Journal of Human-Social Nexus

Contents lists available at: journals.absresearchacademy.com

eISSN: 3136-4519

Research Article

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Artificial Intelligence and Green Total Factor Energy Efficiency: Role of Green Innovation

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Article info

Received: 2026-04-10

Revised: 2026-08-24

Accepted: 2026-08-26

Published: 2026-08-31

Keywords

Green total factor energy efficiency; AI; green innovation; environmental technology; productive capacity

DOI

https://doi.org/10.64939/jhsn.1.2.0010

A B S T R A C T

Achieving high-quality economic growth while reducing energy consumption and emissions has become a pressing global challenge. As a frontier technology of the digital era, artificial intelligence (AI) is increasingly recognized for its potential to transform industrial systems and accelerate the transition toward cleaner energy use. Yet, empirical evidence on whether AI truly enhances green total factor energy efficiency (GTFEE), and under what conditions this effect strengthens, remains limited. This study investigates the effect of artificial intelligence on green total factor energy efficiency in OECD countries from 2005 to 2022 and examines the moderating role of green innovation. We employ Tobit regression and two-stage least squares (2SLS) instrumental variable estimation to address key econometric challenges, including slope homogeneity and endogeneity. The findings reveal that: (1) AI significantly enhances GTFEE; (2) the mechanism analysis indicates that AI improves GTFEE by increasing productive capacity; and (3) green innovation strengthens the impact of AI on GTFEE. The results suggest that governments should promote the adoption of advanced AI technologies and invest in digital infrastructure to support the green transformation of energy systems. Furthermore, policy frameworks that incentivize green innovation can magnify AI's environmental benefits and help economies achieve sustainable and energy efficient growth.

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HOW TO CITE

Siddique, M., & Hossain, M. A. (2026). Artificial Intelligence and Green Total Factor Energy Efficiency: Role of Green Innovation. Journal of Human-Social Nexus, 1(2). https://doi.org/10.64939/jhsn.1.2.0010

Introduction

Green Total Factor Energy Efficiency (GTFEE) has emerged as a key indicator for evaluating sustainable productivity in the context of global climate commitments. Traditional energy efficiency metrics primarily focus on the ratio between energy input and desirable output, overlooking the environmental damage associated with production (Hu and Wang, 2006). To address these limitations, GTFEE integrates both desirable economic output and undesirable environmental output, enabling a more accurate assessment of green growth performance (Oh, 2010). Based on Data Envelopment Analysis (DEA), particularly the Slack-Based Measure (SBM), GTFEE quantifies how effectively countries or industries transform inputs into sustainable outcomes while minimizing emissions (Tone, 2001). In the context of climate change, resource constraints, and carbon-

neutrality targets, GTFEE provides a scientific basis for identifying where economies lag in the low-carbon transition and for designing effective green technological and policy interventions (Zhang et al., 2023).

The rapid diffusion of Artificial Intelligence (AI) is reshaping industrial processes, resource optimization, and environmental governance. AI driven automation enhances energy management, predictive maintenance, and accurate monitoring of emission intensive activities, thereby supporting the transition toward green and low-carbon production systems (Pan et al., 2023). By reducing information asymmetry and operational inefficiencies, AI contributes to a cleaner energy structure and productivity improvement aligned with environmental objectives (Pham et al., 2024). Green innovation acts as a key transmission mechanism, strengthening the relationship between modern technologies and sustainable efficiency. Investments in clean technologies lead to reductions in undesirable outputs such as CO2 emissions while expanding green production capabilities (Lee and Min, 2015). Patent based innovation indicators show that technological progress significantly enhances GTFEE by encouraging energy saving production and pollution abatement (Chen and Golley, 2014). Thus, economies that prioritize eco-innovation can achieve both competitiveness and environmental benefits. Productive capacity, including human capital, infrastructure, and industrial sophistication, plays a catalytic role in maximizing energy efficiency gains. Economies with stronger innovation systems, diversified industries, and advanced capital equipment are better positioned to adopt clean technologies and improve GTFEE outcomes (Demiral and Demiral, 2023, Lin et al., 2023, Unido, 2022).

Building on the previous discussion, this study aims to address several key questions: 1. Does artificial intelligence (AI) significantly improve Green Total Factor Energy Efficiency (GTFEE) in OECD countries? 2. Through which mechanisms does AI impact GTFEE, and what role does productive capacity play in this relationship? 3. Additionally, can green innovation enhance AI's effect on green total factor energy efficiency? Consequently, the objectives of this study are to empirically assess the direct influence of AI on GTFEE, examine productive capacity as a mediating factor, explore the moderating role of green innovation, and identify the relevant policy insights. This research makes several notable contributions to both academic literature and policy discussions concerning GTFEE and AI. First, it offers strong empirical evidence on AI’s environmental impact by analyzing its effect on GTFEE across OECD countries, filling an important gap where empirical research remains limited. Second, it clarifies the mechanisms connecting AI to energy efficiency by identifying productive capacity as a key mediator, illustrating how technological adoption translates into measurable improvements in energy use and sustainable production. Third, the study emphasizes the moderating role of green innovation, demonstrating that economies with robust eco-innovation systems can boost the environmental benefits of AI adoption. Fourth, by integrating macro-level measures of AI, GTFEE, and innovation capacity, the research offers a comprehensive framework for understanding the interaction between technology, innovation, and energy sustainability. Finally, the findings have clear policy implications, guiding governments to promote clean energy development, design incentives for clean technological innovation, and support infrastructure development that enhances both environmental and economic outcomes. Overall, the study advances the understanding of technological sustainable development and provides actionable insights for achieving green energy transformation efficiently.

The framework of this paper is as follows: Section 2 reviews literature on artificial intelligence and green total factor energy efficiency. Section 3 describes the data, variables, and econometric methods. Section 4 re-

ports the empirical results, followed by broader implications in Section 5. concludes with policy recommendations, limitations, and future research directions.

