeconomic sustainability. Therefore, developing green innovation in Renewable Energy (RE) technologies is essential for sustainable growth. The global energy sector has undergone a remarkable shift in recent years, driven by the convergence of two cutting-edge technologies: AI and green technological innovation, made possible by GPT. As the world grapples with the urgent need to transition to sustainable energy solutions, these innovations have significantly revolutionized how we produce and consume energy [9–11].

With its ability to analyze vast amounts of data and optimize complex systems, AI has found myriad applications in the energy sector. From enhancing the efficiency of RE sources such as solar and wind power to optimizing the operation of nuclear power plants, AI holds immense potential to drive innovation and efficiency in energy production. AI is utilized for various applications, including estimation, planning, optimization, control, distribution, and devising strategies for sustainable energy sources such as wind, solar, hydrogen, and hybrid systems. Additionally, AI can serve as a demonstration tool in RE. For example, AI algorithms can predict electricity demand, optimize energy storage systems, and improve the performance of RE installations [12, 13].

In the energy field, AI plays a vital role in predicting solar energy generation and accurately estimating the scale of photovoltaic systems, both of which are crucial to RE. AI can also help manage the fossil energy procurement process, plan power generation, and inform investment strategies to enhance energy security further [14]. It will also link energy, demand, and RE supply to the grid through autonomous control by intelligent software, optimizing decision-making and operations. Recently, a new alternative, called hybrid nuclear-RE systems, has been proposed [15]. While nuclear scientists have extensively explored AI, most applications in the nuclear industry remain experimental and not yet ready for real-world implementation due to issues such as algorithmic robustness. AI is used to the safety, efficacy, and cost-effectiveness [16] of future energy policies. AI can play a crucial role in fostering innovation for nuclear energy [17,18].

GTI is crucial in addressing climate change and achieving energy policy objectives, including increased access to energy and reduced air pollution. Clean energy transformation is at the heart of stopping climate change, where electricity generation is steered toward low-carbon sources. Increasingly, RE is becoming a viable alternative to fossil fuels, as it can reduce CO_2 emissions and combat climate change. The goal of net-zero emissions means international efforts in the energy sector must be innovative. The degree of GTI can influence how RE policies affect green innovation and should be given greater consideration. When green innovation is high, businesses are better equipped to pursue it, and policy incentives can further stimulate these efforts [19]. GPT can cover a wide range of innovations, from novel solar panel designs to advanced nuclear reactor technologies, all aimed at reducing carbon emissions and mitigating the impacts of climate change [20].

Based on the above discussion, we aim to examine the impact of AI and GTI on the efficiency of RENE across 34 countries, addressing the following research question: How do AI and Green Patent Technologies influence the efficiency and dynamics of RENE systems across countries? This question responds to the pressing global agenda for decarbonization and energy innovation.

This study makes a significant contribution to the existing literature in four key ways. This study contributes to the literature in several distinct and non-incremental ways. First, unlike prior cross-country studies that rely on static, pre-2020 data, this paper explicitly captures the post-2022 artificial intelligence acceleration period, characterized by the rapid diffusion of machine learning, robotics, and AI-driven optimization technologies across energy systems. By extending the analysis through 2024, we empirically identify a structural intensification of AI's impact on renewable and nuclear energy efficiency, which is not observable in datasets ending before the recent AI boom. Second, the study moves beyond aggregate cross-country averages by explicitly

distinguishing between advanced and developing economies. The results reveal that AI and green patent technologies operate through fundamentally different transmission mechanisms across development stages. In advanced economies, AI effects materialize through system optimization, grid intelligence, and nuclear operations, whereas in developing economies, AI adoption initially yields weak effects before turning positive once institutional and technological thresholds are reached. This heterogeneity is systematically overlooked in existing studies. The AI effect in advanced countries appears more significant than in developing countries. Also, the findings demonstrate that green patents alone do not guarantee energy efficiency gains; their effectiveness critically depends on the maturity of AI adoption. By uncovering this conditional and time-dependent complementarity between AI and green innovation, the study not only provides new empirical evidence but also offers a conceptual and empirical benchmark for future research. In particular, it encourages subsequent studies to move beyond static models, pre-AI-boom datasets, and homogeneous country assumptions when evaluating emerging digital technologies in energy and environmental economics.

Methodologically, this study makes a novel contribution by innovatively delving into 2025, employing the recently developed Time-Varying Interactive Fixed Effects (TV-IFE) model [21]. This approach advances conventional panel econometric techniques by simultaneously addressing cross-sectional dependence, structural breaks, and dynamic heterogeneity. Unlike earlier models with static coefficients, the TV-IFE framework allows both regression coefficients and factor loadings to evolve smoothly over time. This enables the accurate modeling of complex interactions among AI, green patent technologies, and energy efficiency in renewable and nuclear systems. The use of TV-IFE is particularly suitable for evaluating policy-relevant dynamics in rapidly transforming energy landscapes. Furhtemore, this study makes a direct contribution to several United Nations Sustainable Development Goals (SDGs). First, by analyzing how AI and GPT enhance RENE's efficiency, the study supports SDG 7: Affordable and Clean Energy, particularly targets 7.2 and 7.3 (doubling the global rate of improvement in energy efficiency). Second, the findings promote SDG 9: Industry, Innovation, and Infrastructure, by highlighting the role of innovation and smart technologies in optimizing energy systems. Third, the study aligns with SDG 13: Climate Action by demonstrating how technological advances can mitigate environmental impacts through cleaner, more efficient energy use. Finally, through its emphasis on cross-country dynamics and equitable technological diffusion, the study indirectly supports SDG 17: Partnerships for the Goals, especially regarding international cooperation on technology and innovation transfer. Moreover, the study provides valuable policy implications, particularly for middle-income economies, based on the empirical results.

The remainder of the paper is structured as follows: Section 2 reviews the literature about the impact of AI and green patterns on renewable and nuclear energy. Section 3 discusses the data and econometrics methodology, while Section 4 presents the empirical findings. The final section addresses the conclusion and policy implications.

2. Literature review

The literature review in this study is divided into two parts. Firstly, we explore the literature concerning AI applications in renewable and nuclear energy. Secondly, we analyze previous studies that demonstrate the impact of GPT on the renewable and nuclear energy sectors.

2.1. Artificial intelligence and energy

AI plays a significant role in energy by using intelligent machines and software to solve specific problems. It can predict energy intake for solar buildings and estimate the scale of PV systems, aiding RE development. AI also aids in fossil energy procurement, power generation planning, and investment strategies, thereby enhancing energy security. AI

optimizes decision-making and operations by integrating energy supply, demand, and renewable sources into the grid, thereby improving energy utilization efficiency and sustainability. AI is poised to transform the energy industry, impacting both human and economic development. While numerous scholars have explored the application of AI in the energy sector, most of their work focuses on technical aspects, such as integrating AI into intelligent energy systems and addressing security and privacy concerns in energy cloud management systems. Bernard [22]conducted an early study on the applicability and use of AI in nuclear power plant operations and process control. The research briefly highlighted unresolved issues in adopting AI techniques for process control and suggested that combining qualitative and quantitative reasoning could enhance automated control systems. The study emphasized that AI and analytical techniques should not be viewed as competing technologies; instead, they can complement each other, potentially leading to enhanced control systems. Later, in 1997, Reifman [23] surveyed the use of AI methods for identifying and detecting faults in nuclear reactor components. The study categorized AI systems intended for this purpose based on three criteria: the computing approach, the methodology, and the diagnostic system's scope. Suman [24] discusses the importance of innovation in the nuclear industry's survival, highlighting AI as a crucial component. The study explores recent advancements in AI, particularly in machine learning, and their potential applications in the nuclear power sector. It identifies the scarcity of operational data, particularly for critical scenarios such as transients and accidents, as a major challenge affecting the accuracy of AI systems in this context. Furthermore, the paper notes the lack of consensus among researchers on the best AI techniques for specific purposes, suggesting the need for collaborative efforts to develop standardized datasets to improve accuracy and support effective technique selection. In a study by Inbamani et al. [25], the importance of sustainability in RE innovation is emphasized. To achieve a cleaner environment, there is a need to uplift innovations in existing mechanisms, ensuring a predictive framework for better outcomes. The study highlights the importance of forecasting and implementing smart grids to balance renewable and conventional energy sources. AI and Machine learning (ML) algorithms are proposed as solutions for predicting electricity demand and supply, leading to greater cost savings and operational efficiency. The study concludes that AI and ML are crucial for the sustainability of energy grids, particularly in managing demand response and operational costs in smart grids. Kumar et al. [26] emphasize the global interest in AI's diverse applications for sustainable development, with initiatives such as the UN Global Compact urging companies worldwide to contribute to the SDGs. Their study highlights the pivotal role of AI in driving economic development, addressing long-term environmental challenges, and advancing social development. Despite challenges such as public apathy and short-term corporate interests, collaborative efforts across sectors are essential to protecting the climate and promoting sustainability. Adopting AI presents significant growth opportunities, particularly in achieving SDGs and transforming industries through intelligent interventions. In a related study, Loi et al. [27] examined the relationship between AI development and the dynamics of the green energy market. Using various AI development indices and green energy market indicators, they employed Bayesian vector heterogeneous autoregression models to analyze the interlinkages over time. The study found significant differences in network interlinkage between these markets, especially during transient events such as the COVID-19 pandemic and the Russia-Ukraine conflict. They observed a shift in roles, with AI development indices transitioning from shock receivers to shock transmitters during these crises. Recent literature emphasizes that the environmental effects of AI are inherently nonlinear and context-dependent. Empirical evidence indicates that AI may initially intensify energy demand and emissions due to scale and rebound effects, but as digital maturity deepens, efficiency gains, renewable integration, and intelligent resource allocation predominate, yielding environmental improvements consistent with an AI-driven Environmental Kuznets Curve (AI-EKC) framework [28]. This nonlinear transition is further conditioned by structural factors such as urbanization, industrial automation, and institutional capacity, which determine whether AI acts as an emissions-amplifying or an emissions-mitigating force [29,30]. Consequently, AI's environmental impact should be interpreted not as uniformly beneficial or harmful, but as contingent on the development stage, the pace of technological diffusion, and the quality of governance.

