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RETRACTED: Non-linear research on artificial intelligence empowering green economic efficiency under integrated governance framework

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Artificial intelligence (AI) plays a pivotal role in the development of the green economy. This paper examines the impact of artificial intelligence (AI) on green economic efficiency (GEE) using panel data from 30 provinces in China spanning 2011–2020. A multiple linear regression model, alongside various endogeneity and robustness tests, is applied to ensure reliable findings. The empirical results indicate that AI significantly enhances GEE. However, the marginal effect of AI on GEE is influenced by different governance approaches. In terms of policy governance, excessive market-based environmental regulation (MER) diminishes the marginal impact of AI, while stronger administrative-command environmental regulations (CER) and informal environmental regulations (IER) amplify it. Regarding technological governance, substantive green technological innovations (SUG) reduce AI's marginal effect, whereas symbolic green technological innovations (SYG) may increase it. Notably, the threshold effect of SUG surpasses that of SYG. In legal governance, both administrative and judicial intellectual property protections reduce the marginal effect of AI, though administrative protection (AIP) exhibits a more significant threshold effect than judicial protection (JIP). These findings offer practical insights for optimizing governance strategies to maximize AI's role in promoting GEE. These insights highlight the need for balanced governance to maximize AI's role in sustainable development. Policymakers should tailor regulations and encourage regional collaboration to harness AI's spatial spillover effects. Enterprises can leverage AI-driven innovations to align growth with ecological goals, fostering coordinated green development.

KEYWORDS

artificial intelligence, green economic efficiency, policy governance, technological governance, legal governance

1 Introduction

In recent decades, China's economy has achieved remarkable growth, positioning it as one of the world's fastest-growing nations, often called the "Chinese economic miracle." However, this rapid economic expansion has come at a considerable cost to the country's resources and environment, leading to severe pollution and resource depletion (Rasheed et al., 2024a). These environmental challenges now act as significant barriers to the sustainable development of the Chinese economy and society (Gao et al., 2024), with potential long-term detrimental effects. As illustrated in Figure 1, Chinese energy consumption dramatically surpasses the other major economies, positioning it as the

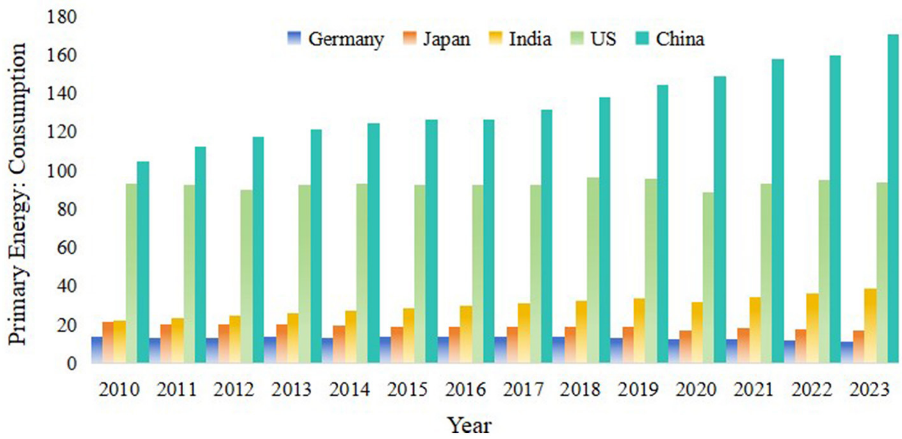

FIGURE 1
Energy consumption in the world's major economies.

globe's largest energy-consuming country. In the past 2023, China's energy usage was about 1.8 times as much as the United States, 4.3 times as much as India, 10 times as much as Japan, and 15 times as much as Germany. The Chinese government realizes that it is not desirable to judge heroes by GDP, and it is necessary to abandon the "speed syndrome," a developmental mindset in which speed produces political results. The Chinese government has called for attention to the problems of environmental pollution and waste of resources in the meantime of economic development, and to adhere to green growth, raise the green economic efficiency (GEE), and get rid of the rough-and-tumble mode of development. It advocates for integrated measures to reduce carbon emissions and pollution, expand green spaces, foster ecological prioritization, conservation, and green low-carbon growth, and push forward comprehensive green transformation in economic development (Lin and Zhou, 2022).

GEE represents a measure that integrates economic growth, resource consumption, and environmental pollution. This indicator assesses the economic efficiency of a country or region while accounting for environmental costs, thereby providing a more comprehensive and accurate reflection of the impact of economic activities (Liu and Dong, 2021). With the advent of AI, China must utilize AI's power to achieve sustainable green development and improve GEE. AI, a seminal "general-purpose technology" following the internet, is pivotal in driving the fourth industrial revolution. AI, leveraging technologies such as deep learning, pattern recognition, and autonomous decision-making, not only supplants traditional technologies but also facilitates rapid evolutionary and iterative advancements through its integration with various application sectors (Abulibdeh et al., 2024; Konya and Nematzadeh, 2024). AI fosters the development of more sustainable and cleaner technologies, decreasing consumption in production processes (Akter et al., 2024; Olawade et al., 2024; Konya and Nematzadeh, 2024). AI has notably enhanced the energy structure, with improvements in energy efficiency identified as the primary factor contributing to the deceleration of CO_2 emissions (Rasheed et al., 2024c). Additionally, AI bolsters green development awareness, ultimately steering societal shifts toward energy-saving and low-carbon behaviors (Nahar, 2024). AI is also seen as one of the tools to tackle air pollution effectively (Shaamala et al., 2024; Cai et al., 2024; Adnan et al., 2024). As a result, AI has infused the green economy with new momentum and emerged as a crucial driver of GEE improvements (Bibri et al., 2023).

Existing studies have established the significant role of AI in advancing green development, such as its contributions to technological innovation, energy efficiency, and carbon emission reduction. However, two critical gaps persist in the literature. First, while AI's general impact on green development has been explored, limited attention has been given to its direct and non-linear effects on GEE, particularly in the context of varying governance frameworks. Second, existing research often isolates governance dimensions rather than adopting an integrated approach that collectively considers policy, technology, and legal mechanisms. This fragmentation overlooks the threshold effects among governance types. To address these gaps, this study uniquely integrates AI with GEE within a comprehensive governance framework, offering a novel perspective on the heterogeneous and threshold effects across governance types. By employing panel data from 30 Chinese provinces (2011–2020), this research provides robust empirical evidence that enriches the understanding of AI's nuanced role in sustainable development.

This paper makes three significant theoretical contributions. Firstly, this paper uniquely integrates AI with GEE within a unified research framework concerning research subjects. Secondly, regarding mechanism pathways, the paper seeks to elucidate the non-linear effects of AI on GEE, contextualized within an overarching governance framework encompassing policy, technology, and law. The AI-empowered GEE is different under the roles of varying kinds of environmental regulation, green technology innovation, and intellectual property protection. Thirdly, regarding research effects, this paper considers the different geographic locations, technological levels, degree of openness, and differences in the effectiveness of AI-empowered GEE.

The structure of this paper is as follows: Section 2, "Literature Review," summarizes relevant studies. Section 3 presents the theoretical analysis and proposes research hypotheses. Section 4 describes the research design, including the model, variable measurements, and data sources. Section 5 provides an empirical study of AI's direct impact on GEE. Section 6 examines the non-linear effect of AI on GEE under the influence of comprehensive governance. Finally, Section 7 concludes the study, summarizes key findings, and offers recommendations.