Literature Review and Research Hypotheses

The widespread advancement in almost every sector defines the modern economic transformation and the global energy sector has undergone significant changes in recent decades. Conventionally energy efficiency is explained as the ability to produce a given level of output using less energy input (Patterson, 1996). However, solely relying on traditional energy efficiency overlooks the environmental externalities associated with production. Energy efficiency can be broadly classified into single factor energy efficiency (SFEE) and total factor energy efficiency (TFEE). While Single factor energy efficiency neglects several important production factors generating biased estimates (Zhou and Qi, 2022), total factor energy efficiency incorporates multiple production inputs, provides more accurate results of energy performance and overcoming the inherent limitations of SFEE [?]. Building on this framework, green total factor energy efficiency (GTFEE) extends the traditional framework by incorporating undesirable outputs into the efficiency evaluation process, thereby providing a more comprehensive and realistic measure of sustainable energy performance by simultaneously considering energy consumption (Xiao et al., 2025, Meng and Qu, 2022), capital and labor (Ren and Wu, 2022, Jebali et al., 2017), economic development (Ma et al., 2024, Zakari et al., 2022), and environmental pollution (Hao et al., 2022, Li and Ma, 2021, Wu et al., 2020). In pursuit of sustainability, researchers have increasingly shifted their attention toward green total factor energy efficiency as a key indicator of energy and environmental performance. Among the most influential drivers of GTFEE, technological innovation, foreign direct investment, green finance (Xu et al., 2024, Ma and Cao, 2022, Li and Ma, 2021, Xu et al., 2025), and economic development and energy structure have been identified as promoting factors (Ma et al., 2024), while factors such as financial agglomeration, industrial structure, land area and trade openness have been constraining the influences (Ma et al., 2024, Li and Ma, 2021). In addition, human capital and institutional quality have been recognized as enhancing factors, though the benefits of technological adoption remain conditional upon income level heterogeneity (Edziah et al., 2025).

Several studies have examined the impact of AI adoption on energy efficiency across various sectors and regions. Empirical evidence confirms that AI significantly improves GTFEE as (Fang and Yang, 2025) demonstrate a robust positive effect across Chinese provinces while, (Liu et al., 2025) reveal that this relationship follows a nonlinear pattern contingent upon regional development stages and urban characteristics. Beyond GTFEE specifically, AI has been shown to enhance broader energy efficiency outcomes with the positive impact being moderated by green technology innovation capability and conditioned by regional development levels (Li et al., 2025, Zeng and Wang, 2025). Digital technology and ICT development are also critical drivers of GTFEE. (Xu et al., 2024) and (Wu et al., 2021) demonstrate that digital technology innovation and internet development facilitate GTFEE improvements through channels including resource allocation optimization and industrial structure upgrading, yet the effects remain spatially heterogeneous and context dependent. (Hao et al., 2022) further highlight that the interplay between ICT and environmental regulation shapes the overall energy efficiency performance, indicating the importance of and policy environments in realizing energy gains from digital technologies.

Despite the growing evidence on the individual effects of AI, digital technologies, green innovation, and productive capacity, integrated studies remain scarce. Few investigations simultaneously examine the moderating role of green innovation in the AI and GTFEE relationship and explore productive capacity as a transmission mechanism through which AI translates into measurable energy efficiency gains. Moreover, while most existing studies focus on Chinese or single-country contexts using SBM or spatial econometric methods (Wu et al., 2020, Shao and Wang, 2023, Xiao et al., 2025), cross-country evidence from OECD economies remains limited, and the combined effects of AI, green innovation, and productive capacity on GTFEE are insufficiently addressed. These gaps highlight the need for more comprehensive analyses that capture the synergistic effects of these factors within advanced economies. In summary, the literature underscores the multifaceted nature of GTFEE determinants. AI and digital technologies provide operational tools to reduce energy intensity, green innovation serves as a moderating force that amplifies AI's environmental benefits, and productive capacity acts as a critical mediating channel ensuring that AI-driven innovations are effectively deployed toward sustainable energy outcomes. Understanding these synergistic effects is crucial for designing policies that foster sustainable, low-carbon economic growth.

Artificial intelligence and green total factor energy efficiency

Artificial intelligence has emerged as a frontier technology reshaping the global energy landscape, with demonstrated applications across power management, industrial optimization, and environmental sustainability (Park and Kim, 2026, Izabela et al., 2025). At its core, AI enhances energy productivity through real-time resource allocation, predictive maintenance, and production workflow optimization, fundamentally shifting energy management from reactive to proactive (Izabela et al., 2025). These capabilities extend beyond operational gains; AI has been shown to drive industrial green transformation through green technological progress and economic agglomeration (Zeng and Yin, 2025), while at the enterprise level, it promotes energy efficiency by stimulating technical innovation and R&D investment (Luo et al., 2025).

Building on this foundation, empirical studies have increasingly examined AI's role in shaping energy efficiency outcomes. Within the GTFEE framework (Fang and Yang, 2025) confirm that AI significantly boosts green total factor energy efficiency, while (Liu et al., 2025) further reveal that this effect follows a nonlinear trajectory shaped by regional development stages. Complementary evidence from broader energy efficiency studies suggests that green technology innovation and industrial structure serve as key channels through which AI translates into efficiency gains (Li et al., 2025, Zeng and Wang, 2025). The role of digital technologies more broadly mirrors these findings as digital technology innovation and internet development have been shown to improve GTFEE through resource allocation optimization and industrial upgrading (Xu et al., 2024, Wu et al., 2021), with environmental regulation further conditioning the strength of this relationship (Hao et al., 2022). Collectively, while the evidence points to a consistent positive association between AI, digital technologies, and energy efficiency, the bulk of existing empirical investigations remain concentrated in the Chinese context, leaving cross-country evidence from OECD economies considerably limited. Given that OECD economies differ substantially from China in terms of digital infrastructure and energy systems, whether these findings generalize to advanced economies remains an open empirical question that the present study seeks to address.

H1: Artificial Intelligence significantly influences green total factor energy efficiency in OECD countries.