Also, in another study, Huang et al. [31] highlight the rapid growth of AI technology and its potential to enhance nuclear use in activities. Their study reviews modern AI algorithms and their applications in nuclear reactor design, optimization, and operation and maintenance (O&M). However, data issues and the black-box dilemma hinder the integration of AI and nuclear reactor technologies. The researchers propose future directions, including the better integration of domain knowledge with data-driven approaches and the use of explainable AI (XAI) technologies to enhance model transparency and reliability. In a study by Wang et al. [32], the authors examined the impact of AI on China's energy sector. They found that China has shifted its energy development strategy towards high-quality energy development (HED), transitioning from qualitative improvements to quantitative changes. AI plays a crucial role in this shift by facilitating clean energy transitions, enhancing energy security, and improving overall energy processes. Analyzing data from 30 provinces between 2007 and 2017, the study finds that AI has a positive impact on HED: a 1 % increase in AI development is associated with a 0.032 % increase in the HED index.

2.2. Green innovation and energy

Recently, there has been a notable focus in academic and policy circles on the intersection of GPT with renewable and nuclear energy. GPT represents technologies that target environmental sustainability and energy efficiency, serving as important drivers for innovation and the shift toward cleaner energy. The growing number of GPTs in renewable and nuclear energy reflects a heightened commitment to advancing sustainable solutions and addressing climate change. Some critical related studies are as follows: In their 2017 study, Noailly and Shestalova [33] investigated knowledge spillovers from RE technologies by analyzing patent citation data from 18 European patent offices between 1978 and 2006. They found that the RE technologies of wind, storage, and solar get more citations than the rest. While wind innovations do remain within their scope, most innovations in solar energy and storage technologies spill over to applications outside the power generation sector. This paper attempted to explain how regulations and policies influence green patent generation, as Bia et al. [34] investigated regarding the evolution of RE technologies and green energy. Consideration of the numerous factors involved ranges from green investment and spillover effects to their influence on these results. It will show wide differences in systems of green innovation and investments in RE markets [35]. Recent cross-country studies further emphasize that AI mainly supports sustainable development through innovation, infrastructure, and advanced industrial upgrading, with varying effects depending on development levels and urbanization stages [36]. In urban and industrial settings, automation technologies like industrial robots influence the link between economic activity and emissions by improving production efficiency and energy use, especially once adoption surpasses key thresholds [29]. These results highlight that AI-driven sustainability improvements depend on additional structural changes rather than being automatic results of digitalization.

Fernández et al. [37] investigated the role of technological innovation in addressing climate change and achieving energy policy objectives. Their research aimed to analyze innovation in energy technology across countries and sectors, and to investigate the factors influencing the diffusion of patented knowledge in energy technologies, including renewables and nuclear sources. Using patent citations as indicators, they found that patents citing more prior scientific literature and those

with more citations to prior patents experienced greater diffusion. Joint patents with firms or universities had minimal impact on renewables. However, they negatively affected the diffusion of other energy technologies, suggesting policy implications for enhancing the incorporation of scientific knowledge and co-inventorship in energy innovation.

In their most recent study, Yang et al. [38] conducted a patent analysis to forecast future trends in green hydrogen technology, addressing the lack of detailed studies on green hydrogen production technology. They surveyed global green hydrogen projects and classified hydrogen-related technologies by network category and RE source. Over a thousand patents from the past two decades were collected and analyzed, focusing on water electrolysis and system operation technologies. The analysis revealed a greater emphasis on system integration and control strategies over the production of green hydrogen. They also predicted near-term trends for commercial water electrolysis types, noting the varying stages of maturity among different approaches. Additionally, they identified the most impactful patents in various technology areas, providing insights into future green hydrogen technology development. In contrast to existing studies that rely primarily on static panel or mean-based estimators, this study adopts a dynamic and distribution-sensitive econometric framework. By doing so, it extends the literature beyond average effects and provides new evidence on the time-varying and heterogeneous roles of AI and green innovation in shaping the efficiency of renewable and nuclear energy. Beyond energy and emissions, recent sustainability research demonstrates that development-environment trade-offs persist even at advanced stages, with evidence of N-shaped and threshold-dependent Environmental Kuznets Curve dynamics across countries. Moreover, human development gains may continue to exert ecological pressure unless accompanied by technological upgrading and international integration, reinforcing the need for multidimensional sustainability assessments [39,40]. This broader perspective motivates the present study's focus on nonlinear effects and heterogeneous impacts when evaluating AI's role in environmental sustainability.

3. Data and methodes

3.1. Data

This study examines the effect of AI and GPT on Renewable and Nuclear Energy Efficiency (RENE), considering the influence of GDP, Foreign Direct Investment (FDI), Population (POP), research and development (R&D), and energy prices (Oil). The selection of variables in this study is grounded in the theoretical and empirical literature that links technological innovation to energy outcomes. In this study, AI is conceptualized and explicitly measured within the context of its application to energy efficiency and system optimization. While AI encompasses a diverse set of technologies, including self-driving vehicles, virtual assistants, and healthcare platforms, our focus is limited to AI tools relevant to energy system modeling, smart grid operations, predictive maintenance, and energy consumption forecasting. This narrowed scope ensures alignment between the theoretical construct and the empirical proxy used in the analysis. The data sources used, such as energy-related AI patent counts and sector-specific AI deployment indices, reflect this targeted definition and exclude broader, unrelated AI applications to maintain conceptual validity AI and green patents serve as proxies for technological advancement and environmental innovation, both of which are increasingly acknowledged as critical for enhancing energy efficiency and facilitating clean energy transitions [41,42]. Green technological innovation is proxied by green patent data obtained from the OECD database. Patents were identified using internationally recognized environmental technology classifications, including the OECD ENV-TECH taxonomy and relevant Cooperative Patent Classification (CPC) codes associated with renewable energy, energy efficiency, emissions reduction, and nuclear-related clean technologies. The complete list of CPC codes and keyword filters used to

construct the green patent indicator is available upon request. It follows the OECD ENV-TECH classification to ensure replicability and international comparability (see Fig. 1).

GDP and FDI are included to capture the economic context and capital inflows that often support large-scale energy infrastructure, including nuclear and renewable projects. R&D expenditures reflect a country's innovation capacity, which can directly influence the deployment of technological innovations in energy systems. Population and energy prices are standard controls in energy economics, accounting for scale effects and market incentives, respectively. To address concerns about the rapid evolution of artificial intelligence technologies, this study explicitly incorporates post-2022 observations, reflecting the recent global AI acceleration period marked by the widespread deployment of machine learning, robotics, and large-scale data-driven optimization. The time-varying framework allows us to detect structural shifts in AI–energy efficiency relationships. As shown in Figs. 2–4, the magnitude and direction of AI effects change markedly after 2022, particularly in advanced economies, confirming that earlier datasets are insufficient for capturing contemporary AI-energy dynamics. The base model for this study can be written as follows (eq. (1)):

$$RENE_{it} = \beta_0 + \beta_1 GDP_{it} + \beta_2 GPT_{it} + \beta_3 AI_{it} + \beta_4 FDI_{it} + \beta_5 POP_{it} + \beta_6 RD_{it}$$
$$+ \beta_7 OIL_{it} + \varepsilon_{it}$$

$$(1)$$

Where:

β_0 is the intercept term, representing the baseline level of renewable and nuclear energy efficiency when all independent variables are zero. β_1 to β_7 are the slope coefficients corresponding to the independent variables AI, GPT, GDP, FDI, POP, OIL, and RD, respectively. Each coefficient captures the marginal effect of the associated variable on the dependent variable RENE. ε_{it} represents s the error term accounting for unobserved factors and random disturbances affecting energy efficiency that are not captured by the explanatory variables. To account for potential non-stationarity and scale disparities, selected variables were transformed using natural logarithms. Specifically, the variables GDP, GPT, and POP. This transformation allows for elastic interpretation of coefficients and helps stabilize variance.

Based on the streaming literature REF, we can hypothesize the signs of the respective coefficients of the parameters mentioned in Eq. (1), which are the signs of the $\beta_2, \beta_3, \beta_4$ and $\beta_6 > 0$ and β_1 , β_5 , $\beta_7 < 0..$ Table 1 provides a brief account of the variables of interest, including abbreviations and summary statistics. Fig. 2 presents trend data for 34 economies from 2000 to 2019.

