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ARTIFICIAL INTELLIGENCE AND GREEN ECONOMIC EFFICIENCY: MECHANISM ANALYSIS IN THE GUANGDONG-HONG KONG-MACAO GREATER BAY AREA

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ABSTRACT

Faced with problems such as low energy efficiency, serious environmental pollution, and ecological degradation caused by rapid economic growth, it has become crucial to seek a balance between economic vitality and ecological management. Improving green economic efficiency, that is, the ability of an economy to minimise ecological pollution while achieving sustainable growth, can play a vital role in solving these issues. Opting for the Guangdong-Hong Kong-Macao Greater Bay Area as the case study, this research illustrates the key contribution of artificial intelligence (AI) to improving the efficiency of the green economy. Through the economic dependence theory, the level of regional economic dependence is quantified, and then a multiple regression model is constructed to empirically analyse the relationship between AI, economic dependence, industrial structure, and green economic efficiency. Research results demonstrate that AI has a significant positive effect on the improvement of green economic efficiency. This desirable positive effect can be further strengthened through the mediating variable of industrial structure rationalisation. In addition, economic dependence moderates the relationship between AI and green economic efficiency, indicating that AI has a positive contribution to optimising resource allocation and reducing ecological impact. The significance of this study is far-reaching, showing that AI not only supports sustainable economic growth but also promotes the balanced development of *ecology and economy. By integrating AI, regions can achieve higher efficiency and sustainability. Finally, this study provides reference suggestions for the layout of smart industries in the Guangdong-Hong Kong-Macau Greater Bay Area and the improvement of other regional economic development and green efficiency.*

Keywords: *artificial intelligence, economic dependence, empirical analysis, Greater Bay Area, green economy efficiency*

INTRODUCTION

Under the high-speed growth model of rapid economic expansion and rapid industrialisation, a series of potential problems have emerged, such as low energy efficiency, serious environmental pollution, and ecosystem degradation (Wang, Ge et al., 2023). These problems have inhibited high-quality economic development to a certain extent. Traditional economic models often fail to adequately address environmental issues, so innovative approaches are needed to balance economic development and ecological protection. According to Lal et al. (2021), as environmental degradation and climate change intensify, green development and sustainable growth have become critical academic and industry issues and one of the global development goals. These are also used as indicators of an economy's ability to achieve environmentally sustainable growth while minimising resource depletion and ecological impacts (Li, 2019; Su & Fan, 2022; Yuan et al., 2020). With the acceleration of industrialisation, the adoption of technology plays a key role in optimising and upgrading industrial quality and promoting the green growth of economic intelligence. Through the close combination of information technology and traditional production factors such as labour, capital, and resources, the centralised integration and efficient utilisation of production factors can be realised (Ren et al., 2021). To a certain extent, this may lead to profound transformation, optimisation of enterprises, and the green transition of industries.

Artificial intelligence (AI) refers to technologies that utilise tools such as algorithms and computers to simulate human thinking to a certain extent. Its concept was first formally proposed at the Dartmouth Conference in 1956 (Wang, Choo, et al., 2024). AI technologies can effectively solve the monitoring problem using advanced data analysis, predictive modelling, and optimisation strategies. Moreover, they are capable of predicting potential environmental problems (Zhou et al., 2020). According to Qian et al. (2022), AI plays an important role in improving green efficiency and promoting sustainable development, from refining energy efficiency and optimising transportation systems to enhancing waste management and monitoring biodiversity. With the rapid progress of industry, new industrial forms and organisational changes are presenting new trends of intelligence, digitisation, networking, and green development. This suggests that the intelligent adoption, diffusion, and application of information technology significantly contribute to industrial transformation and upgrading. Additionally, it facilitates high-level planning and strategic rationalisation. However, the literature on AI and green economy in industrial transformation is relatively scarce, and the specific endogenous relationship needs further analysis.

Faced with problems such as low energy efficiency, serious environmental pollution, and ecological degradation caused by rapid economic growth, it has become crucial to seek a balance between economic vitality and ecological management. Improving green economic efficiency (GEE), that is, the ability of an economy to minimise ecological pollution and resource consumption while achieving sustainable growth, can play a vital role in solving these issues and is a key metric for assessing high-quality, sustainable development (Li, 2019). Even though efficiency is becoming more and more crucial in the green economy, the role of AI in driving and enhancing sustainability remains relatively under-represented. Therefore, the focus of this research is to explore the relationship between AI development and GEE. To be more specific, this research focuses on various indicators of GEE, such as AI, industrial structure, economic dependence, and so on. We also evaluate the connection between AI and GEE, as well as the endogenous relationship among various variables. The main research objectives are as follows:

1. To identify the relationship between AI development and GEE indicators. The study aims to understand whether the adoption and development of AI can improve the environmental performance of economies and drive green economic growth.