2 Literature review

A thorough literature review, conducted across the ScienceDirect and Web of Science databases up to July 2024, uncovers an extensive corpus of scholarly work focused on economic efficiency and the green economy paradigm. Nonetheless, a significant absence of academic discourse is evident regarding the specific concept of GEE. Moreover, the direct impact of AI on bolstering GEE has been explored in an exceedingly sparse number of studies, as illustrated in Figure 2.

This study integrates insights from multiple theoretical perspectives to construct a comprehensive governance framework. Policy governance draws on the Porter Hypothesis, which posits that appropriate environmental regulations can stimulate innovation and offset compliance costs (Porter and van der Linde, 1995). Technological governance builds upon the theory of technological progress, emphasizing the transformative role of green innovations in improving resource efficiency (Dao et al., 2024). Legal governance leverages institutional theories, highlighting how intellectual property protection can foster innovation while potentially creating barriers to knowledge diffusion (DiMaggio and Powell, 1983). Unlike prior studies focusing on isolated dimensions, this study synthesizes these theoretical approaches into an integrated framework, providing a holistic view of how governance moderates AI's influence on GEE.

Some scholars have already paid attention to AI's enormous energy and explored whether AI can contribute to green development. AI technologies significantly foster the development of green technologies and contribute to developing a green economy (Zhao et al., 2022). AI positively influences green economic transformation through its varied effects on internal factors and markedly reduces carbon intensity in conjunction with natural resource markets (Feng et al., 2024). Notably, industrial robots decrease pollutant emission intensity, sharply reduce energy efficiency, and have a noticeable negative spatial spillover effect on carbon emission efficiency (Zhou et al., 2024a,b). AI supports the sustainable development of urban environments through real-time monitoring and data-driven approaches, facilitating the achievement of green development goals (Bibri et al., 2024).

Several scholars have discussed the impact of technological advances on GEE. They highlighted significant contributions from innovations in renewable energy technologies and the digital economy, which boosted urban GEE (Chen and Yang, 2024; Huang et al., 2023). Technological innovations densely concentrated in specific areas enhance GEE, while digital finance drives urban GEE via green technology innovations (Liu and Dong, 2021; Li and Xu, 2023). In addition, Yang et al. (2021b) argues that technological progress contributes to the decoupling of economic growth from CO_2 emissions and that Internet development can curb haze pollution through technological innovations, confirming technological advances' impact on GEE.

Others have explored the impact of other socio-economic factors on GEE. Some pointed out that human capital mismatches considerably detract from GEE, while openness and environmental regulation exhibit significant U-shaped non-linear effects (Shuai and Fan, 2020). Digital transformation has notably increased GEE by 2.6%, and economic resilience interacts beneficially with GEE (Lv and Chen, 2024; Wang and Zhou, 2024). These studies collectively provide a robust theoretical foundation and logical starting point for the in-depth exploration in this paper. Nevertheless, there is a notable gap in discussions concerning the immediate effect of AI on GEE, the mechanisms through which AI enhances GEE, and the potential heterogeneity in AI's effects.

In summary, existing research on AI's role in promoting green sustainable development and the factors influencing GEE has yielded significant findings. However, few studies have specifically examined AI's direct effects on GEE. Additionally, the potential role of integrated governance in the AI-empowered GEE relationship remains largely unexplored. To address these gaps, this paper investigates the impact of AI on GEE and the role of integrated governance, thereby extending previous research.

3 Theoretical analysis and research hypothesis

3.1 The direct impact of artificial intelligence on green economic efficiency

On the one hand, it aligns with traditional theories of technological progress, positioning AI as the apex of various advanced information technologies. AI shares characteristics with other information technologies yet possesses unique technical features that distinguish it from its predecessors (Ahmed et al., 2022). Secondly, AI significantly enhances production process efficiency through automation and intelligent systems, reducing waste and optimizing resource allocation, lowering energy and raw material consumption per output unit, thereby improving GEE (Tian et al., 2023). Thirdly, as a pioneering technology, AI supports the development of clean energy technologies, fostering innovation in the green economy (Li et al., 2024). Fourthly, AI's application in energy management optimizes energy consumption patterns, ensures precise energy use, minimizes unnecessary waste, and enhances overall energy efficiency. Within the supply chain, AI predicts demand, optimizes inventory management, reduces transportation costs, and lowers the carbon footprint (Rasheed et al., 2024b).

On the other hand, from an economic system efficiency optimization perspective, the widespread adoption of AI blurs the boundaries between different sectors' economic activities, strengthens horizontal and vertical industry linkages, and promotes industrial agglomeration and collaborative development, especially among clean, high-tech industries (Yang et al., 2021a, 2022). AI has reduced outdated production capacity and pollutant emissions, which positively influenced the green development of

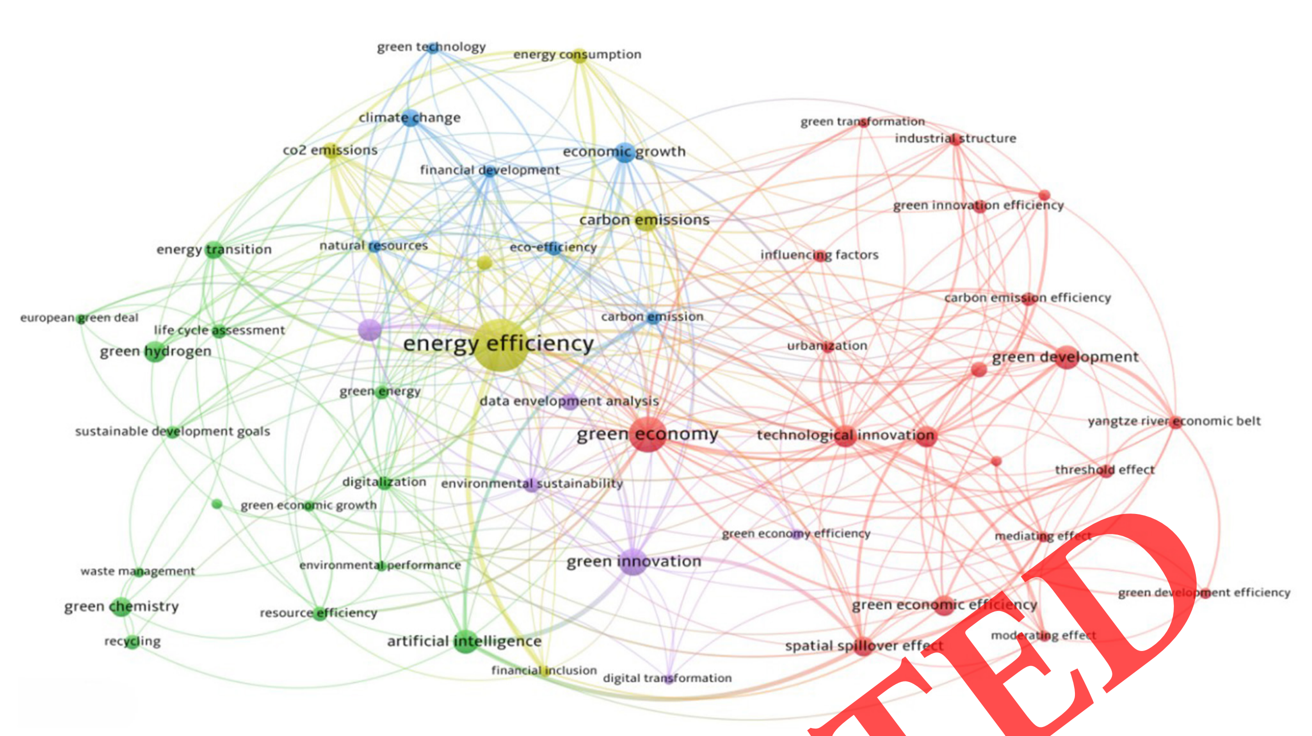

FIGURE 2
Research status of artificial intelligence empowering green economy efficiency.

the region (Liu and Zhang, 2021). Moreover, AI's broad application establishes intelligent economic circulation channels at the macro level, considerably improving production and resource utilization efficiencies. These efficient channels mitigate the adverse effects of external market segmentation and other inhibitory factors, facilitating economic efficiency advances. AI supports balanced development across economic growth, resource conservation, and environmental protection. Consequently, this study proposes the hypothesis:

H1: AI may directly enhance GEE.