3.2. Methodology

3.2.1. The TV-IFE technique

One major drawback of these techniques is their assumption of normality in the dependency distribution, which limits the generalizability of their outcomes. Accordingly, the estimated coefficients from the OLS technique are not well-suited for investigating the nexus between variables at specific points in the joint distribution [43]. Therefore, the specification introduced by Ref. [44], the TV-IFE model recently proposed by Ref. [21], represents a significant advancement in panel econometrics. The TV-IFE framework addresses CSD, structural breaks, and dynamic heterogeneity, making it particularly well-suited for modeling global markets and interlinked systems such as those found in energy and environmental economics [45]. Unlike conventional panel models that assume fixed coefficients and constant factor loadings over time, the TV-IFE model incorporates time-varying coefficients. This enables flexible modeling of unobserved common shocks and their heterogeneous impacts across CSDs, thereby enhancing estimation accuracy in the presence of temporal and structural instability. The TV-IFE model permits both the regression coefficients and factor loadings to evolve smoothly over time, capturing dynamic adjustment
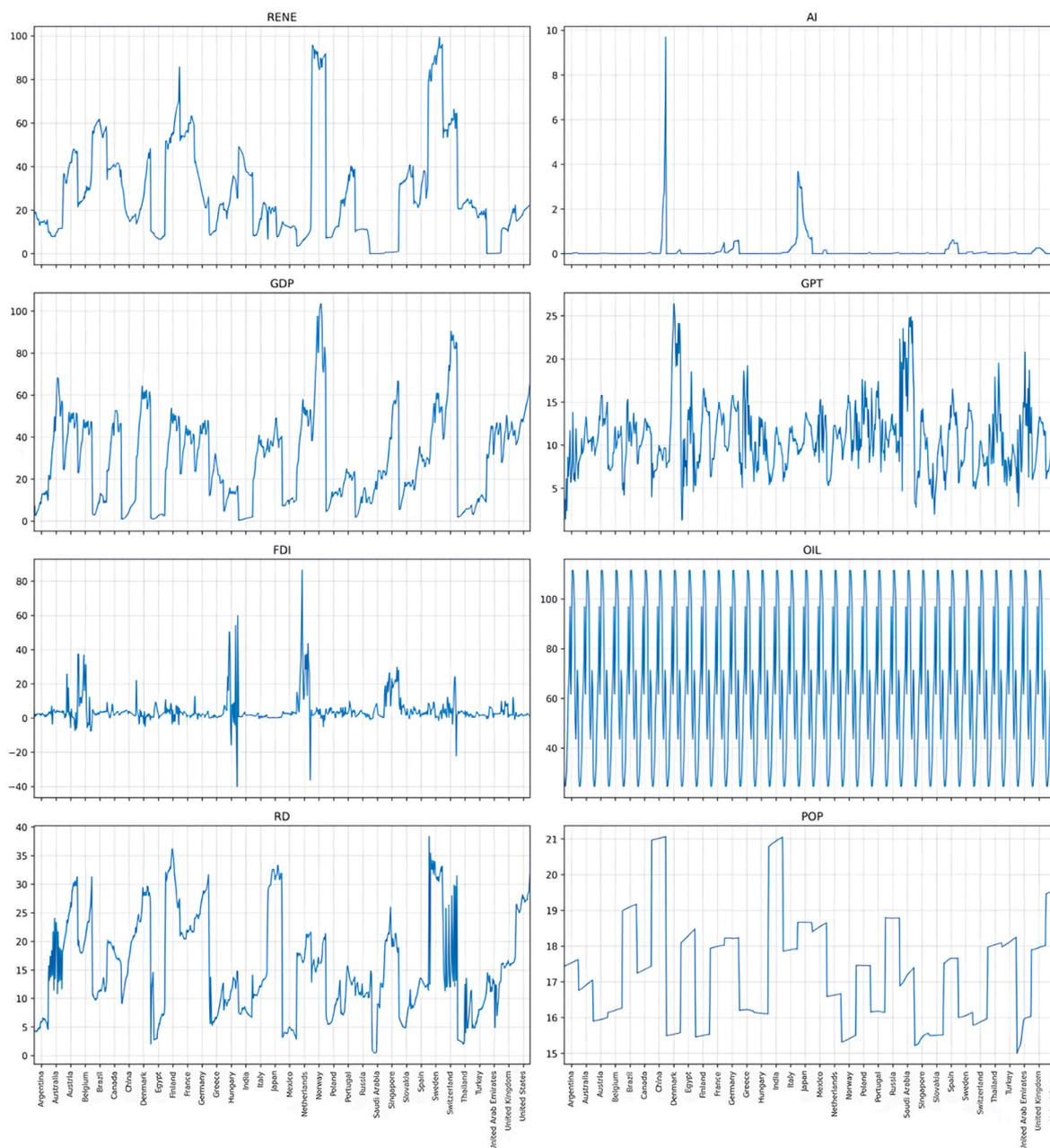
Fig. 1. Data trend.

processes across countries, sectors, and firms The model can be estimated using a local least squares (LLS) approach, combined with principal component analysis (PCA), to capture temporal variation in coefficients and factor structures efficiently. This approach also supports the identification of nonlinear dynamics, making it highly relevant for research in climate finance, energy transition, and environmental risk modeling, where structural and policy-related changes are gradual and continuous.

3.2.2. Panel quantile estimation

In empirical studies, PSQR may be used as a complementary or robustness tool to strengthen conclusions obtained through TV-IFE. Although TV-IFE is effective in capturing hidden time-varying unobserved heterogeneity via a flexible factor structure, it primarily emphasizes estimating conditional mean relationships. In many applications, and particularly those involving financial risk, inequality, and heterogeneous policy responses, mean effects do not fully capture

the distributional dynamics of the dependent variable. In this sense, PSQR offers a valuable complement by estimating conditional quantiles and revealing how covariate effects change throughout the outcome distribution [46,47]. Although standard quantile regression successfully estimates conditional quantiles of a dependent variable, it has limitations in estimating standard errors and confidence bands when applied to heteroskedastic, non-normal, or small-sample models. To alleviate these drawbacks, BQR extends the bootstrap, a nonparametric resampling technique, by repeatedly sampling with replacement from the original data and refitting the QR regression model on these bootstrap samples. Quantile estimation methods have been widely applied in the literature, driven by recent developments and increasing interest in their use in panel data models [33–36]. To control for unobserved heterogeneity at the unit level, standard panel-data specifications often include fixed effects. This method has been generalised to quantile panel regressions by adding fixed effects. However, existing studies have documented several concerns with estimating fixed effects under the quantile
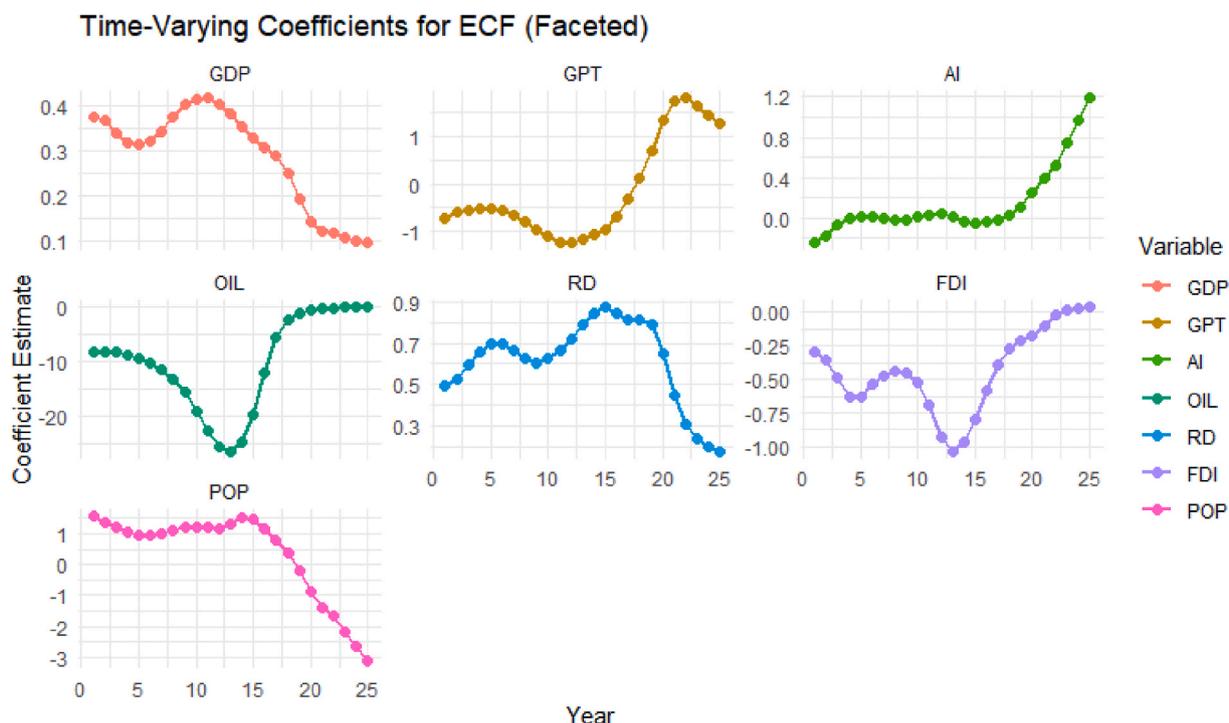
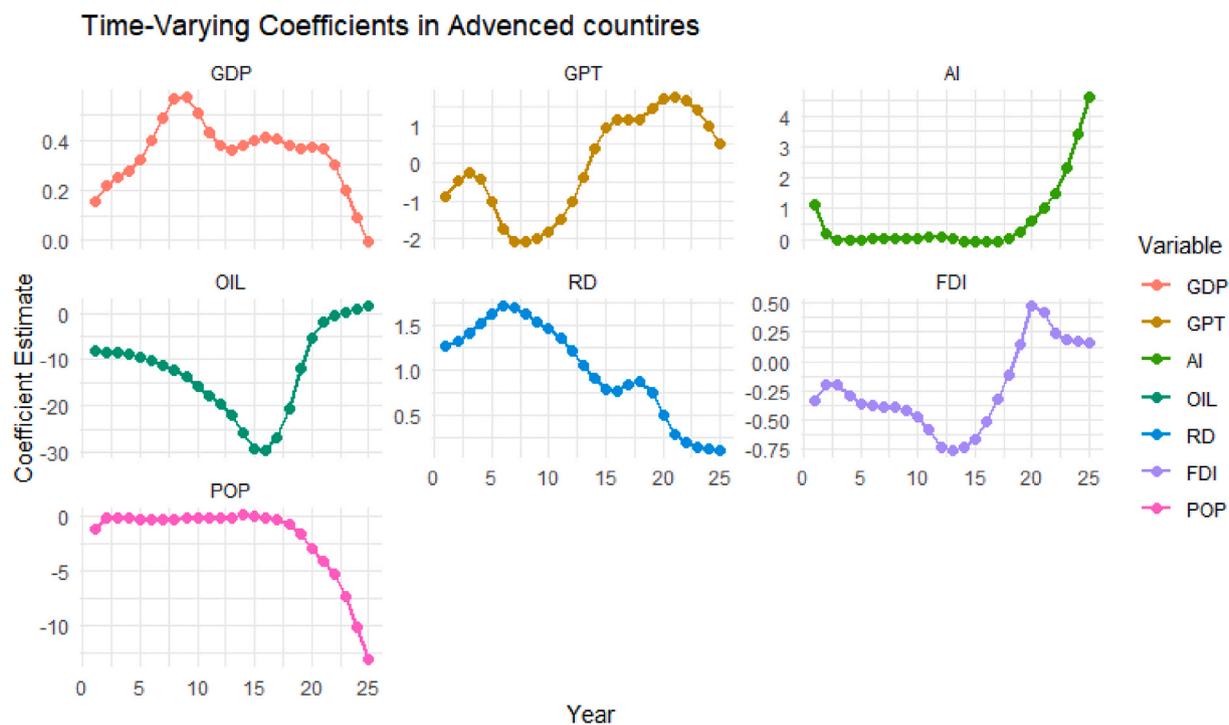**Fig. 2.** TV-IFE Regression Results for total countires