Mechanism of artificial Intelligence, productive capacity and green total factor energy efficiency

Drawing on the UNCTAD Productive Capacities Index, which captures a country's foundational development drivers spanning human capital, energy systems, digital infrastructure, and institutional frameworks, this study argues that productive capacity mediates the relationship between artificial intelligence and GTFEE. Economies equipped with stronger productive capacities are better positioned to absorb, deploy, and scale in AI technological ways that generate meaningful energy efficiency improvements. Evidence suggests that productive capacity is further reinforced by sustainable energy adoption, globalization, and innovation, while geopolitical risks and governance deficiencies present notable constraints (Ge and Mehmood, 2024, Pal et al., 2024). Moreover, historical analyses also confirms that improvements in productive capacity systematically reduce energy intensity and contribute to long-term efficiency gains (Schurr, 1984, Li et al., 2014), suggesting that even frontier technologies such as AI require industrial upgrading and effective governance environments to fully materialize their potential in efficiency boosting. Accordingly, this study posits that productive capacity constitutes a significant mediating pathway through which artificial intelligence enhance green total factor energy efficiency in OECD countries.

H2: AI improves green total factor energy efficiency through the channel of productive capacity.

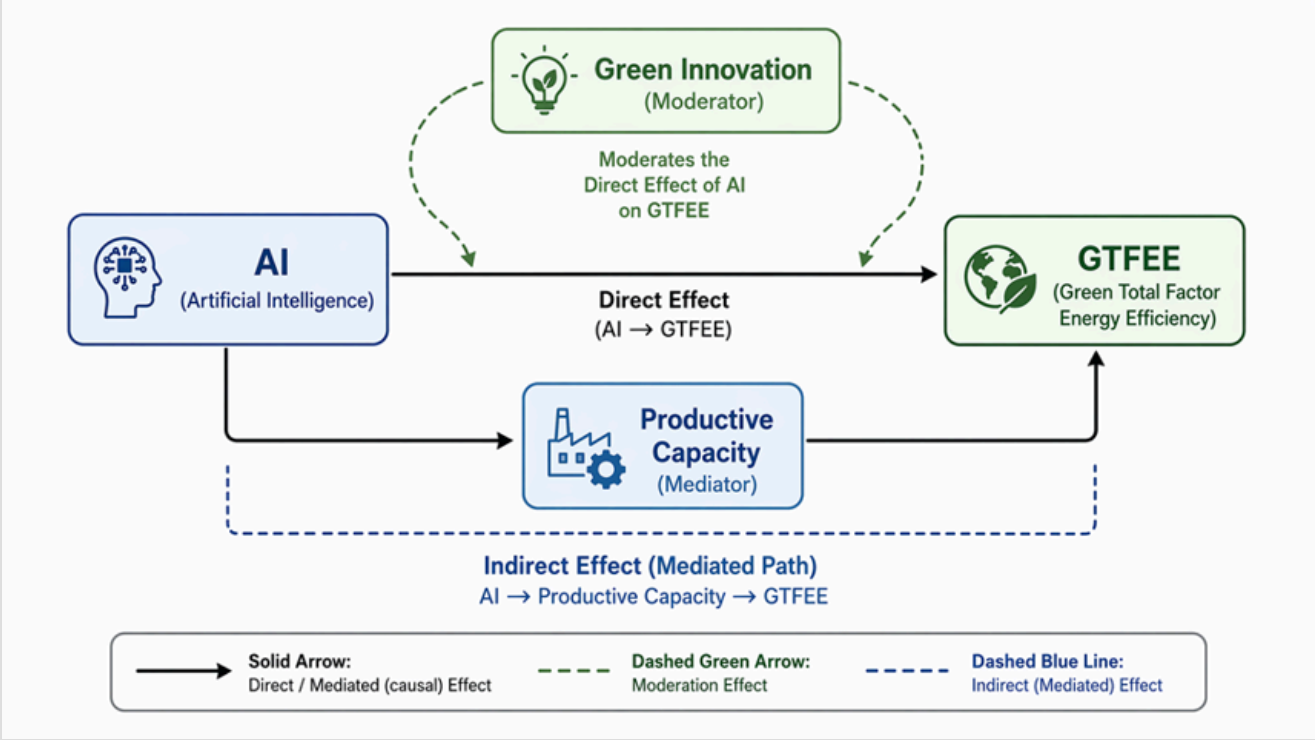

Figure 1. *Conceptual Framework*

Moderator of green innovation, artificial Intelligence and green total factor energy efficiency

Green innovation, also referred to as eco-innovation, is defined as the production and adoption of new technologies that contribute to a reduction of environmental risk, pollution, and the negative impacts of resource and energy use (Castellacci and Lie, 2017). Building on this definition, empirical evidence confirms that green innovation in its cooperative and heterogeneous forms, exerts a significant positive effect on CO2 and energy efficiency through transmission channels containing industrial structure upgrading and energy intensity reduction (Xu et al., 2021, Zhao et al., 2023). Furthermore, green innovation has been recognized as a strategic

organizational resource that mediates the relationship between environmental management practices and firm performance outcomes (Zhang and Ma, 2021), and is further shaped by institutional environments and ownership structures in emerging economies (Wang and Jiang, 2021). Critically, the interaction between digital technological development and green innovation is conditional. In early stages of DE development may constrain the efficiency of green innovation due to resource competition and technological lock-in effects but higher levels of digital development amplify it (Wu et al., 2024). This conditional dynamic is relevant to the AI and GTFEE nexus, as artificial intelligence represents the frontier of digital technological advancement. When economies cultivate robust green innovation ecosystems, AI technologies are more effectively channeled into clean energy systems and low-carbon frameworks, thereby amplifying their GTFEE enhancing effects. Accordingly, this study posits that green innovation positively moderates in across OECD's.

H3: Green Innovation positively moderates the relationship between artificial intelligence and green total factor energy efficiency.

According to the stated hypotheses, Figure 1 illustrates the conceptual framework underpinning this study. The framework proposes a direct relationship between AI and GTFEE, an indirect relationship operating through productive capacity, and a moderating effect of green innovation on the AI–GTFEE nexus.