3.2 The non-linear effect of artificial intelligence on green economic efficiency under integrated governance

Integrated governance involves multiple stakeholders, including governments, enterprises, social organizations, and citizens, sharing resources and collaborating to address public affairs and maximize public interest. The integrated governance model breaks through the limitations of the traditional government's single-subject management and emphasizes multiple subjects' joint participation and synergy (Amsler, 2016). These stakeholders leverage their strengths to create complementary effects during the governance process. For instance, governments can augment GEE, driven by AI, by establishing mandatory regulations, supportive policies, and incentives such as tax benefits, R&D subsidies, and green credits. Social organizations and the public amplify their influence through media engagement, while companies invest in developing green technologies and AI. Judicial institutions safeguard the rights of innovators in the green economy by enacting and enforcing intellectual property laws. Collectively, these actions contribute to advancements in GEE facilitated by AI. Consequently, this paper explores how AI enhances GEE within the framework of collaborative governance involving policy, technology, and law, as shown in Figure 3.

3.2.1 The non-linear impact of artificial intelligence on green economic efficiency under policy governance

With the prominence of resource and environmental problems, China has adopted a series of ecological regulatory instruments to alleviate the issues of resource depletion and environmental pollution. According to the theory of "Porter's hypothesis," adopting specific environmental regulation measures can motivate the innovation vitality of corporations and Strengthen the competitiveness of products, thus offsetting or even exceeding the cost of compliance brought about by environmental regulations and facilitating the green economy. Therefore, examining the impact of environmental regulations on AI-empowered GEE is crucial for establishing a green economic system and achieving the "dual carbon" goals. Environmental regulation encompasses a comprehensive set of policies, laws, standards, and measures developed by governments and relevant agencies to protect the environment, reduce pollution, improve ecological conditions, and guide or restrict the actions of enterprises, individuals, and other societal actors. Its primary goal is minimizing negative

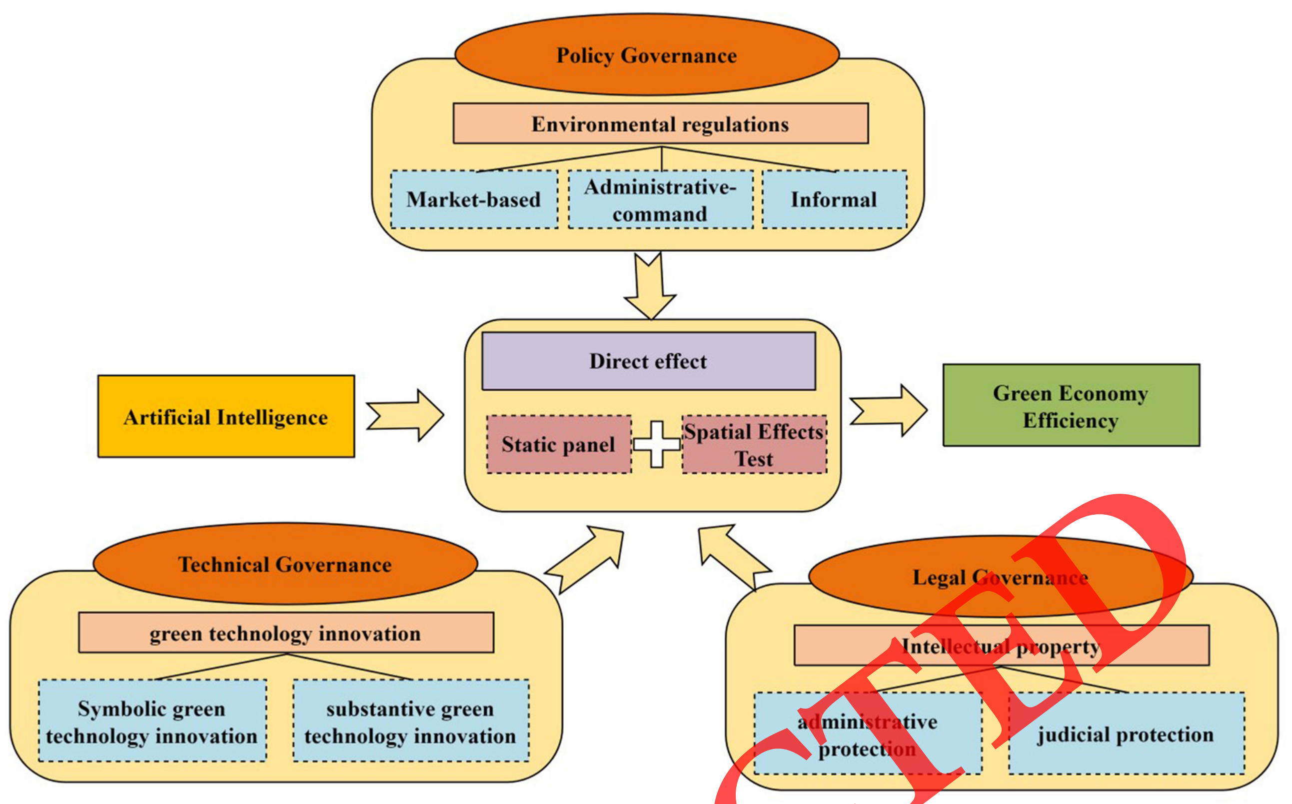

FIGURE 3
Theoretical framework.

environmental impacts while supporting sustainable development and economic growth. The three main types of environmental regulation—market-based environmental regulation (MER), administrative-command environmental regulations (CER), and informal environmental regulation (IER)—represent the approaches employed by governments, markets, and society. Together, these regulatory dimensions provide a holistic framework for assessing the intensity and effectiveness of environmental regulation through mandatory control measures, economic guidance tools, and social constraints (Song et al., 2024). This study categorizes environmental regulations into market-based, administrative-command, and informal for analytical purposes (Wang et al., 2022, 2023a).

MER is the government's way of guiding enterprises to green innovation by establishing special funds for research and development, environmental protection, technological reform, tax breaks, loan preferences, financial subsidies, and other means. MER shapes corporate environmental strategies, steering businesses from traditional end-of-pipe pollution control toward digital and cleaner production models, thereby enhancing GEE (Yang et al., 2023; Kazemzadeh et al., 2023). However, overly stringent MER may escalate operational costs for businesses, diminishing their inclination to invest in AI. Companies might prioritize short-term investments with immediate cost benefits over long-term sustainable growth, thus undermining commitment to green transformation (Koengkan et al., 2024).

CER, enacted by government bodies, sets precise environmental standards and mandates for compliance, compelling technological innovation, leading to more accurate investments in AI and green technologies, and the firms to explore new green products and services to enhance GEE (Naeem et al., 2024; Chen et al., 2021). Nevertheless, suppose CER is loosely enforced, and penalties for non-compliance are minimal. In that case, firms may be inclined to ignore regulations to cut costs, potentially exacerbating pollution and resource exploitation and worsening environmental challenges.