Fig. 3. TV-IFE regression results for advanced countires.

regression framework, especially when the time dimension (T) is small, such as in the following relationship for Qy(τ|X) under a location-scale model. To address these shortcomings, Machado and Silva [48] develop a new panel-data quantile regression procedure (QRPD). Their key innovation is the possibility of including additive individual effects (αi), which enables them to derive the conditional distribution of the dependent variable given individual characteristics, αi |Dit. The location-scale variant model is written in equation (2):

$$Y_{it} = a_i + X'_{it}b + \left(\vartheta_i + Z'_{it}d \right) U_{it} \qquad (2)$$

Where $P(ci + Zit'\gamma > 0) = 1$ represents a probabilistic constraint ensuring that the conditional quantile function is properly defined within the estimation framework. Specifically, it implies that the influence of un-observed heterogeneity *ci* and observable covariates ($Zit'\gamma$) on the quantile-specific outcome is positive with probability 1. This condition is commonly used in quantile regression models with individual effects
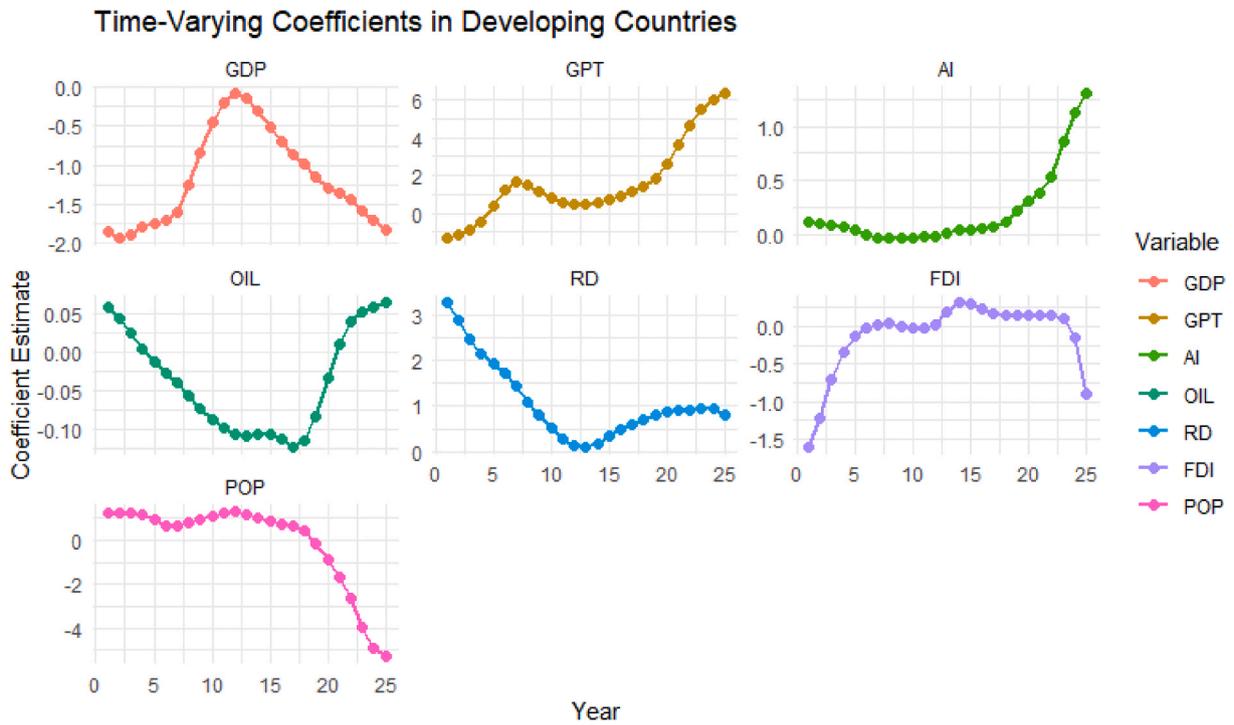
Fig. 4. TV-IFE regression results for developing countries.

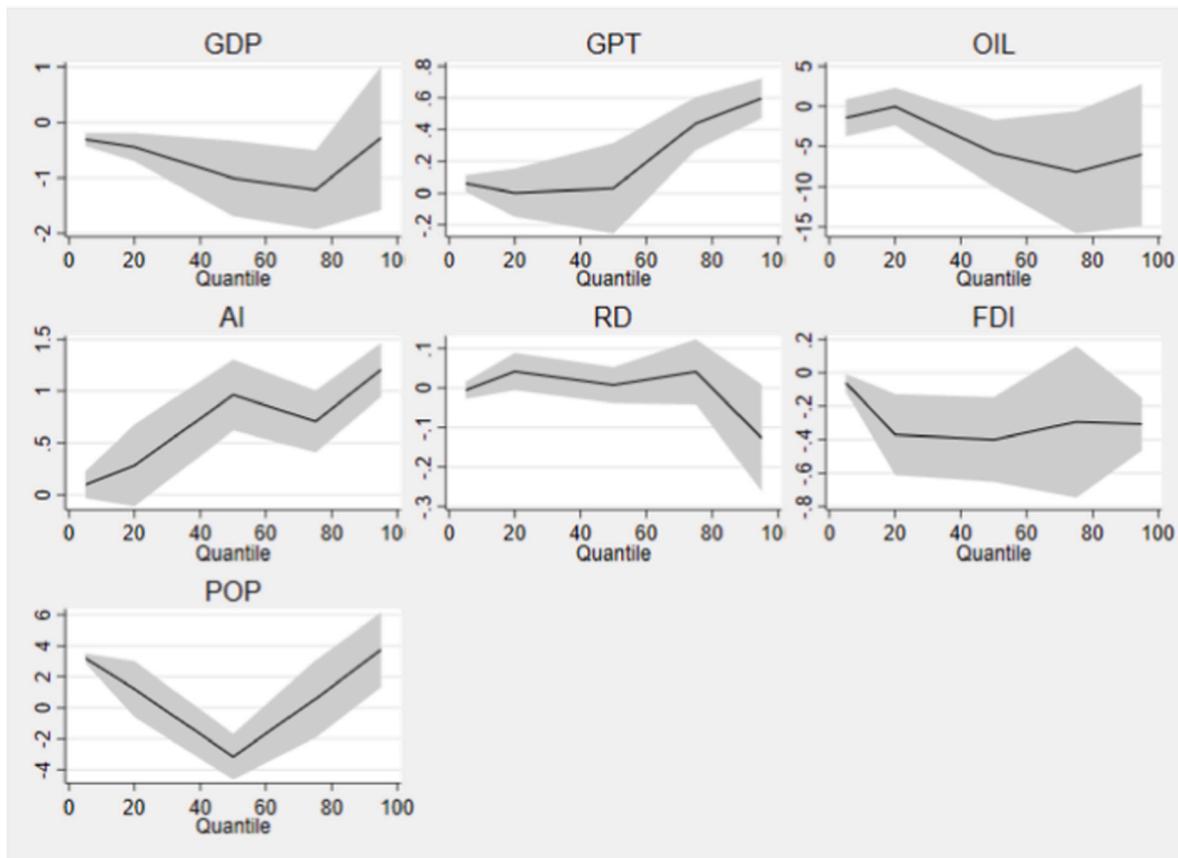**Fig. 5.** BSQR results.

to ensure model identifiability and to restrict the estimation to the relevant support of the conditional distribution [49]. In this context, it guarantees that the estimated quantile process captures heterogeneity across units without violating the monotonicity property of quantile functions.