Methodology and Data

We developed a panel dataset using the data of OECD countries from 2005 to 2022, incorporating factors of green total factor energy efficiency, artificial intelligence, environmental technology, and productive capacity. Data was collected from reliable sources. Notably, ***Table 1*** represents the definition and sources used for each variable.

Table 1. Variable's descriptions

Variables type	Definition	Symbol	Measurement	Sources
Dependent variable	Green total factor energy efficiency	SBM	Index by DEA methed	Author calculated
Independent variable	Artificial intelligence	lAI_Patents	AI related patents	OECD.AI (2025) and IFR
Moderating variable	Environmental technology	lERTpi	Environment related technology % innovation	OECD
Mediating Variable	Productive capacity	lPCI	Productive capacity index	UNCTAD
	Economic development	lGDPp	GDP per capita (constant 2015 US$)	WDI
Control variables	Industrial growth	lINDSg	Industry (including construction), value added (annual % growth)	WDI
	Urbanization	lURBp	Urban population (% of total population)	WDI
	Research and Development	lRD	*R&D expenditure % GDP*	WDI
	Trade	lTD	Trade (% of GDP)	WDI

	Domestic credit to the private sector	lDCPS	Domestic credit to private sector (% of GDP)	WDI

Regression Models

The Tobit regression model, originally introduced by (Tobin, 1958), is specifically designed for situations where the dependent variable is bounded within a defined range, making it particularly appropriate for the analysis of efficiency scores derived from data envelopment analysis (Uddin et al., 2024, Sağlam, 2017). In this study, the SBM-based green total factor energy efficiency scores are constrained between 0 and 1 by construction, where values at the upper bound indicate full efficiency and values approaching the lower bound reflect complete inefficiency. To address potential endogeneity, we further implemented the Two-Stage Least Squares (2SLS) approach (Theil, 1953, Basmann, 1957, Wooldridge, 2010). This approach helps to isolate the exogenous variation in endogenous regressors by using instruments in the first stage, followed by regression in the second stage.

Baseline Regression

We posit the panel data regression technique to examine the impact of artificial intelligence on the green total factor energy efficiency. To examine this, we employed the following model:

In this study, $(SBM)_{it}$ represents green total factor energy efficiency, while $(AI\underline{P}atents)_{it}$ denotes the AI related patents as the key explanatory variable. $(GDPp)_{it}$ denotes GDP per capita in constant 2015 US dollars, $(INDSg)_{it}$ represented industrial growth. $(URBp)_{it}$ is measured as the percentage of the total population living in urban areas, and $(RD)_{it}$ gross domestic expenditures on research and development (R&D), expressed as a percent of GDP. $(TD)_{it}$ trade is the sum of exports and imports of goods and services. Finally, domestic credit to the private sector is represented by $(DCPS)_{it}$, which measures Domestic credit to the private sector refers to financial resources provided to the private sector by financial corporations, such as through loans, purchases of non-equity securities, and trade credits and other accounts receivable, that establish a claim for repayment. For some countries, these claims include credit to public enterprises. The subscripts i and t correspond to the specific country and time, respectively.

The variables are log-transformed in the following equation:

The study investigates the influence of the artificial Intelligence (AI_Patents) on green total factor energy efficiency (SBM). θ_1 serves as the principal coefficient that captures the direction and magnitude of this relationship. The seven parameters θ_1 to θ_7 in the regression equation reflect the marginal effects of the independent variables on the dependent variable. The model specification also incorporates a stochastic error term ϵ_{it}.

Moderating Effect

To examine the moderating role of green innovation, a foundational interaction model is established, as represented in **Equation 3.**

$$(lSBM)_{it} = \partial_0 + \partial_1 (lAI\underline{P}atents)_{it} + \partial_2 (lMod)_{it} + \partial_3 lAI\underline{P}atents (\times lnMod)_{it} + \sum_{n=4}^{9} \partial_n (lCont \quad (1)$$

Here, in equation (3) $(lMod)_{it}$ refers to the moderating variable of green innovation.. The coefficients ∂_2 and ∂_3 represents the AI _patents and the interaction term, while ∂_ndenotes the set of control variables such as $(lGDPp)_{it}$, $(lINDSg)_{it}$, $(lURBp)_{it}$, $(lIRD)_{it}$, $(lTD)_{it}$, and $(lDCPS)_{it}$. The model is initially estimated

without interaction terms to evaluate the base effect, followed by a second estimation that includes interaction terms. A statistically significant interaction term indicates the presence of a moderating effect; otherwise, no such effect suggested. This previous study also applied a moderating effect to examine how AI's impact fluctuates between cities (Zeng and Wang, 2025), and some other studies who used moderating effects (Li et al., 2025, Hao et al., 2022).

Mediating effect

Mediating effects are examined to understand how certain intermediary factors influence the strength or direction of the primary relationship. Previous studies have identified the presence of mediating variables in the relationship between ICT, artificial Intelligence, digitalization, and GTFEE (Fang and Yang, 2025, Gao et al., 2022, Zeng and Wang, 2025, Wu et al., 2021). To test the mediating effect, we develop models as presented in equations 4 and 5.

$$(lMed)_{it} = \vartheta_0 + \vartheta_1 l\,(AI\underline{P}atents)_{it} + \sum_{n=2}^{7} \vartheta_n\,(lControl)_{it} + \epsilon_{it}\,(4) \tag{2}$$

$$(lSBM)_{it} = \delta_0 + \delta_1\,(lAI\underline{P}atents)_{it} + \delta_2 l\,(Med)_{it} + \sum_{n=3}^{8} \delta_n\,(lControl)_{it} + \epsilon_{it}\,(5) \tag{3}$$

In equations (4 & 5) $(lMed)_{it}$ denotes the mediating variable, such as productive capacity. while $\vartheta_0 and \delta_0 are constant terms, \vartheta_n and \delta_n$ represent the set of control variables such as $(lGDPp)_{it}$, $(lINDSg)_{it}$, $(lURBp)_{it}$, $(lIRD)_{it}$, $(lTD)_{it}$, $and\,(lDCPS)_{it}$. The residual terms are represented by ϵ_{it} and ϵ_{it}.