IER refers to norms and behaviors that are not legally enforceable but which can influence the environmental actions of enterprises and individuals. These regulations typically originate from non-governmental sources such as social culture, public awareness, civil society organizations, and the media. The public increases demand for environmentally friendly products and actively participates in environmental management by reporting polluting behaviors to the media and authorities. This will curb corporate misbehavior and enhance corporate social responsibility. It motivates enterprises to adopt AI to analyze consumer demand accurately, optimize production processes to reduce environmental pollution and improve GEE (Zhang et al., 2023, 2022). Therefore, this paper formulates the following hypotheses:

H2a: Excessive MER weakens AI-empowered GEE.
H2b: CER strengthens AI-empowered GEE.
H2c: IER enhances AI-empowered GEE.

3.2.2 The non-linear impact of artificial intelligence on green economic efficiency under technical governance

As green technology innovation progresses, the enhancement of GEE by AI exhibits variability. Drawing from studies by Lian et al. (2022), it is evident that companies undertake both substantive green technology innovations (SUG) and symbolic green technology innovations (SYG) driven by varying motivations. SUG, characterized by long development cycles, significant challenges, and substantial investments, delivers high degrees of innovation and technical content, epitomizing high-quality green innovation activities. However, they are subject to cumulative and threshold effects; excessive investment in these innovations without timely monetization can escalate production costs, potentially restricting other non-green R&D activities and diminishing a company's overall competitiveness and profitability, thereby reducing the potential enhancement effect of AI on GEE (Fang et al., 2022). SYG involves secondary innovations that extend functionalities and improve technology without altering the fundamental technological principles of products. These innovations, which have shorter development cycles and require lesser investment, can be quickly integrated into corporate production and development, offering practical benefits. They primarily align with government environmental regulatory strategies or seek advantages through the "quantity" and "speed" of innovation. Requiring less investment and being more strategically driven, SYG allows companies to rapidly respond to market or policy pressures without significantly impacting other non-green R&D efforts. SYG enhances publicity, improves competitiveness, increases profits, and promotes further investment in AI and green technologies, thereby strengthening AI's role in enhancing GEE. Compared to the more superficial SYG, SUG stands for a profound technological breakthrough that has had a remarkable impact on optimizing production processes, improving resource efficiency, and reducing environmental pollution (Chen et al., 2024b). The influence of SUG on GEE facilitated by AI is markedly significant. Therefore, this paper formulates the following hypotheses:

H3a: Excessive SUG weakens AI-empowered GEE.
H3b: SYG strengthens AI-empowered GEE.
H3c: The threshold effect of SUG is more potent than SYG's.

3.2.3 The non-linear impact of artificial intelligence on green economic efficiency under legal governance

Intellectual property is defined as a monopolistic property right granted to creators over their intellectual creations. Intellectual property protection ensures that rights holders can fully operate these rights. Due to the externality characteristics of green innovation activities, it is difficult for innovation subjects to avoid imitation or even plagiarism by other competitors, jeopardizing innovation subjects' vested interests and weakening their willingness to carry out green innovation activities (Hall and Helmers, 2013). By reducing the externality of green innovation, intellectual property protection helps secure the monopoly profits of innovators (Song et al., 2022). However, excessive protection of these monopoly rights can discourage the sharing of technological achievements, potentially diminishing the monopolist's profits (Song and Chen, 2023). Based on the theory of "economic man," rights holders are generally disinclined to share under these circumstances. Excessive intellectual property protection reinforces the monopoly position of the rights holder, thereby impeding the diffusion of technology and weakening the incentives of other entities to research, develop, and innovate. Therefore, excessive administrative intellectual property protection (AIP) and judicial intellectual property protection (JIP) can restrict GEE empowerment by AI. AIP, typically managed by government agencies, directly influences corporate decisions regarding technological and green innovation. JIP, handled by courts, addresses complex issues of technological infringement and interprets intellectual property laws. Given their generally more independent nature, judicial institutions tend to have a less direct impact on business operations. The adverse effects of excessive AIP, imposed by governments, are generally more significant than those resulting from excessive JIP. Therefore, this paper formulates the following hypotheses:

H4a: Excessive AIP weakens AI-empowered GEE.
H4b: Excessive JIP weakens AI-empowered GEE.
H4c: The threshold effect of AIP is greater than that of JIP.

4 Research design

4.1 Econometric model

To substantiate the enhancement of GEE by AI, the following econometric model is constructed:

$$Gee_{it} = \alpha + \beta AI_{it} + \varsigma \sum Control + u_t + \lambda_i + \epsilon_{it} \qquad (1)$$

In this model, *Gee* represents green economic efficiency, *AI* represents artificial intelligence, *Control* is control variable, u_t and λ_i represent time effects and individual effects, and ϵ is the random disturbance term.

4.2 Variable descriptions

4.2.1 Dependent variable: green economic efficiency

The traditional Data Envelopment Analysis (DEA) model is widely used to evaluate the efficiency of decision-making units; however, it cannot account for the impact of undesirable outputs on efficiency and fails to differentiate among multiple efficient units (Tone, 2001). To address these limitations, Tone improved the DEA model by introducing a non-radial, non-angular super-efficiency DEA approach that incorporates undesirable outputs, known as the super-efficiency Slack-Based Measure (SBM) model based on undesirable outputs (Aparicio et al., 2017). This model integrates relaxation variables and resolves the issue of distinguishing efficiency values >1 in traditional SBM models, making it widely applicable in efficiency measurement (Li and Shi, 2014). This paper draws on the research of Zhou et al. (2018) to measure GEE by adopting the super-efficient SBM model, including

TABLE 1 Green economic efficiency evaluation index system.

Index type	Variable	Index calculation
Input	Labor input	Number of employees at year end (10,000 people)
	Capital input	Fixed asset investment (million yuan)
	Electricity input	Electricity consumption (billion kWh)
	Water resource input	Water consumption (billion cubic meters)
	Natural gas resource input	Natural gas consumption (billion cubic meters)
Output	Economic benefit	Regional GDP (billion yuan)
Non-desired output	Wastewater discharge	Industrial wastewater (10,000 tons)
	Waste gas emissions	Industrial sulfur dioxide (10,000 tons)
	Dust emissions	Industrial dust emissions (10,000 tons)

non-expected outputs, selecting labor force, capital, electricity, water resources, and natural gas resources as the input indexes, and selecting the GDP to represent the expected outputs, and selecting the "three wastes" are chosen to represent the non-desired outputs (Table 1). The GEE is calculated as follows:

$$Gee^* = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}_i}{x_{ik}}}{\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{\bar{y}_r^g}{y_{rk}^g}+\sum_{r=1}^{s_2}\frac{\bar{y}_r^b}{y_{rk}^b}\right)} \tag{2}$$

$$S.t.\begin{cases}\bar{x} \geq \sum\limits_{j=1,j\neq k}^{n} x_j\lambda_j \\ \bar{y}^g \leq \sum\limits_{j=1,j\neq k}^{n} y_j^g\lambda_j \\ \bar{y}^b \geq \sum\limits_{j=1,j\neq k}^{n} y_j^b\lambda_j \\ \bar{x} \geq x_0, \bar{y}^g \leq y_0^g, \bar{y}^b \geq y_0^b, \bar{y}^g \geq 0, \lambda \geq 0\end{cases} \tag{3}$$

Where Gee^* denotes the value of GEE, n represents the number of the study area, k denotes the serial number of each province, m is the input of each province, s_1 and s_2 denotes the desired output and non-desired output of each province, respectively, x denotes the input indicator of each province for the period, y^g and y^b denote the desired output indicator and non-desired output indicator of each province during the period, respectively.