Z defines a k-vector of operators in X, this signifies conversions

Table 1

Variables description.

Data	Abbreviation	Transofrmation	Source
Renewable and nuclear energy	RENE	RE + NE consumption as % of total energy	EIA, (2024)
AI	AI	Rebot use/1000	International Federation of Robotics
Green patents	GPT	% of total patents	OECD (2024)
Economic growth	GDP	Log-transformation US $ GDP per capita/10 (LnGDP)	WDI (2024)
Population	POP	Log-transformation Population (LnGPT)	WDI (2024)
FDI	FDI	Net flow as % of GDP	WDI (2024)
Research and development	RD	RD as % of GDP	OECD (2024)
Energy prices	OIL	Oil brint prices US $	EIA, (2024)

Footnote: "Ln" denotes natural logarithm transformation.
Source: authors' elaboration

differentiable by factor l, given in equation (3):

$$Z_i = Z_i(X), i = 1, \ldots, k \tag{3}$$

Xit and *Uit* are i.i.d and also do not vary over time (*t*). *Uit* is orthogonal to *Xit* to follow the switching circumstance. In this regard, after some changes in equation (2), we obtain equation (4):

$$Q_y(\tau|X_{it}) = (a_i + c_i q(\tau)) + X'_{it} b + Z'_{it} dq(\tau) \tag{4}$$

In equation-4, $Q_y(\tau|Xit)$ represents the distribution quantile distribution *Yit* depending on the position of the independent factors observed in *Xit*.

For this purpose, we employ the Granger causality [50]. This methodology has several advantages, particularly in considering heterogeneous slopes in null and alternative hypotheses. This method may be susceptible to substantial size distortions.

4. Results

4.1. Preliminary tests

Before investigating the model estimation results, it is essential to perform a statistical analysis of the variables in Table 2. It is also worth mentioning that the RENE, which represents the consumption/efficiency associated with renewable and nuclear energies, averages approximately 29 with a significant standard deviation of 24, indicating different policies for these energy sources The AI variable indicates that the incorporation of AI is in its infancy and highly variable, with a highly right-skewed distribution, resulting in a highly asymmetrically shaped distribution. The incidence data show differences in economic and productive measures, with mean GPT at 10.83 and GDP at 30.49. The skewness and kurtosis of the variables indicate a non-symmetric distribution, with heavy tails and outliers, particularly for AI, which has a high kurtosis value. Therefore, the Jarque-Bera Test results are confitm the non notmal disctrubtion data.

The correlation coefficients presented in Table 3 indicate statistically significant associations between the explanatory variable RENE and its determinants. The correlation between RENE, indicating a negligible linear relationship. Its negligible correlation with GPT indicates that RENE will not be significantly affected by technological and productivity developments. The correlation between RENE and GDP is positive and moderate, with a value. The relationship with FDI is characterized by a weak negative correlation. The correlation between AI and RENE suggests no meaningful linear association between the two variables. A moderate positive correlation with RD is notable, indicating that RENE's connection to innovation is significant, as sustainable energy investment often accompanies greater R&D activity. The weak negative correlation with POP suggests that high population levels do not have an adverse effect at higher RENE levels (see Table 4).

The VIF is a diagnostic tool employed to identify multicollinearity among the independent variables in regression analysis. Multicollinearity occurs when there are substantial correlations between two or more predictor variables, potentially leading to imprecise and unstable estimates of the regression coefficients. The Variance Inflation Factor (VIF) values for all explanatory variables are below 5, which falls within the commonly accepted threshold, indicating no serious concerns about multicollinearity [51]. While some studies use higher cutoffs of 8 or 10, we adopt the more conservative threshold of 5 to ensure robustness in the estimation [52,53].

4.2. CSD results

The findings from the CD test are presented in Table 5, incorporating three distinct tests for robust analysis [54–56]. The outcomes of these assessments corroborate the hypothesis of CSD presence across the dataset. Notably, the evidence suggests common shocks across the nations under study, indicating that latent factors or concurrent shocks systematically influence the variables across regions.

4.3. Homogeneity test

Table 6 presents the outcomes of the slope-heterogeneity (SH) tests. These results confirm that the effects of AI and GPT on the efficiency of renewable and nuclear energy vary significantly across countries. In this context, heterogeneity refers to differences in how countries respond to technological and innovation-related drivers of energy efficiency. These differences may stem from variations in national policy frameworks, levels of AI and green technology adoption, energy infrastructure maturity, and institutional capacities. Recognizing this heterogeneity is crucial for ensuring that econometric models capture the diverse dynamics at play across the sample of countries (see Table 7).

4.4. TV-IFE finding

The figure illustrates how the coefficient estimates for selected explanatory variables affecting nuclear and renewable energy efficiency change over time. The TV-IFE model can account for heterogeneity in effects across countries as well as structural changes. This value becomes

Table 2

Statistical characteristics.

	RENE	AI	GPT	GDP	FDI	RD	OIL	POP
Mean	29,12	0,61	10,83	30,49	5,00	17,32	63,23	17,35
Median	22,41	0,01	10,49	29,60	2,48	14,94	59,81	17,45
Maximum	115,24	160,04	36,73	103,55	246,73	328,17	111,63	21,10
Minimum	0,01	0,00	1,30	0,44	−40,09	0,42	24,46	15,00
Std.D	23,83	6,72	4,11	21,43	12,74	16,00	25,60	1,50
Skewness	1,20	19,33	1,32	0,56	9,78	11,06	0,44	0,63
Kurtosis	4,00	417,96	6,87	2,80	162,57	193,70	2,41	2,87
Jarque-Bera	238,72	6151402,00	778,95	46,03	915340,60	1305237	39,51	55,99
Probability	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00

Table 3
Statistical characteristics.

	AI	FDI	GDP	GPT	OIL	POP	RD	RENE
AI	1							
FDI	−0,030	1						
GDP	0,213	0,072	1					
GPT	0,334	−0,094	0,254	1				
OIL	−0,022	−0,011	−0,032	−0,011	1			
POP	0,015	−0,098	−0,484	−0,146	0,183	1		
RD	0,003	0,008	0,475	0,078	0,045	−0,135	1	
RENE	0,015	−0,065	0,384	0,098	−0,028	−0,228	0,298	1

Table 4
Multicollinearity results.

Variable	VIF	1/VIF
GDP	2.48	0.402
RD	1.92	0.521
POP	1.61	0.621
OIL	1.36	0.735
GPT	1.29	0.775
AI	1.22	0.820
FDI	1.09	0.917
Mean		1.57

Table 5
CSD results.

Test	Test statistics	p-value
Breusch-Pagan Lagrange Multiplier	2249.317	0.00
Pesaran Scaled LM	49.912	0.00
Pesaran CD test	15.847	0.00

Note: 0.000 indicates statistical significance at the 1 % level.

Table 6
Slope homogeneity.

	Statistics	p-value
Pesaran and Yamagata (2008) [57]	11.984	0.000
Δ adj	15.972	0.000
Blomquist and Westerlund (2013) [58]	27.846	0.000
Δ adj	37.914	0.000

Table 7
Dumitrescu-Hurlin Causality Test results.

H_0	W-Stat.	p-value	Decision (H_0)	Type
OIL ⇏ RENE	**10.243**	**0.000**	**Yes**	Uni-directional
RENE ⇏ NRP	0.742	0.476	No	
GPT ⇏ RENE	**6.621**	**0.001**	**Yes**	Uni-directional
RENE ⇏ GPT	0.186	0.831	No	
GDP ⇏ RENE	**8.054**	**0.000**	**Yes**	Uni-directional
RENE ⇏GDP	0.547	0.579	NO	
FDI ⇏ RENE	0.219	0.805	NO	No causality
RENE ⇏FDI	2.203	0.112	NO	
RENE ⇏AI	0.053	0.949	NO	Uni-directional
AI ⇏ RENE	**1.982**	**0.048**	**Yes**	
RD ⇏ RENE	**7.048**	**0.001**	**Yes**	Uni-directional
RENE ⇏ RD	0.648	0.523	NO	
POP ⇏ RENE	**10.887**	**0.000**	**Yes**	Uni-directional
RENE ⇏ POP	0.165	0.849	NO	