Measurements of Variables

Dependent Variable:

Green total factor energy efficiency (SBM). It is measured by the non-radial Data Envelopment Analysis (DEA) model proposed by (Charnes et al., 1978). This method is consistent with widely adopted approaches in prior studies (Zhang and Choi, 2013, Tone and Tsutsui, 2010, Pan et al., 2025, Chang et al., 2013). The model incorporates three inputs and two outputs. On the input side, energy consumption captures the total primary energy use of each economy, capital stock reflects the accumulated productive assets available for economic activity, and labor represents the employed workforce contributing to national output. On the output side, GDP serves as the desirable output representing economic performance, while CO2 emissions constitute the undesirable output reflecting the environmental cost of production.

Independent Variable

This study used the total number of AI patent applications from OECD database. Patent-based measures have been widely adopted as reliable proxies for technological innovation, given their quantitative comparability, output-oriented nature, and wide availability across countries and time periods (Griliches, 1990, Haščič and Migotto, 2015). Within the AI innovation literature specifically, patent counts have been employed as indicators of AI-specific knowledge accumulation and technological capability at both the firm and aggregate levels, capturing the dynamic learning effects and knowledge diffusion associated with frontier technology development (Igna and Venturini, 2023). Following this established practice, this study employs AI patent into two categories: 1) Application date, applicant, and inventor; 2) Priority date, applicant, and inventor.

Moderating Effects

Green Innovation (ERTpi) acts as a moderator to determine how variation in environmental technology performance strengthens the relationship between AI and GTFEE across OECD countries. Green finance and innovation serve as effective mechanisms for reducing environmental pollution and alleviating climate change risks by enabling cleaner technology and lowering carbon emissions (Umar and Safi, 2023). Prior research has explored moderating effects. For example, (Gans, 2012) states that climate policy stimulates innovation in environmentally friendly technologies, particularly those that directly reduce carbon emissions. Firms adopt green innovation strategies as a competitive approach to achieve sustainable development and respond to environmental challenges (Song and Yu, 2018). Green innovation significantly alleviates climate risks by decreasing carbon emission intensity and improving energy efficiency (Fang, 2025). According to (Chien et al., 2021), ecological innovation plays a vital role in reducing carbon emissions and air pollution in major Asian economies.

Mechanism Analysis

Productive capacity (PCI) is measured using the UNCTAD PCI Index. PCI provides countries' overall ability to produce goods and services by integrating multiple dimensions. This study examined the potential to improve green total factor energy efficiency through cleaner energy sources, technological upgrades, and better resource allocation. Prior evidence suggests that productive capacity contributes to environmental improvements by enhancing industrial efficiency and reducing energy intensity (Ge and Mehmood, 2024, Schurr, 1984). Globalization and innovation further strengthen productive capacity, whereas geopolitical risks hinder its development (Pal et al., 2024). Sustainable energy use also supports productive capability and long-term ecological outcomes (Li et al., 2014). Together, these studies indicate that productive capacity can serve as an important mediating mechanism in promoting GTFEE.

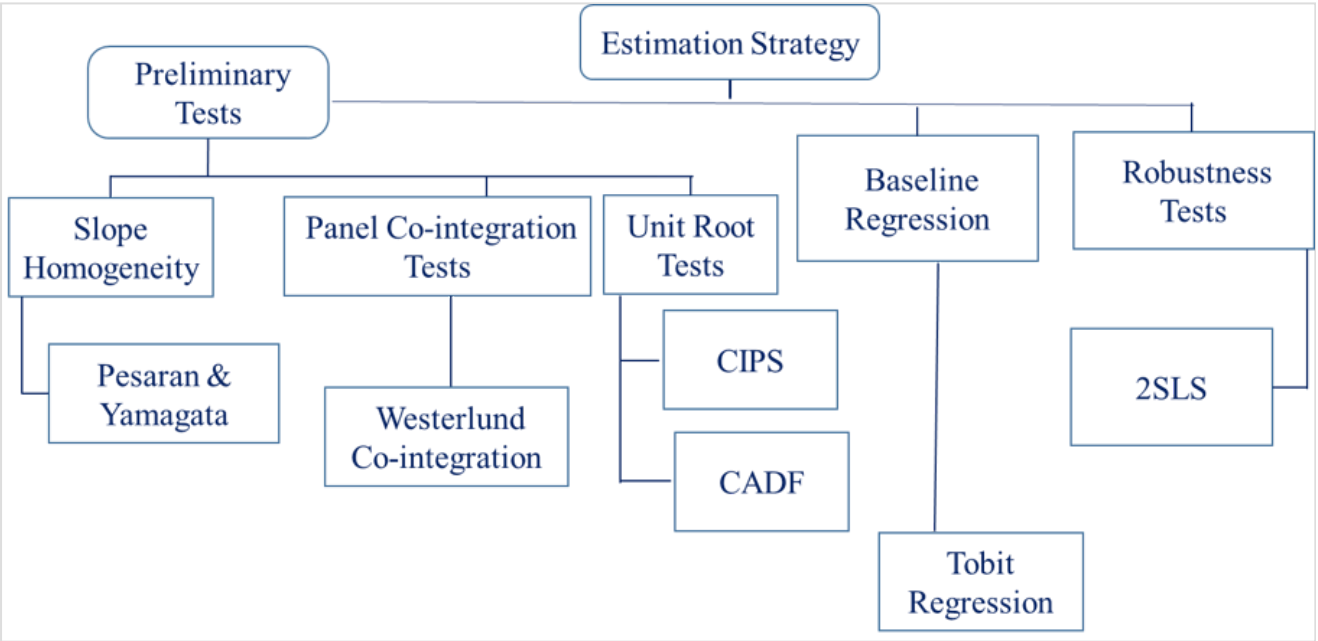

Figure 2. *Estimation Procedure*

Estimation Strategy

To ensure the reliability of the empirical analysis, a series of preliminary diagnostics were performed before model estimation. Slope homogeneity among OECD nations was checked using the Pesaran–Yamagata procedure (Pesaran and Yamagata, 2008), where rejection of the null indicates unequal slope coefficients. To assess multicollinearity, the Variance Inflation Factor (VIF) test was applied, with values above 10 commonly considered indicative of potential multicollinearity issues (O'brien, 2007). The integration properties of the data were then evaluated through second-generation unit root tests, CADF & CIPS which incorporate cross-sectional interdependence and common factor influences (Pesaran, 2007). Moreover, the presence of a long-term equilibrium among the model variables was validated using the Westerlund Panel Cointegration framework (Westerlund, 2007). Details of all diagnostic outcomes are presented in the **Appendix 1-4.**