4.2.2 Core explanatory variable: artificial intelligence

Following the approach of Liu et al. (2020), this paper uses the number of industrial robots installed in each province to represent AI. The calculation method, shown in Equation 4, reflects the relationship between robot stock and labor supply, potentially offering a more effective measure of AI (Tao, 2024).

It is assumed that the distribution of industrial robots across Chinese provinces is uniform, meaning each province has the same industrial robot installation density. Thus, the industrial robot installation density = total national industrial robot installations/total national employment. Therefore, the industrial robot installations in each province = industrial robot installation density × employment in each province. The specific formula is as follows:

$$AI_{it} = L_{it} \times \frac{Robot_t}{L_t} \tag{4}$$

Equation 4, AI_{it} indicates the number of industrial robots installed in the i region during the t period; $Robot_t$ indicates the total number of industrial robots installed nationally during the t period; L_{it} indicates the number of employed persons in the i region during the t period; L_t indicates the total number of employed persons nationally during the t period. To eliminate the effect of dimension, the natural logarithm is taken for the number of industrial robots installed in each province.

4.2.3 Control variables

This paper selects the following control variables to make the model estimation results more accurate: internet infrastructure conditions (IIS), expressed using the logarithm of number of internet broadband access ports; level of economic development (PGDP), expressed using the logarithm of per capita gross regional product; industrial structure (ISU), expressed using the region's share of the value added of the tertiary industry in the value added of the secondary sector; level of industrialization (IL), described by the ratio of the current year's industrial added value to the current year's GDP (Zhou et al., 2024b; Feng et al., 2024).

4.2.4 Policy governance: environmental regulation

MER: measured by the ratio of completed investment in industrial pollution treatment to industrial value added (Xu, 2024). This indicator reflects the financial incentives and cost pressures imposed on firms to adopt environmentally friendly practices, aligning with the Porter Hypothesis, which suggests that appropriate environmental regulations can stimulate innovation.

CER: measured by the logarithm of granted environmental administrative penalty cases (Zhang et al., 2024b). This captures the enforcement strength of environmental policies, directly reflecting the regulatory pressure imposed on enterprises to comply with environmental standards.

IER: constructed using entropy weighting of factors such as per capita disposable income (per capita disposable income of urban residents), educational levels (proportion of employees with college education or above), population density (year-end permanent population measure) and age Structure (measured by the proportion of population under 15 years old) (Shen et al., 2023). These components represent societal engagement in environmental governance, highlighting public awareness and the role of social norms in promoting green economy.

4.2.5 Technical governance: green technology innovation

Green patents intuitively reflect the extent and level of green technology innovation. Considering that granted patents have undergone authoritative certification, this paper uses the logarithm of granted green invention and utility patents to depict SUG and SYG (Lian et al., 2022; Zhang et al., 2024a).

4.2.6 Legal governance: intellectual property protection

The number of cases closed refers to the cases adjudicated and closed, reflecting the achievements and the capacity of judicial or administrative authorities to handle cases within a certain period. The number of cases filed may be influenced by selective filing, which has high uncertainty. Thus, the number of cases closed provides a more objective measure. This paper uses the logarithm of administrative closures of patent infringement cases to indicate the level of AIP and the logarithm of judicial closures of patent infringement cases to indicate the level of JIP (Li and Yuan, 2024).

4.3 Data sources

Considering the fact that Chinese officials did not publish the China Artificial Intelligence White Paper until 2015, the relative lack of data on AI before 2015, and the lag in the disclosure of data on industrial robots by the International Federation of Robotics (IFR), this paper collects the panel data of 30 provinces in mainland China (Missing data for Tibet, not included in statistics) from 2011 to 2020 as the research sample. The data come from the patent database of the China Intellectual Property Office, the National Bureau of Statistics, the China Statistical Yearbook, and statistical bulletins issued by provinces. All variables are standardized to improve estimation accuracy and eliminate the effects of dimensions. Table 2 presents the variable descriptive statistics.

TABLE 2 Descriptive statistics results.

Variables	Obs	Mean	Std. Dev.	Min	Max
GEE	300	0.220	0.220	0.000	1.000
AI	300	0.310	0.280	0.000	1.000
IIS	300	0.630	0.190	0.000	1.000
PGDP	300	0.480	0.190	0.000	1.000
ISU	300	0.040	0.080	0.000	1.000
IL	300	0.500	0.170	0.000	1.000
CER	300	0.070	0.140	0.000	1.000
MER	300	0.110	0.120	0.000	1.000
IER	300	0.170	0.160	0.000	1.000
SUG	300	0.130	0.190	0.000	1.000
SYG	300	0.080	0.120	0.000	1.000
AIP	300	0.598	0.220	0.000	1.000
JIP	300	0.542	0.188	0.000	1.000

5 Direct effects of artificial intelligence on green economy efficiency

5.1 Benchmark regression analysis

Based on the econometric model (1), a fixed effects model was applied following the Hausman test, controlling time and individuals. Multiple regression analysis was then used to assess the effect of AI's empowerment on GEE. The relationship between AI and GEE under the dynamic effect of various variables is examined by gradually introducing control variables. The benchmark regression results are displayed in Table 3. The estimation results reported in Model (1)–Model (5) show that the regression coefficients and significance of the core explanatory variables and control variables did not change radically during the gradual approach to introducing the control variables. Considering control variables, for every 1% improvement in AI, GEE increases by about 0.281%, which is significant at the 1% level, indicating that AI can improve GEE and preliminarily verify H1.

5.2 Robustness tests

To ensure the robustness of the results of the benchmark regression, this paper conducts robustness tests from three aspects: winsorize, changing estimation methods, and replacing core variables, with results shown in Table 4. First, for winsorize, using the method of deleting 1% extreme samples, the results are shown in column (1) of Table 4; the coefficient of AI is 0.281 and passes the 1% significance level test. Second, this paper employs the system GMM regression model for re-estimation, with results displayed in column (2). The regression coefficient for AI is 0.512, which is significant at the 1% level. Third, by changing the independent variable to the number of AI companies as a substitute, the results in column (3) show an AI regression coefficient of 0.595, tested by the 1% significance level. These robustness test results are aligned with the benchmark regression, further verifying the positive influence of AI on GEE.

5.3 Endogeneity tests

To address the endogeneity, this paper employs the two-stage instrumental variable least squares (IV-2SLS) method for testing. This paper uses the first lag of the dependent variable as an instrumental variable. The endogeneity test results in Table 5 indicate that the instrumental variable is significantly at the 1% level and passes the weak identification test and the non-identification test, confirming the effectiveness of the instrumental variable selection. According to column (2), the original hypothesis that AI facilitates GEE remains valid. The conclusion of the benchmark regression is robust and reliable, thereby verifying H1.

5.4 Heterogeneity analysis

To verify the geographical heterogeneity of AI's impact on GEE, this study categorizes the samples based on economic levels into

TABLE 3 Benchmark regression results.