positive across all lag years. This transformation illustrates the progressive impact of AI technologies on energy efficiency over the years, likely driven by advances in AI integration, greater data accessibility, and the automation of energy systems. Likewise, GPT is initially negative but becomes positive at the end of the sample, indicating the lagged, increasing contribution of green patent innovations to energy efficiency. In the context of AI's role in energy, our study aligns with the findings of [18,32,59], showcasing AI's potential to revolutionize energy supply, trade, and consumption. However, our analysis extends beyond technical aspects to examine the specific impact of AI on the efficiency of renewable and nuclear energy, providing policymakers and stakeholders with valuable insights. Furthermore, our study contributes to the discourse on AI in the nuclear industry, building upon the early work of [22,60] by exploring recent advancements in AI and machine learning and their potential applications in the nuclear power sector. While studies [33] focus on the effectiveness of RE policies and knowledge spillovers in green innovation, our study examines the specific impact of AI and GPT on the efficiency of RENE. Similarly, our study builds upon [61] by exploring the impact of regulations and policies on green patent generation, highlighting significant variation in innovation systems across countries. Additionally, our analysis complements [37] by delving into global competition and the diffusion of RE technologies, emphasizing the roles of innovation and policy in addressing climate change. The findings align with recent evidence that AI's environmental role follows a nonlinear trajectory rather than a monotonic pattern. Consistent with the AI-EKC literature, AI initially raises energy demand but subsequently contributes to emissions mitigation through efficiency improvements and renewable integration as technological adoption matures. Our results also complement studies showing that automation and intelligent technologies mitigate urban and industrial emissions only beyond critical adoption thresholds. Importantly, this study extends prior work by demonstrating that AI's environmental benefits are conditional on structural readiness, reinforcing the argument that

digitalization alone is insufficient without complementary institutional and financial support [39,40]. The coefficient of the GDP starts at a moderate positive value, then gradually increases to maximum values around periods 7 and 12, respectively, and then steadily decreases until the end of the sample. This may suggest that at earlier times, higher GDP was associated with greater improvements in RENE efficiency, possibly due to greater investment capacity and infrastructure, as well as greater support for innovative ideas in wealthier countries. However, the downward trend in recent years could also indicate declining marginal returns or a shift in the structure of GDP toward energy-efficiency objectives. It could also mean that, once a certain level of development is reached, countries become more reliant on existing energy systems or face institutional constraints that hinder further improvements in energy efficiency. The finding aligns with the previous studies [62]. The FDI impact is consistently adverse throughout the entire period, with its most substantial negative influence occurring around period 12. This tendency may suggest that foreign direct investment in the analyzed years was primarily directed towards traditional energy sources rather than renewables or nuclear power development. There is a moderate tendency for the AI coefficient to become increasingly positive over time, with the effect being more substantial at the end of the sample. This leads to the conclusion that AI applications have been improving energy efficiency, likely because AI technology has become more mature and integrated into energy management systems. The finding contradicts a prior study [63], which found that FDI contributes to RENE consumption in emerging countries. The trend in the R&D coefficient is on a continuous, statistically significant rise, reflecting a strong, consistently positive impact of research and development on energy efficiency gains. Finally, POP has a negative and diminishing impact,

indicating that population growth will induce energy efficiency gains in the short term via scale economies and demand-driven technology adoption; however, over the long term, its effect becomes weaker. The effect of oil prices is strongly negative for both samples of firms, but it reverses and becomes negative mid-period; however, it relaxes in period 5. This trend suggests that high oil prices will not only initially hinder RENE efficiency by providing an incentive to continue reliance on fossil fuels, but that this will change as long-term price fluctuations and policy interventions alter the equation.

Figs. 2–4 provide clear evidence that the impact of artificial intelligence and green technological innovation on the efficiency of renewable and nuclear energy is neither time-invariant nor development-neutral. In particular, the post-2022 period marks a structural break in AI coefficients, with sharply rising effects in advanced economies and delayed but strengthening effects in developing countries. This divergence highlights that AI-driven energy efficiency gains depend not only on technological availability but also on institutional readiness, infrastructure maturity, and complementary innovation ecosystems. Static panel estimators cannot capture these patterns and represent a central empirical contribution of this study. While recent studies [64–66] have examined the relationship between artificial intelligence, innovation, and energy outcomes using static or mean-based estimators, the present analysis departs fundamentally from this literature by focusing on time-varying, post-AI-boom dynamics and development-specific heterogeneity. In contrast to prior work that relies on pre-2020 data or homogeneous slope assumptions, our results reveal that AI's contribution to energy efficiency intensifies only after recent technological breakthroughs and differs substantially between advanced and developing economies. This explains why earlier studies report weaker or ambiguous effects and underscores the importance of adopting dynamic econometric frameworks when evaluating rapidly evolving technologies such as AI.

4.5. Robustness test

We performed BSQR to validate and assess the robustness of our main findings in Fig. 4, which confirm the results and show that heterogeneity remains consistent across quantiles. In particular, for RENE, we find a robust, significant positive effect of AI that becomes stronger at higher quantiles. GPT has a similar shape, with a more pronounced effect at the top quantiles; this probably results from the fact that patenting green activities is more meaningful for top-performing countries. In contrast, GDP shows a slight negative impact in the lower quantiles but reverses at the upper quantiles, suggesting nonlinearity between economic development and energy efficiency. The negative association between GDP and RENE efficiency at higher quantiles is indeed counterintuitive, as higher-income countries are generally expected to invest more in advanced energy systems and sustainability technologies. One possible explanation is that some high-GDP countries continue to rely heavily on legacy energy infrastructure, such as aging nuclear reactors or centralized grid systems, which may not meet current efficiency standards. Additionally, higher energy consumption levels in wealthier economies, driven by industrial activity, urban density, and consumer demand, could offset the gains from efficiency improvements. This finding may also indicate that beyond a certain income threshold, the marginal gains in energy efficiency from GDP diminish or even reverse, particularly when efficiency targets have already been met or plateaued. Further heterogeneity in energy policy ambition and enforcement could also account for this unexpected pattern.

Similarly, in middle-income economies, the analysis of R&D's impact on RE efficiency reveals a distinct pattern, particularly evident across specific quantiles. The consistent adverse effect of FDI on RENE efficiency across all quantiles, particularly in middle-income countries, raises critical questions about the structure and orientation of foreign investment. This pattern suggests that FDI may be disproportionately directed toward traditional energy sectors, such as fossil fuels or outdated infrastructure, rather than supporting innovation in clean or efficient energy systems. One possible explanation is that the regulatory frameworks in many middle-income economies may not offer sufficient incentives or protections to attract FDI into RENE, inadvertently reinforcing reliance on conventional energy sources. Alternatively, RE markets in these countries may still be underdeveloped or perceived as high-risk, limiting FDI inflows to the sector. These findings highlight the need for targeted policy reforms to redirect foreign capital toward sustainable energy development. Oil has a substantial adverse effect, especially at the lower and median quantiles, corroborating the notion that fossil energy consumption has a negative impact. POP exhibits a U-shaped effect, being negative at lower and median quantiles, as it undermines energy efficiency. Conversely, it becomes significantly positive in high quantiles, possibly due to higher-quality urban energy infrastructure in more developed settings. These results validate the robustness of the main findings and the generalizability of conclusions, as they remain consistent across different estimation techniques. (See Fig. 5)

4.6. Causality association

Table 8 shows the null hypothesis of no causality from explanatory variables to RENE except for the causality with FDI, indicating unidirectional causality from Oil, GPT, AI, POP, and RD to RENE, and no causality with FDI.

5. Conclusions and policy implications

This study examined the effect of AI and GPT on RENE in developed and developing countries, utilizing the TV-IFE and BSQR techniques. AI has consistently shown uniformly positive results, especially in recent years and at upper quantiles, indicating a growing impact on energy optimization and the development of integrated systems. There is a nonlinear behavior in the GPT, initially ranging from negative, but turning strongly positive in more recent periods and upper quantiles, signaling a better connection with sustainable energy objectives. GDP has a non-monotonic effect: its impact is initially positive but becomes negative later. FDI is inversely correlated with RENE efficiency, suggesting that energy investments could be better targeted to conventional forms of energy. The oil price has a significant adverse impact, indicating that the continued use of fossil fuels still dominates inefficient power systems. On the other hand, RD investment has a positive impact, emphasizing the persistent nature of RD in technology development. The effects of POP and urbanization vary across different periods and exhibit a U-shaped relationship with energy efficiency.

5.1. Policy implications

The findings offer several important implications for policymakers,

Table 8
List of abbreviations.

Abbreviation	Definition
AI	Artificial Intelligence
BSQR	Bootstrap Quantile Regression
CSD	Cross-Sectional Dependence
FDI	Foreign Direct Investment
GDP	Gross Domestic Product
GPT	Green Patent Technologies
GTI	Green Technological Innovation
OIL	Oil Price
POP	Population
R&D (RD)	Research and Development
RE	Renewable Energy
NE	Nuclear Energy
RENE	Renewable and Nuclear Energy Efficiency
SH	Slope Heterogeneity
TV-IFE	Time-Varying Interactive Fixed Effects