Empirical Results and Discussion

Results of Descriptive statistics and preliminary diagnostics

The descriptive statistics presented in **Table 2** summarize the key characteristics of the variables employed in the empirical analysis. The indicators include their total observations, minimum and maximum values, along with mean and standard deviation, which help illustrate the overall distribution patterns. The average SBM value is 0.692, with a standard deviation of 0.37, indicating considerable variation in green total factor energy efficiency across the sample. The minimum and maximum values are 0.231 and 2.101, respectively. The log-transformed AI patents variable has a mean value of –0.515 and a standard deviation of 1.456, and a minimum and maximum range from –5.357 to 3.132. In **Table 3** presents the pairwise correlations among the main variables. Log AI_patents show a positive correlation with the green total factor energy efficiency (0.38). Most of the correlations are statistically significant at the 1% level, indicating a meaningful linear association among these variables.

Table 2. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
SBM	648	.692	.37	.231	2.101
lAI Patents	648	-.515	1.456	-5.357	3.132
lERTpi	648	-1.127	2.095	-5.298	3.399
lGDPg	648	.924	.78	-3.738	3.198
lINDSp	648	3.196	.217	2.592	3.895
lRD	648	.436	.709	-1.806	1.741
lURBp	648	4.333	.152	3.942	4.587
lTD	648	4.411	.491	3.14	5.531
lDCPS	648	4.473	.538	2.729	5.719

Table 3. Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) SBM	1.000								
(2) lAI_-Patents	0.379	1.000							
	(0.000)								

(3) lERTpi	0.431	0.872	1.000						
	(0.000)	(0.000)							
(4) lGDPp	0.487	0.315	0.545	1.000					
	(0.000)	(0.000)	(0.000)						
(5) lINDSp	-0.121	-0.121	-0.094	-0.253	1.000				
	(0.002)	(0.002)	(0.017)	(0.000)					
(6) lRD	0.287	0.375	0.611	0.772	-0.254	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
(7) lURBp	0.181	0.194	0.373	0.355	-0.288	0.281	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
(8) lTD	-0.280	-0.480	-0.439	-0.023	0.160	0.037	-0.415	1.000	
	(0.000)	(0.000)	(0.000)	(0.563)	(0.000)	(0.348)	(0.000)		
(9) lDCPS	0.343	0.330	0.524	0.665	-0.354	0.531	0.384	-0.349	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Baseline Estimation Result

Table 4 reports the estimation outcomes of the Tobit model using green total factor energy efficiency as the dependent variable and the artificial intelligence patents as the key explanatory variable. The results reveal a statistically significant positive relationship between the artificial intelligence (AI_patents) and green total factor energy efficiency (SBM), with a coefficient of 0.062, at 1% level, indicating that artificial intelligence promotes green total factor energy efficiency. This result aligns with our findings that AI serves as a key driver of GTFEE through multiple channels, including technological innovation, industrial agglomeration, and marketization (Fang and Yang, 2025). Additionally, economic development, research and development and domestic credit to the private sector have a positive effect that indicates a facilitating nature toward sustainable energy efficiency. In contrast, industrialization, urbanization and trade have a negative effect.

Table 4. Baseline Regression

	(M1)
	SBM
lAI_Patents	0.062***
	(0.010)
lGDPg	0.043***
	(0.015)
lINDSp	-0.068
	(0.055)
lRD	0.063***
	(0.021)
lURBp	-0.011
	(0.085)
lTD	-0.133***

	(0.032)
lDCPS	0.061**
	(0.027)
_cons	1.212**
	(0.517)
var(e.SBM)	0.072***
	(0.005)
N	648
R^2	

The notations *, **, and *** specify significance levels of 10%, 5% and 1%, respectively. Standard errors in parentheses

Endogeneity test: Two-Stage Least Squares (2SLS)

To address potential endogeneity concerns in assessing the impact of the artificial Intelligence (AI_Patents) on green total factor energy efficiency (SBM), this study applies two-stage least squares (2SLS) with instrumental variables (IVs). The key challenge lies in identifying the causal effect of AI_Patents on SBM. To overcome this, the lag of AI_patents employed as instruments, as they are strongly correlated with AI_Patents but only weakly correlated with the error term, ensuring validity. This approach follows the established practice of using appropriate instruments to isolate the exogenous component of the potentially endogenous regressor (Han, 2016, Cao et al., 2021).

Panel A of **Table 5** reports the first-stage regression results, where lagged terms of AI_Patents are highly significant at the 1% level, with a coefficient of 0.966, confirming the relevance and strength of the instruments.

Panel B presents the second-stage results, showing that lAI_Patents has a significant positive impact on green total factor energy efficiency. Specifically, the coefficient for lAI_Patents is 0.065 significant at the 1% level. These findings provide robust evidence that the artificial intelligence contributes to enhance in OECD countries.

Table 5. nstrumental variable regression results

Panel A: First stage regression	(M1)
Dependent variables: Artificial intelligence	lAI_Patents
L. lAI_Patents	0.966***
	(0.008)
Control	Yes
_cons	0.335
	(0.437)
No. obs.	612
Panel B: Second stage regression	(M1)
Dependent variables: Green total factor energy efficiency	SBM
lAI_Patents	0.065***

	(0..015)
Control	Yes
_cons	0.668
	(0..538)
No. obs.	612
Post Estimation test	(M1)
Instrumental variables	L.lAI_Patents
Under-identification test	
Kleibergen-Paap rk LM statistic	136.613***
Weak instrumental variable test	
Cragg-Donald Wald F statistic	1.4e+04
Kleibergen-Paap rk Wald F statistic)	3937.111
Stock-Yogo bias critical value	16.38 (10%)

The notations *, **, and *** specify significance levels of 10%, 5%, and 1%, respectively. The Std. Err. is reported in parentheses

Mechanism Analysis

Table 6 In column (M1) show the impact of AI_Patents on productive capacity (PCI). In column (M2) shows the impact of AI_patents on green total factor energy efficiency after the incusion of mediating variable, the influence coefficient of AI_Patents on the green total factor energy efficiency (SBM) is highly significant (0.052), indicating that the AI leads GTFEE through productive capacity.