	(1)	(2)	(3)	(4)	(5)
Variables	GEE	GEE	GEE	GEE	GEE
AI	0.231*** (6.750)	0.253*** (7.130)	0.266*** (7.310)	0.261*** (7.170)	0.281*** (7.830)
IIS		0.329** (2.160)	0.398** (2.510)	0.395** (2.490)	0.435*** (2.810)
PGDP			−0.255 (−1.550)	−0.228 (−1.380)	−0.479*** (−2.760)
ISU				0.064 (1.260)	0.060 (1.220)
IL					0.354*** (3.850)
Cons	0.641*** (29.410)	0.486*** (6.450)	0.633*** (5.220)	0.608*** (4.950)	0.693*** (5.700)
id	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
N	300	300	300	300	300
R^2	0.937	0.938	0.939	0.939	0.943

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with robust t-statistics in parentheses.

TABLE 4 Robustness tests regression results.

	(1)	(2)	(3)
Variables	GEE	GEE	GEE
L.GEE		−0.491 (−1.580)	
AI	0.281*** (7.830)	0.512*** (2.750)	0.595*** (11.790)
IIS	0.435*** (2.810)	0.377 (0.630)	0.344*** (2.580)
PGDP	−0.479*** (−2.760)	−2.258** (−2.030)	−0.162 (−1.080)
ISU	0.0598 (1.220)	−0.191 (−1.070)	0.0391 (0.890)
IL	0.354*** (3.850)	0.773* (1.83)	0.263*** (3.230)
Cons	0.693*** (5.700)		0.521*** (4.740)
id	Yes	Yes	Yes
Year	Yes	Yes	Yes
N	300	300	300
R^2	0.969		0.954
AR(2)		0.596	
Hansen test		0.156	

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with robust t-statistics in parentheses.

TABLE 5 Endogeneity tests regression results.

Variables	IV1	
	(1)	(2)
L.AI	0.826*** (17.100)	
Japan_AI		
AI		0.399*** (7.890)
Cons	−0.082 (−0.880)	0.680*** (4.860)
Controls	Yes	Yes
Province	Yes	Yes
Year	Yes	Yes
R^2		0.969
Cragg-Donald Wald F	292.546***	
Kleibergen-Paap rk Wald F	58.580***	
Kleibergen-Paap rk LM statistic	689.349***	

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with robust t-statistics in parentheses.

Eastern, Central, and Western regions; based on openness into coastal and non-coastal areas; and based on Technology Intensity into technology-intensive and non-technology-intensive regions for a heterogeneity analysis.

First, in the Eastern and Central regions, the coefficients of AI on GEE are 0.331 and 0.209, and by the test of significance at the 1% level, which is insignificant for the Western region. This indicates that AI contributes the most to GEE in the East, followed by the Center, and not significantly in the West. Next, in coastal areas, the coefficients of AI on GEE are 0.329 and 0.106, significant at the 1% level, suggesting that AI has a more substantial impact on GEE in coastal areas than in non-coastal areas. Lastly, in technology-intensive areas, the coefficient of AI on GEE is 0.440, significantly at the 1% level, while in non-technology-intensive areas, the coefficient is positive but insignificant. This reveals that AI fosters GEE in technology-intensive regions, but its impact is insignificant in non-technology-intensive areas.

5.5 Spatial effects test of artificial intelligence empowering green economic efficiency

AI not only promotes the efficient flow of technology and information, breaking through the constraints of time and space and compressing geographic limitations, impacting the economic system with long-term, extensive, and holistic effects; on the other hand, the rapid advancement of AI will unleash the tremendous energy of the "connected economy," generating demonstration effects and economic linkage effects in geographically and economically adjacent areas through technology spillover, knowledge sharing, talent exchange, and

TABLE 6 Heterogeneity test results.

Variables	Eastern	Central	Western	Coastal	Non-coastal	Technology-intensive	Non-technology-intensive
	GEE	GEE	GEE	GEE	GEE	GEE	GEE
AI	0.331*** (5.160)	0.209*** (4.970)	0.035 (0.350)	0.329*** (4.870)	0.106** (2.490)	0.440*** (6.450)	0.039 (0.920)
Controls-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	120	80	100	100	200	100	200
R^2	0.944	0.943	0.954	0.934	0.961	0.946	0.949

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with robust t-statistics in parentheses.

TABLE 7 Moran's I indices for green economic efficiency and artificial intelligence.

Year	AI				GEE			
	Geographic matrix		Economic geographic nested matrix		Geographic matrix		Economic geographic nested matrix	
	I	*P*-value	I	*P*-value	I	*P*-value	I	*P*-value
2011	0.108*	0.074	0.038**	0.032	0.149**	0.018	0.024*	0.070
2012	0.110*	0.071	0.038**	0.032	0.151**	0.013	0.027*	0.051
2013	0.086	0.122	0.025*	0.071	0.150**	0.016	0.027*	0.058
2014	0.089	0.114	0.027*	0.060	0.169***	0.008	0.036**	0.030
2015	0.093	0.103	0.028*	0.059	0.142**	0.026	0.024*	0.080
2016	0.116*	0.059	0.035**	0.037	0.107*	0.076	0.009	0.198
2017	0.163**	0.016	0.066***	0.004	0.146	0.025	0.027*	0.068
2018	0.187**	0.007	0.080***	0.001	0.127**	0.045	0.017	0.129
2019	0.188**	0.006	0.075**	0.002	0.114*	0.067	0.012	0.171
2020	0.193**	0.006	0.084***	0.001	0.105*	0.083	0.005	0.241

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with robust t-statistics in parentheses.

regional coordination. Thus, from the standpoint of spatial spillover effects, further analyzing the role of AI-driven technology in enhancing GEE can provide valuable decision-making references and policy insights for authorities to comprehensively assess AI technology features, formulate forward-looking industrial policies, and create a new pattern of regional synergy optimization in GEE.

5.5.1 Moran's I test

To recognize spatial effects, the first step is to use the Moran's I index for testing spatial correlations (building an economic inverse distance spatial weight matrix W using the reciprocal of provincial capital distances, then integrating economic factors to construct an economic and geographical nested matrix), with results shown in Table 7. Moran's I index of AI is over 0 and passes the significance test in most years, indicating that AI has strikingly positive spatial dependence properties. Figure 4 illustrates the spatial distribution of AI for the years 2011, 2015, 2018, and 2020, consistently showing positive spatial correlation. In addition, the Moran'I index of GEE is over 0 in both matrices. Most years, it passes the significance test, indicating that GEE demonstrates a clear positive spatial dependence property.

5.5.2 Spatial econometrics test

In this paper, we compare the fitness of SAR and SEM using the LM test and further use Wald and LR to test whether SDM can degrade to SAR and SEM. Table 8 shows that the LM lag and RLM lag tests in the geographic weighting matrix satisfy the 1% level of significance, the LM error defies the 5% level of significance, and the RLM error does not fulfill the significance test; the economic-geographic nesting matrix in which the LM lag test for significance at the 5% level, the RLM lag is tested for significance at the 1% level, the LM error and RLM error do not pass the significance test. Both Wald and LR tests for the geographic weight matrix rejected the degeneration hypothesis into the SEM, and the economic, geographic nested matrix passed all significance tests. Therefore, the SDM and SAR are considered for analysis in this study.