regulators, and energy stakeholders seeking to accelerate the clean energy transition through innovation and strategic investment. Key to policymakers, regulators, and energy practitioners, these results reveal important roles for AI and GPT in achieving the efficiency of RENE systems under differing national contexts. High-income countries such as the US, Japan, Germany, and France were innovation ecosystems that are advanced, work to institutionalize AI applications throughout the entire energy infrastructure, especially in grid management and nuclear operations and energy storage systems but also on an accelerated pathway to commercialized GPT using various mechanisms such as tax credits, fast track patenting for green technologies and green tech incubators. More concretely, public policy in middle-income economies, such as China, India, Brazil, and Turkey, should focus on building the institutional and technical capacity needed to deploy AI at scale in energy systems. This involves deploying AI pilot programs in utilities, reorienting patent frameworks to align with clean energy objectives, and establishing innovation funds that can accelerate GPT development. In high-income and emerging countries, technology deployment should be a priority. This can be achieved by incentivizing investment in AI for energy projects, including through subsidies, by designing markets to internalize externalities, or by otherwise rewarding enhanced carbon efficiency, as well as reducing distortions that currently hinder power sector investments. Such projects can also help democratize access to green technology, which is something else you could reasonably assume. Nevertheless, we need a comprehensive national approach that utilizes AI and GPT to enhance the efficiency of energy transition policies across all income levels. Those strategies should encompass regulations that support the ethical deployment of AI, evaluation mechanisms for long-term performance tracking, and innovative funding instruments to catalyze the translation of research into innovation. For developed countries, the findings suggest that policy priorities should shift from expanding basic renewable capacity toward deepening AI integration across existing energy systems, including smart grids, predictive maintenance in nuclear facilities, and AI-enabled demand–supply optimization. Since these economies already have mature innovation ecosystems, the marginal gains from green patents materialize primarily as AI adoption scales and is institutionalized. Accordingly, policies should focus on accelerating the commercialization of green patents, strengthening data infrastructure, and embedding AI governance frameworks that support safe and efficient deployment in both renewable and nuclear energy systems. In developing countries, the results imply that AI-driven energy-efficiency gains are conditional on meeting minimum technological and institutional thresholds. Early-stage AI adoption alone does not immediately translate into efficiency improvements, highlighting the importance of capacity building, regulatory readiness, and complementary investments in human capital and digital infrastructure. For these economies, policy efforts should prioritize targeted AI pilot programs in the energy sector, technology transfer mechanisms, and incentives that align foreign investment and green patent activity with clean energy objectives. Such strategies can help accelerate the transition from delayed to sustained efficiency gains and reduce the technological gap between developing and developed countries.

5.2. Limitations study

The manuscript outlines various limitations that could be a fundamental framework for future research. The sample is limited in number of countries based on data availability, which may affect the generalizability of the results. This study acknowledges the potential impact of certain institutional, macroeconomic, and financial variables that have been overlooked in previous analyses.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

References

[1] X. Li, S. Aghazadeh, M. Liaquat, A.A. Nassani, B. Sunday Eweade, Transforming Costa Rica's environmental quality: the role of renewable energy, rule of law, corruption control, and foreign direct investment in building a sustainable future, Renew. Energy 239 (2025), https://doi.org/10.1016/j.renene.2024.121993.
[2] R. Gotoh, Quantitative text analysis of sustainability reporting: decarbonization strategies and company characteristics in Japan, Energy Rep. 13 (2025) 2722–2739, https://doi.org/10.1016/j.egyr.2025.02.016.
[3] S. Han, B.H. Bin Kamaruddin, X. Shi, J. Zhu, Achieving energy resilience: studying renewable and fossil fuel energy generation drivers and COPE-28 pathways of China, Energy Strategy Rev. 58 (2025) 101669, https://doi.org/10.1016/j.esr.2025.101669.
[4] A. Nema, A. Kumar, V. Warudkar, An in-depth critical review of different carbon capture techniques: assessing their effectiveness and role in reducing climate change emissions, Energy Convers. Manag. 323 (2025) 119244, https://doi.org/10.1016/j.enconman.2024.119244.
[5] T. Xu, C. Feng, E. Guluzada, C. Chao, Evaluating the advancement of sustainable development objectives in recently industrialized nations by tying gold prices, fossil fuel prices, and energy use, Energy Strategy Rev. 56 (2024) 101575, https://doi.org/10.1016/j.esr.2024.101575.
[6] M. Ali, A. Samour, S.A. Soomro, W. Khalid, T. Tursoy, A step towards a sustainable environment in top-10 nuclear energy consumer countries: the role of financial globalization and nuclear energy, Nucl. Eng. Technol. 57 (2024) 103142, https://doi.org/10.1016/j.net.2024.08.011.
[7] M. Sadiq, R. Shinwari, F. Wen, M. Usman, S.T. Hassan, F. Taghizadeh-Hesary, Do globalization and nuclear energy intensify the environmental costs in top nuclear energy-consuming countries? Prog. Nucl. Energy 156 (2023) 104533.
[8] S.W. Oh, J.H. Park, H.S. Jo, M.G. Na, Development of an AI-based remaining trip time prediction system for nuclear power plants, Nucl. Eng. Technol. 56 (2024) 3167–3179, https://doi.org/10.1016/j.net.2024.03.017.
[9] Q. Wang, F. Zhang, R. Li, J. Sun, Does artificial intelligence promote energy transition and curb carbon emissions? The role of trade openness, J. Clean. Prod. 447 (2024) 141298, https://doi.org/10.1016/j.jclepro.2024.141298.
[10] A. Al-maadid, Mohamed Sami, B. Ali, K.S. Mohammed, Assessing the impact of climate risk on ecological quality in the context of the circular economy using kernel regularized quantile regression, Discov. Sustain. 6 (2025).
[11] M. Sami, B. Ali, A. Al-maadid, K.S. Mohammed, Assessing the role of environmental legislation in mitigating climate risk in GCC : a quantile ARDL approach, Econ. Anal. Pol. 88 (2025) 801–816, https://doi.org/10.1016/j.eap.2025.10.007.
[12] A. Kristian, T. Sumarsan Goh, A. Ramadan, A. Erica, S. Visiana Sihotang, Application of AI in optimizing energy and resource management: effectiveness of deep learning models, Int. Trans. Artif. Intell. 2 (2024) 99–105, https://doi.org/10.33050/italic.v2i2.530.
[13] Q. Qerimi, B.S. Sergi, The case for global regulation of carbon capture and storage and artificial intelligence for climate change, Int. J. Greenh. Gas Control 120 (2022) 103757, https://doi.org/10.1016/j.ijggc.2022.103757.
[14] M.R. Tür, Energy supply security and artificial intelligence applications, Insight Turkey 24 (2022) 213–233, https://doi.org/10.25253/99.2022243.13.

[15] M.R. Abdussami, A. Verma, Future energy landscapes: analyzing the cost-effectiveness of nuclear-renewable integrated energy systems in retrofitting of coal power plants, Appl. Energy 377 (2025) 124460, https://doi.org/10.1016/j.apenergy.2024.124460.

[16] F.E. Arhouni, M.A.S. Abdo, S. Ouakkas, M.L. Bouhssa, A. Boukhair, Artificial intelligence-driven advances in nuclear technology: exploring innovations, applications, and future prospects, Ann. Nucl. Energy 213 (2025) 111151, https://doi.org/10.1016/j.anucene.2024.111151.

[17] P. Chen, Z. Chu, M. Zhao, The road to corporate sustainability: the importance of artificial intelligence, Technol. Soc. 76 (2024) 102440, https://doi.org/10.1016/j.techsoc.2023.102440.

[18] D. Christopher Selvam, Y. Devarajan, T. Raja, Exploring the potential of artificial intelligence in nuclear waste management: applications, challenges, and future directions, Nucl. Eng. Des. 431 (2025) 113719, https://doi.org/10.1016/j.nucengdes.2024.113719.

[19] J. Rahko, A.A. Alola, The effects of climate change technology spillovers on carbon emissions across European countries, J. Environ. Manag. 370 (2024) 122972, https://doi.org/10.1016/j.jenvman.2024.122972.

[20] T.E. Rehm, Advanced nuclear energy: the safest and most renewable clean energy, Curr. Opin. Chem. Eng. 39 (2023) 100878, https://doi.org/10.1016/j.coche.2022.100878.

[21] X. Wang, S. Jin, Y. Li, J. Qian, L. Su, On time-varying panel data models with time-varying interactive, J. Econom. 249 (2025) 105960, https://doi.org/10.1016/j.jeconom.2025.105960.

[22] A.B. John, Applications of artificial intelligence to reactor and plant control, Nucl. Eng. Des. 113 (1989) 219–227, https://doi.org/10.1016/0029-5493(89)90073-3.

[23] J. Reifman, Survey of artificial intelligence methods for detection and identification of component faults in nuclear power plants, Nucl. Technol. 119 (1977) 76–97.

[24] S. Suman, Artificial intelligence in nuclear industry: chimera or solution? J. Clean. Prod. 278 (2022) https://doi.org/10.1016/j.jclepro.2020.124022.

[25] A. Inbamani, P. Umapathy, V.V. Kathirvel Chinnasamy, S.V. Kumar, Artificial intelligence and internet of things for renewable energy systems, Artif. Intell. Internet Things Renew. Energy Syst. 12 (2021) 1–40, https://doi.org/10.1515/9783110714043-001.

[26] N. Kumar, D. Kumar, A. Layek, S. Yadav, Renewable energy and sustainable development: a global approach towards artificial intelligence, Artif. Intell. Renew. Energy Syst. Woodhead Publ. Ser. Energy (2022) 305–328, https://doi.org/10.1016/B978-0-323-90396-7.00011-0.

[27] N.T. Loi, N.T.T. Huyen, T.T. Thanh, L.T. Ha, Network interlinkages between artificial intelligence and green energy dynamics during the War in a Pandemic: an application of Bayesian vector heterogeneous autoregressions, Environ. Chall. 13 (2023) 100796, https://doi.org/10.1016/j.envc.2023.100796.

[28] Q. Wang, T. Liu, R. Li, Artificial intelligence and environmental sustainability: investigating the AI-EKC nexus for SDG 7 and SDG 13, Sustain. Dev. (2025) 1–26, https://doi.org/10.1002/sd.70294.

[29] F. Zhang, Q. Wang, R. Li, Industrial robots and urban carbon emissions: exploring mechanisms and implications, Sustain. Dev. 33 (2025) 5351–5373, https://doi.org/10.1002/sd.3401.