Table 6.

Table 6. Mechanism Analysis

	(M1)	(M2)
	lPCI	SBM
lAI_Patents	0.011***	0.052***
	(0.002)	(0.010)
lPCI		0.955***
		(0.183)
lGDPg	0.005	0.039***
	(0.003)	(0.015)
lINDSp	-0.010	-0.060
	(0.012)	(0.054)
lRD	0.046***	0.019
	(0.005)	(0.022)
lURBp	0.131***	-0.138
	(0.018)	(0.086)
lTD	0.057***	-0.188***
	(0.007)	(0.033)

lDCPS	0.092***	-0.027
	(0.006)	(0.032)
_cons	2.878***	-1.519**
	(0.109)	(0.724)
var(e.lPCI)	0.003***	
	(0.000)	
var(e.SBM)		0.069***
		(0.005)
N	648	648
R^2		

The notations *, **, and *** specify significance levels of 10%, 5%, and 1%, respectively. The Std. Err. is reported in parentheses

Moderating Effect

We incorporate interaction terms (e.g., lAI_Patents × lERTpi), as outlined in **Table 7**. These interaction terms allow us to understand whether the influence of AI on SBM varies with differing levels of adoption in environmental related technology across OECD countries. As shown in **Table 7,** the coefficient interaction term (lAI_Patents × lERTpi) for Model 1 is (0.020) and statistically significant, indicating that the positive effect of AI on green total-factor energy efficiency (SBM) is strengthened in countries with higher adoption of environmental-related technologies.

Table 7. Moderating Effect

	(M1)
	SBM
lAI_Patents	0.059***
	(0.019)
lERTpi	0.039***
	(0.014)
lAI_Patents lERTpi	0.020***
	(0.003)
lGDPp	0.363***
	(0.028)
lINDSp	-0.112**
	(0.052)
lRD	-0.148***
	(0.025)
lURBp	-0.231***
	(0.079)

lTD	-0.156***
	(0.029)
lDCPS	-0.149***
	(0.027)
_cons	-0.262
	(0.524)
var(e.SBM)	0.053***
	(0.004)
N	648
R^2	

The notations *, **, and *** specify significance levels of 10%, 5%, and 1%, respectively. The Std. Err. is reported in parentheses.

Discussion

This study empirically investigates the role of artificial intelligence (AI) in promoting green total factor energy efficiency (GTFEE) in OECD countries, with particular attention to the mediating role of productive capacity and the moderating role of green innovation. The findings reveal several noteworthy patterns: First, the baseline Tobit estimation confirms a significant positive impact of AI on GTFEE with the coefficient 0.062 at the 1% significance level, suggesting AI adoption generates measurable and economically meaningful gains in sustainable energy performance. These findings are theoretically consistent with (Fang and Yang, 2025) who document a robust positive AI-GTFEE relationship across Chinese provinces through channels including technological innovation and marketization, and with (Li et al., 2025), who find similar efficiency gains at the enterprise level through R&D stimulation. However, (Liu et al., 2025) reveal a nonlinear trajectory in which AI's initial efficiency gains are followed by a temporary decline before recovering, a divergence that likely reflects the more advanced and institutionally homogeneous digital infrastructure of OECD economies relative to the regionally heterogeneous Chinese context. Furthermore, the significant negative coefficient of trade openness −0.133 suggests that greater trade integration increases energy consumption through expanded transportation and production activity, exerting a downward pressure on GTFEE. The insignificant coefficients of industrial structure and urbanization reflect the already advanced state of industrialization and urbanization across OECD economies, where limited cross-country variation reduces the detectable influence of these variables on GTFEE. Second, to address potential endogeneity concerns, the 2SLS estimation using lagged AI patents as instruments shows a robust and consistent positive effect on GTFEE. The strong first-stage coefficient of 0.966 at the 1% significance level confirms the relevance and strength of the instrument, satisfying the instrument validity condition. This outcome reinforces the view that the contribution of AI to green efficiency improvement is not merely a reflection of pre-existing development advantages but arises from genuine technological productivity enhancement (Cao et al., 2021, Han, 2016). Third, the mechanism analysis provides direct evidence that productive capacity serves as a significant transmission channel through which AI improves GTFEE, also providing support for hypothesis 2 of this paper. The reduction in AI coefficient from 0.062 to 0.052 after inclusion of productive capacity confirms partial mediation, indicating that AI operates through direct and indirect both pathways. AI not only directly improves GTFEE but also does so indirectly by strengthening a country's foundational productive capabilities, including human capital, digital infrastructure, energy

systems, and institutional frameworks as captured by the UNCTAD Productive Capacities Index. This finding is theoretically consistent with (Pal et al., 2024) that innovation and effective institutions strengthen productive capacity, suggesting that economies with stronger productive capabilities are better positioned to achieve sustained efficiency improvements. Eventually stronger productive capacity provides a structural foundation by adopting advanced technologies more efficiently, ultimately improving GTFEE. Fourth, the moderating effect analysis reveals that the positive impact of AI on GTFEE is significantly amplified in countries with higher adoption of environmental technologies, as evidenced by the positive and statistically significant interaction coefficient of 0.020 and this supports our hypothesis 3, green innovation has a moderating effect on the artificial intelligence and green total factor energy efficiency. This result aligns with (Wu et al., 2024) who demonstrate that the efficiency-promoting role of digital technologies is conditional upon the level of green innovation development, and with (Zhao et al., 2023), who show that cooperative green innovation enhances energy efficiency through industrial structure upgrading. Conversely, OECD countries with weaker environmental technology ecosystems may experience slower AI-driven green transitions. Overall, these results demonstrate that AI is not only a technological product but a strategic driver of green and productive development. OECD countries with advanced technology adoption capabilities are better positioned to capitalize on AI enabled efficiency gains, whereas those with weaker innovation support systems may experience slower transitions, highlighting the need for complementary policy frameworks that incentivize sustainable development alongside clean energy efficiency.