5.5.3 Spatial econometrics regression

Table 9 presents the results of the spatial spillover effects across two weight matrices and various spatial models. The estimated coefficient of AI's spatial effect on GEE is significantly positive, indicating that AI in a given region enhances the GEE of neighboring areas. This suggests that AI not only boosts local

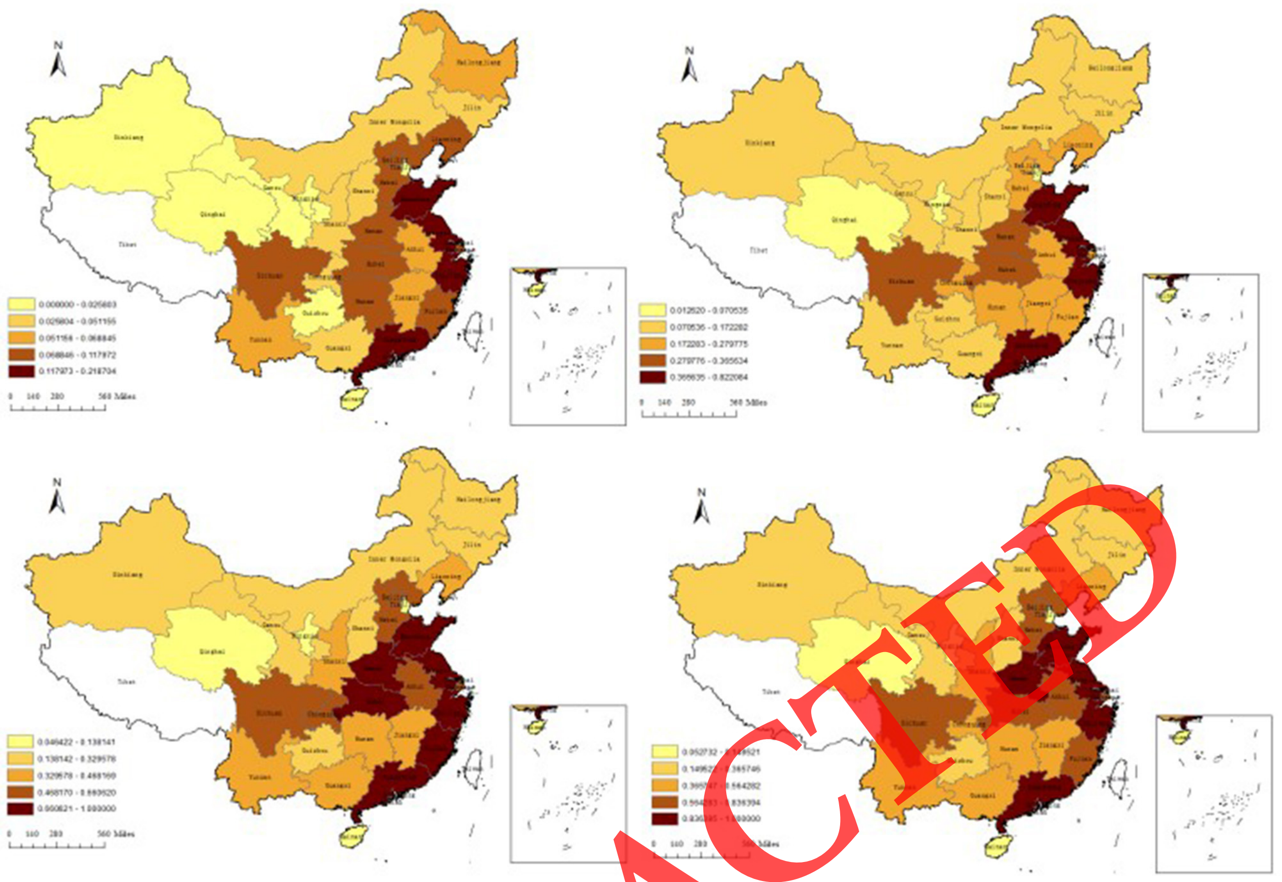

FIGURE 4
Spatial distribution of artificial intelligence.

TABLE 8 Results of spatial econometrics tests.

Test method	Geographic matrix	Economic geographic nested matrix	Test method	Geographic matrix	Economic geographic nested matrix
LM-spatial lag	43.196***	5.319**	Wald-SDM/SEM	10.150*	22.770***
Robust LM-spatial lag	38.646***	6.567***	LR-SDM/SEM	9.910*	21.490***
LM-spatial error	5.278**	0.057	Wald-SDM/SEM	8.420	17.560***
Robust LM-spatial error	0.728	1.305	LR-SDM/SEM	8.380	17.100***

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with robust t-statistics in parentheses.

TABLE 9 Spatial econometric analysis results.

Matrix	Geographic matrix		Economic geographic nested matrix	
Molds	SDM	SAR	SDM	SAR
Variables	GEE	GEE	GEE	GEE
AI	0.295*** (8.300)	0.188*** (5.510)	0.283*** (8.250)	0.189*** (5.600)
W × AI	0.195* (1.760)		0.530** (2.43)	
Controls-FE	Yes	Yes	Yes	Yes
Province-FE	Yes	Yes	Yes	Yes
Year-FE	Yes	Yes	Yes	Yes
R^2	0.351	0.309	0.344	0.270

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with robust t-statistics in parentheses.

GEE but also exerts a spatial spillover effect, radiating and driving improvements in the GEE of neighboring regions.

6 Non-linear impact of artificial intelligence on green economic efficiency

6.1 The non-linear impact of artificial intelligence on green economic efficiency under policy governance

The results in Table 10 show that different threshold effects of various environmental regulation policies influence AI-empowered GEE. MER and CER satisfy the single threshold significance test, while IER meets the single and double threshold significance test criteria.

This paper further examines the threshold effects of heterogeneous environmental regulation, as presented in Table 11. When MER exceeds the threshold, the regression coefficient decreases from 0.441 to 0.238, weakening the positive impact of AI on GEE. This finding supports H2a. Conversely, when the intensity of CER surpasses the first threshold, the coefficient rises from 0.101 to 0.249, enhancing AI's positive impact on GEE, which supports H2b. Similarly, for IER, when its intensity exceeds the first threshold but remains below the second, the coefficient increases from 0.123 to 0.269. Upon crossing the second threshold, the coefficient increases to 0.408, which is significant at the 1% level. These results indicate that a higher intensity of IER strengthens AI's effect on GEE, supporting H2c.

6.2 The non-linear impact of artificial intelligence on green economic efficiency under technological governance

Table 12 results show that GEE enabled by AI is influenced by different threshold effects of heterogeneous green technology innovations. SUG has passed single and double threshold significance tests, while SYG has passed the single threshold significance test.

This study investigates the thresholds of heterogeneous green technologies innovation, as summarized in Table 13. When SUG's intensity exceeds the first threshold but remains below the second, the coefficient decreases from 0.555 to 0.122. Beyond the second threshold, the coefficient rises to 0.319. These results indicate that the marginal effect of AI on GEE diminishes significantly after SUG surpasses the first threshold but partially recovers upon exceeding the second threshold. However, the effect remains weaker than observed before crossing the first threshold, supporting H3a. For SYG, when their intensity surpasses the first threshold, the coefficient increases from 0.084 to 0.249. This finding suggests that SYG enhances the marginal effect of AI on GEE, supporting H3b. Additionally, the threshold effects of SUG (0.433 and 0.197) are greater than those of SYG (0.165), supporting H3c.

6.3 The non-linear impact of artificial intelligence on green economic efficiency under legal governance

The results in Table 14 illustrate that AIP and JIP get through the single threshold significance test, signaling that the efficiency of AI-empowered GEE is affected by the threshold effect of AIP and JIP.