[30] C. Zhang, R. Li, Q. Wang, Artificial intelligence and sustainable development: a global nonlinear analysis of the moderating roles of human capital and renewable energy, Renew. Sustain. Energy Rev. 228 (2026) 116574, https://doi.org/10.1016/j.rser.2025.116574.

[31] Q. Huang, S. Peng, J. Deng, H. Zeng, Z. Zhang, Y. Liu, et al., A review of the application of artificial intelligence to nuclear reactors: where we are and what's next, Heliyon 9 (2023) e13883, https://doi.org/10.1016/j.heliyon.2023.e13883.

[32] B. Wang, J. Wang, K. Dong, R. Nepal, How does artificial intelligence affect high-quality energy development? Achieving a clean energy transition society, Energy Policy 186 (2024) 114010, https://doi.org/10.1016/j.enpol.2024.114010.

[33] J. Noailly, V. Shestalova, Knowledge spillovers from renewable energy technologies: lessons from patent citations, Environ. Innov. Soc. Transit. 22 (2017) 1–14, https://doi.org/10.1016/j.eist.2016.07.004.

[34] Y. Bai, B.S. Eweade, S. Aghazadeh, R.O. Bamidele, Y. Xu, Pathways to environmental sustainability: do fintech, natural resources, and environmental patents matter in E−7 nations? Renew. Energy 247 (2025) 122987 https://doi.org/10.1016/j.renene.2025.122987.

[35] R. Benammar, K.S. Mohammed, N. Arfaoui, Exploring the impact of geopolitical risk and global uncertainty on ESG-based sustainability uncertainty: evidence from Vietnam, Finance Res. Lett. 89 (2026) 109323, https://doi.org/10.1016/j.frl.2025.109323.

[36] Q. Wang, Y. Li, R. Li, Rethinking the environmental Kuznets curve hypothesis across 214 countries: the impacts of 12 economic, institutional, technological, resource, and social factors, Humanit. Soc. Sci. Commun. 11 (2024) 1–19, https://doi.org/10.1057/s41599-024-02736-9.

[37] A.M. Fernández, E. Ferrándiz, J. Medina, The diffusion of energy technologies. Evidence from renewable, fossil, and nuclear energy patents, Technol. Forecast. Soc. Change 178 (2022), https://doi.org/10.1016/j.techfore.2022.121566.

[38] D. Yang, J. Lee, N.C. Song, S.L. D, S. Kim, S. Lee, et al., Patent analysis on green hydrogen technology for future promising technologies, Int. J. Hydrogen Energy 48 (2023) 32241–32260, https://doi.org/10.1016/j.ijhydene.2023.04.317.

[39] Q. Wang, X. Wang, R. Li, Rethinking sustainability: human development and ecological footprint under deglobalization pressures, Sustain. Dev. (2025) 1–34, https://doi.org/10.1002/sd.70250.

[40] Q. Wang, S. Zhang, R. Li, Artificial intelligence in the renewable energy transition: the critical role of financial development, Renew. Sustain. Energy Rev. 226 (2026) 116280, https://doi.org/10.1016/j.rser.2025.116280.

[41] K.S. Mohammed, R. Magdalena, H. Alofaysan, A. Hagiu, The impact of green and energy investments on environmental sustainability in China: a technological and financial development perspectives, Environ. Model. Assess. (2025), https://doi.org/10.1007/s10666-025-10040-2.

[42] H. Ugur, U. Cali, Exploiting green energy potential via FinTech: the role of DLT-based crowdfunding in PV and ESS investments, Renew. Energy 228 (2024) 120528, https://doi.org/10.1016/j.renene.2024.120528.

[43] Y. Shin, B. Yu, M. Greenwood-Nimmo, Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework, SSRN Electron. J. (2014) 1–61, https://doi.org/10.2139/ssrn.1807745.

[44] T.S. Breusch, Testing for autocorrelation in dynamic linear models, Aust. Econ. Pap. 17 (1978) 334–355, https://doi.org/10.1111/j.1467-8454.1978.tb00635.x.

[45] K.S. Mohammed, New development: E-government, eco-innovation, and public policies—shaping transparency, accountability, and corruption control in the EU, Publ. Money Manag. 962 (2025) 1–5, https://doi.org/10.1080/09540962.2025.2597949.

[46] H. Chen, L. Zhang, S. Pinzon, H. Chen, B. Chen, Decarbonizing the G7: renewable energy, economic growth, globalization, and policy pathways to sustainability, Renew. Energy 244 (2025) 122671, https://doi.org/10.1016/j.renene.2025.122671.

[47] M.Z. Chishti, M. Salam, S. Xaisongkham, A.M. Du, Influence of green ICT and socioeconomic factors on sustainable development: evidence from Chinese provinces, Res. Int. Bus. Finance 73 (2025) 102624, https://doi.org/10.1016/j.ribaf.2024.102624.

[48] J.A.F. Machado, J.M.C. Santos Silva, Quantiles via moments, J. Econom. 213 (2019) 145–173, https://doi.org/10.1016/j.jeconom.2019.04.009.

[49] R. Koenker, G. Bassett, Regression quantiles REGRESSION QUANTILES' 46 (1978).

[50] E.I. Dumitrescu, C. Hurlin, Testing for granger non-causality in heterogeneous panels, Econ. Modell. 29 (2012) 1450–1460, https://doi.org/10.1016/j.econmod.2012.02.014.

[51] A.S. Allam, H.A. Bassioni, W. Kamel, M. Ayoub, Estimating the standardized regression coefficients of design variables in daylighting and energy performance of buildings in the face of multicollinearity, Sol. Energy 211 (2020) 1184–1193, https://doi.org/10.1016/j.solener.2020.10.043.

[52] T. Kyriazos, M. Poga, Dealing with multicollinearity in factor analysis: the problem, detections, and solutions, Open J. Stat. 13 (2023) 404–424, https://doi.org/10.4236/ojs.2023.133020.

[53] H.I. Dertli, D.B. Hayes, T.G. Zorn, Effects of multicollinearity and data granularity on regression models of stream temperature, J. Hydrol. 639 (2024) 131572, https://doi.org/10.1016/j.jhydrol.2024.131572.

[54] M.H. Pesaran, Estimation and inference in large heterogeneous panels with a multifactor error structure author (s): m . Hashem Pesaran, Econometrica 74 (2006) 967–1012. Published by : The Econometric Society Stable URL : http://www.jstor.org/stable/3805914.ESTIMATIONANDINFERENCEINLARGEHETEROGE.

[55] M.H. Pesaran, General Diagnostic Tests for Cross Section Dependence in Panels, vol. 3, Univ Cambridge, USC 2004. Working Paper No.0435, June 2004.

[56] T.S. Breusch, A.R. Pagan, The lagrange multiplier test and its applications to model specification in econometrics, Rev. Econ. Stud. 47 (1980) 239, https://doi.org/10.2307/2297111.

[57] M.H. Pesaran, A. Ullah, T. Yamagata, A bias-adjusted LM test of error cross-section independence, Econom. J. 11 (2008) 105–127, https://doi.org/10.1111/j.1368-423X.2007.00227.x.

[58] J. Blomquist, J. Westerlund, Testing slope homogeneity in large panels with serial correlation, Econ. Lett. 121 (2013) 374–378, https://doi.org/10.1016/j.econlet.2013.09.012.

[59] A. Luqman, Q. Zhang, S. Talwar, M. Bhatia, A. Dhir, Artificial intelligence and corporate carbon neutrality: a qualitative exploration, Bus. Strat. Environ. (2024) 1–18, https://doi.org/10.1002/bse.3689.

[60] J. Reifman, Survey of artificial intelligence methods for detection and identification of component faults in nuclear power plants, Nucl. Technol. 119 (1997) 76–97, https://doi.org/10.13182/NT77-A35396.

[61] Y. Bakkar, Jabeur S. Ben, K. Si Mohammed, Arfi W. Ben, Environmental transition dynamics under external conflict risk: new evidence from European countries, J. Clean. Prod. 472 (2024) 143510, https://doi.org/10.1016/j.jclepro.2024.143510.

[62] E.N. Udemba, M. Tosun, Moderating effect of institutional policies on energy and technology towards a better environment quality: a two dimensional approach to China's sustainable development, Technol. Forecast. Soc. Change 183 (2022) 121964, https://doi.org/10.1016/j.techfore.2022.121964.

[63] M. Elheddad, A.J.K. Alfar, R. Haloub, N. Sharma, P. Gomes, The impact of foreign direct investment (FDI) on renewable and non-renewable energy in Bangladesh: does the global climate change emergencies required? Int. J. Emerg. Serv. 11 (2022) 409–421, https://doi.org/10.1108/IJES-12-2021-0083.

[64] R. Magdalena, M. Sharif Karimi, K. Si Mohammed, M. Dumitru, A. Hagiu, Pioneering sustainable energy: a dynamic analysis of AI and green patents in renewable and nuclear power, J. Appl. Econ. 28 (2025), https://doi.org/10.1080/15140326.2025.2519068.

[65] Y. Chen, R. Zhang, J. Lyu, Y. Hou, AI and nuclear: a perfect intersection of danger and potential? Energy Econ. 133 (2024) https://doi.org/10.1016/j.eneco.2024.107506.

[66] A. Al-Maadid, M.S. Ben Ali, Mohammed K. Si, Driving the energy transition in the GCC: the role of artificial intelligence, technology and energy prices, Energy Strategy Rev. 63 (2026) 102029, https://doi.org/10.1016/j.esr.2025.102029.