Conclusion and Policy Implications

This study provides new empirical evidence on the role of artificial intelligence in promoting sustainable clean energy efficiency across OECD countries. By integrating Tobit and 2SLS estimation techniques, the results demonstrate that AI significantly improves green total factor energy efficiency (GTFEE), confirming that digital innovation contributes to decoupling economic growth from energy consumption. The mechanism analysis further reveals that enhanced productive capacity serves as a key pathway through which AI drives energy efficiency gains. Additionally, the moderating effect of green innovation shows that countries with stronger environmental technology adoption can better leverage AI for green transformation. Overall, the findings highlight that AI is not merely a productivity tool but a strategic driver of clean, resilient, and high-quality economic growth. These findings have several key implications for policymakers and relevant entities. First, Governments should formulate long-term digital transformation roadmaps that guide AI applications toward energy intensive industries and clean production systems, where efficiency gaps are largest and returns are highest. Early efforts should focus on sectors where intelligent technologies can optimize energy allocation, reduce wastage, and strengthen green manufacturing competitiveness. Prioritized investment in mature and scalable AI technologies can minimize systemic risks and ensure efficient resource utilization. Second, improving policy stability and the legal environment is essential to foster synergy between AI adoption and ecological objectives. OECD countries should implement clearer rules on data security, energy related digitalization incentives, and environmental accountability. Coordinated regulatory frameworks will accelerate AI diffusion while preventing rebound effects that counteract environmental gains. Third, financial support instruments such as green patent subsidies, tax incentives, and targeted R&D funds should be expanded to encourage the integration of AI into clean technologies, thereby strengthening human capital, digital infrastructure and in-

stitutional quality. The mechanism analysis confirms that productive capacity serves as a critical pathway through which AI drives efficiency gains, underscoring the importance of simultaneously building foundational capabilities alongside AI deployment. Public-private partnerships and cross-disciplinary innovation networks can bridge technological bottlenecks, amplify productivity improvements, and unlock AI's role as a catalyst for eco-friendly industrial upgrading. Finally, given the substantial differences in digital infrastructure and industrial structure across OECD economies, policy interventions should be tailored to each country's developmental context. The moderating analysis further confirms that green innovation and AI function as strategic complements, meaning that policy frameworks should incentivize their simultaneous development rather than treating them as separate agendas. Economies with advanced technological foundations can prioritize accelerated deployment of intelligent energy systems, while less digitalized members should first build foundational green innovation and productive capacity before pursuing frontier AI applications, ensuring inclusive and coordinated improvements in GTFEE across territories.

Limitation and Future Scope

Despite the meaningful findings, this study has several limitations. First, the exclusive focus on OECD countries limits generalizability to developing economies, where AI development and energy transition differ significantly. Second, while the 2SLS estimation confirms result stability, additional robustness checks using alternative AI proxies remain an avenue for future research. Third, the exclusion restriction of the instrumental variable cannot be formally tested, representing a maintained assumption standard in IV estimation. Fourth, this study focuses on productive capacity as the primary mediating channel, and other potential transmission pathways such as industrial structure upgrading and human capital development remain unexplored. Fifth, the high correlation between AI patents and environmental technology (lERTpi = 0.872) in the moderation model is acknowledged, and results are interpreted with appropriate caution. Sixth, visualization of the moderating effect across different levels of green innovation was not provided, which future research should address. Finally, future studies could apply quasi-natural experiments or machine learning based causal techniques to further improve robustness.

Funding

This research received no external funding.

Author contributions

Meherun Siddique: Conceptualization, Investigation, Software, Writing – review & editing, Formal analysis.
Md. Amzad Hossain: Validation, Supervision, Methodology, Conceptualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare no conflicts of interest.

Ethics statement

Not applicable.

Data availability

Data available on request from the corresponding author.

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Appendix A

Table A1. Results of Multicollinearity.

Variables	VIF	1/VIF	
lAI_Patents	1.70	0.588	
lGDPp	3.42	0.293	
lINDSp	1.19	0.840	
lRD	2.84	0.352	
lURBp	1.50	0.666	
lTD	2.11	0.473	
lDCPS	2.37	0.422	
Mean VIF	2.16		

Table A2. Results of the Slope Homogeneity test

	Delta	p-value
	5.413***	0.000
adj.	7.263***	0.000

The notations *, **, and *** specify significance levels of 10%, 5% and 1%, respectively. Standard errors in parentheses.

Table A3. Results of the Westerlund cointegration test.

Statistics	Value	Z-value	P-value
Gt	-4.518***	-16.152	0.000
Ga	-19.796***	-7.124	0.000
Pt	-19.479***	-7.923	0.000
Pa	-16.843***	-7.925	0.000

The notations *, **, and *** specify significance levels of 10%, 5% and 1%, respectively. Standard errors in parentheses

Table A4. Results of panel unit root tests

Variables	CADF		CIPS	
	Level	First difference	Level	First difference
SBM	-1.617	-3.058***	-1.950	-3.738***
lAI_Patents	-1.932	-3.397***	-2.702***	-4.749***
lERTpi	-2.028***	-2.907***	-2.262***	-4.285***
lGDPp	-2.001**	-2.142***	-1.508	-2.743***
lINDSp	-1.276	-2.322***	-1.489	-3.331***
lRD	-1.735	-2.271***	-1.628	-3.018***
lURBp	-2.280***	-1.636	-0.978	-1.290
lTD	-1.431	-2.230***	-1.428	-3.088***
lDCPS	-1.374	-2.149***	-1.324	-2.742***

The notations *, **, and *** specify significance levels of 10%, 5% and 1%, respectively. Standard errors in parentheses

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