This paper further examines the role of heterogeneous intellectual property protection thresholds, as depicted in Table 15. When the intensity of AIP exceeds the first threshold, the coefficient decreases from 0.423 to 0.165, significantly diminishing the marginal effect of AI on GEE. This finding supports H4a. Similarly, when the JIP surpasses the first threshold, the coefficient declines from 0.232 to 0.150, reducing AI's marginal effect on GEE and supporting H4b. Moreover, the threshold effect of AIP (0.258) is greater than that of JIP (0.082), providing evidence for H4c.

7 Discussion and conclusion

7.1 Discussion

The significant contribution of AI to enhancing green economic efficiency aligns with the findings of Luo and Feng (2024) and Wang et al. (2024a). However, it contrasts with the conclusions of Lee et al. (2024), who consider the initial application stage of AI. During this stage, AI may negatively affect the energy transition. Over time, as AI progresses beyond its early implementation phase, its positive impacts are expected to outweigh the adverse effects associated with technological development and scale, ultimately driving the energy transition. The conclusion that variations in environmental regulation influence the marginal impacts of AI-empowered GEE aligns with the findings of Sun et al. (2023) and Wang et al. (2023b). However, it may diverge from the conclusions of You et al. (2024), who overlooked the cost impacts associated with environmental regulation. The conclusion regarding the marginal effect of heterogeneous green technology innovation on AI-empowered GEE aligns with the findings of Lian et al. (2022) and Chen et al. (2024a). However, Wang et al. (2024b) warn that green innovation may escalate corporate debt default risks, thereby affecting financial performance and reducing GEE. Excessive AIP and JIP may reduce the marginal effects of AI on GEE. Wang et al. (2024c) and Hudson and Minea (2013) have highlighted the non-linear impact of intellectual property protection on the green innovation capabilities of the manufacturing sector and innovation at large. Hu et al. (2023) particularly underscore the importance of stringent regulatory enforcement of intellectual property protection levels to foster innovation. Various scholars have examined the relationship between AI and GEE across different geographical contexts. Some have demonstrated that AI may enhance GEE in economies with development levels similar to China's. For instance, Akram et al. (2024) found that AI supports high-quality economic development in emerging economies by facilitating energy transition and green technology innovation. Similarly, Salman et al. (2024) confirmed that technological progress has raised the carbon neutrality rates of G20 countries. On a global scale, other studies provide

TABLE 10 Testing the threshold effects of heterogeneous environmental regulations.

Threshold variable	Model	*F*-value	*P*-value	Number of bootstraps	Threshold estimate
MER	Single threshold	31.860	0.047	300	0.019
CER	Single threshold	41.570	0.003	300	0.190
IER	Single threshold	93.060	0.000	300	0.226
	Double threshold	17.330	0.097	300	0.283

TABLE 11 Threshold effect regression results of heterogeneous environmental regulations.

Threshold variable	Threshold interval	Coefficient	Controls	Fixed effects	R^2
MER	MER<0.019	0.441***	Yes	Yes	0.471
	0.019≤MER	0.238***			
CER	CER<0.190	0.101***	Yes	Yes	0.486
	0.190≤CER	0.249***			
IER	IER<0.226	0.123***	Yes	Yes	0.584
	0.226≤IER<0.283	0.269***			
	0.283≤IER	0.408***			

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with robust t-statistics in parentheses.

TABLE 12 Testing the threshold effects of heterogeneous green technology innovations.

Threshold variable	Model	*F*-value	*P*-value	Number of bootstraps	Threshold estimate
SUG	Single threshold	78.210	0.000	300	0.013
	Double threshold	18.120	0.053	300	0.420
SYG	Single threshold	82.520	0.000	300	0.204

TABLE 13 Threshold regression results of heterogeneous green technology innovations.

Threshold variable	Threshold interval	Coefficient	Controls	Fixed effects	R^2
SUG	SUG<0.013	0.555**	Yes	Yes	0.543
	0.013≤SUG<0.420	0.122***			
	0.420≤SUG	0.319***			
SYG	SYG<0.204	0.084**	Yes	Yes	0.513
	0.204≤SYG	0.249***			

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with robust t-statistics in parentheses.

TABLE 14 Testing the threshold effects of heterogeneous intellectual property protection.

Threshold variable	Model	*F*-value	*P*-value	Number of bootstraps	Threshold estimate
AIP	Single threshold	41.780	0.083	300	0.873
JIP	Single threshold	16.390	0.087	300	0.518

TABLE 15 Threshold effect regression results of heterogeneous intellectual property protection.

Threshold variable	Threshold interval	Coefficient	Controls	Fixed effects	R^2
AIP	AIP<0.873	0.423***	Yes	Yes	0.499
	0.873≤AIP	0.165***			
JIP	JIP<0.518	0.232***	Yes	Yes	0.443
	0.518≤JIP	0.150***			

***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, with robust t-statistics in parentheses.

evidence that AI can enhance GEE. Tao (2024) reported that AI has boosted global green productivity. Additionally, Lee et al. (2024) confirmed that AI has promoted energy transition and reduced carbon emissions across 69 countries. Despite variations in countries and economic conditions, AI promotes green and sustainable development through technological advancements, thereby extending the conclusions of this paper.

7.2 Conclusion and practical implications

7.2.1 Conclusion

This paper reveals the following findings: (1) AI significantly improves GEE, substantially impacting eastern, more open, and technologically advanced provinces. (2) In policy governance, excessive MER reduces AI's marginal effect, whereas strengthening CER and IER increases AI's marginal effect. (3) In technological governance, SUG reduces AI's marginal effect, while SYG may increase it, though SUG has a greater threshold effect than symbolic innovation. (4) In legal governance, AIP and JIP may reduce AI's marginal effect, with AIP showing a larger threshold effect than judicial protection. This study integrates AI with GEE within a comprehensive governance framework, providing a novel perspective on the heterogeneous and threshold effects across various governance types.

7.2.2 Practical implications

This paper draws the following conclusions based on previous research findings: First, the government should enhance policy support for technological innovation in AI. Second, the government should employ a combination of governance measures to maximize AI's empowering effects. In the policy governance process, the government should carefully leverage the roles of CER, fully utilize IER, and control MER intensity. In technical governance, enterprises should prioritize SUG over SYG while maintaining moderate investment in green technology R&D. For legal governance; the government should continuously strengthen intellectual property protection, ensuring that AIP is balanced to guide behavior without excessive intervention. Third, the green economic efficiency of spatially connected regions is influenced by the radiating and driving effects of local AI development; therefore, regions should facilitate the flow of human, technical, knowledge, and technological resources to support regional green synergistic development.

7.3 Limitations and prospects

This paper has shortcomings in the following aspects, which deserve to be supplemented and improved in subsequent studies. First, the research is limited to China, and future studies might consider expanding this geographical scope. Second, upon collecting all variable data, numerous missing values were identified after 2020. Additionally, due to the COVID-19 outbreak, substantial changes in policy and market conditions may have rendered data from the pandemic period incomparable with data from other periods. Consequently, the data has only been updated through 2020 to ensure availability and reliability. Third, environmental protection outputs are not included in the indicator system when assessing GEE. Future research should further investigate the direct impacts of AI on green economic efficiency, specifically through the lenses of industrial structure and green innovation. Fourth, this study primarily focuses on the efficiency of AI during the operational phase without comprehensively evaluating the entire lifecycle of AI models, including the resource-intensive training and deployment phases that may increase carbon emissions. Future research should assess the green economic efficiency across the whole lifecycle of AI models.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found at: International Federation of Robotics.

Author contributions

ZS: Data curation, Formal analysis, Funding acquisition, Methodology, Resources, Software, Writing – original draft, Writing – review & editing. YD: Investigation, Methodology, Resources, Writing – original draft.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

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