2. To explore the internal mechanism by which AI promotes GEE. This study conducts in-depth research on endogenous relationships, such as the impact of economic dependence and industrial structure on the relationship path between AI and GEE.

LITERATURE REVIEW

The term “green economy” first appeared in 1989 by David Pearce (Pearce, 1992). A green economy is defined as an economic model that aims to achieve economic growth and social well-being while reducing environmental impact and resource consumption (Loiseau et al., 2016). With the rise of ecological economics in the late 1980s, the concept of conservation of dematerialised and irreplaceable natural capital focused on measures such as structural change to achieve sustainable development (Ekins et al., 2003; Loiseau et al., 2016). Seminal research has established green finance as a critical catalyst, simultaneously propelling the advancement of AI and enhancing energy efficiency within the urban sustainable development paradigm of Chinese cities (Zeng & Zhang, 2024). Based on the theories of environmental economics and ecological economics, the green economy uses methods such as waste reuse, restoration, and recycling to improve resource utilisation efficiency and industrial ecology, thereby enhancing environmental, economic, and social benefits (Loiseau et al., 2016).

The establishment of the Sustainable Development Goals and the organisation of the Conference of the Parties framework after the 21st century has allowed the green economy to once again play an important role at the national and international levels (Georgeson et al., 2017). The academic community will also pay more attention to specific measures for the green economy and research on how to improve the efficiency of the green economy. However, most scholars only focus on a single study of economic and trade dependence, industrial structure, or technological development, and seldom try to effectively combine these three aspects by verifying the endogenous relationship of green economic development (Wang et al., 2020). Research tends to focus on single administrative cities or state/provincial levels, with little attention to regional perspectives. Moreover, there has not been a comprehensive and systematic study on the relevant development background and impact mechanism from the time or space dimension.

Regarding the specific internal mechanism and linear relationship between digital technology and green economic growth, many scholars have put forward hypotheses and corresponding research (Qian et al., 2022). Zhu (2022) believes that technological innovation and adoption can effectively alleviate and solve potential problems in industries with high energy consumption, high pollution, and overcapacity, and can also mitigate and prevent the expansion and waste of resources to a certain extent. At the same time, Zhu (2022) also analysed and verified that there is a significant correlation between green credit and technological innovation. Wang, Sun et al. (2024) explored the complex relationship between AI and green innovation in countries with different economic levels and verified that there is a robust and significant positive correlation between the two. In other words, AI may replace low-skilled labour and increase labour productivity and GEE. To a certain extent, it might also increase economic output, improve economic efficiency, and promote the research, development, and adoption of technology, thereby driving sustainable and stable economic growth. In addition to this, the adoption of AI could reduce energy consumption and pollution emissions and improve energy efficiency to a certain extent (Javaid et al., 2022; Li, Li et al., 2022; Wang, Zhang et al., 2024). Data mining, deep learning, independent decision-making, and other technologies support the precise operation of AI (Li, Chen et al., 2022). These technologies offer high-quality assurance for production, along with more reasonable resource allocation and cost control. To a certain extent, it can be assumed that they have effectively improved the efficiency of the green economy. Therefore, it can be concluded that by adopting technologies such as AI, the output of enterprises can be increased while reducing energy consumption and pollution emissions, thereby enhancing GEE. Accordingly, hypothesis 1 is put forward:

H1: AI has a positive effect on improving the efficiency of the green economy.

According to Rajput (2022), AI including multiple linear regression, artificial neural networks, algorithms and other specific methods, might effectively alleviate some potential environmental problems, and may also improve the green efficiency of regional development to some extent, but the specific endogenous relationship is still uncertain. Meanwhile, in order to promote the development of a green economy and reduce energy consumption, Zhong et al. (2020) used slack model (SBM) analysis to believe that regional economic benefits have certain spatial agglomeration and economic dependence, and there is also an endogenous relationship between industrial structure and economic benefits. However, the impact of technological progress on energy-related economic benefits is not significant, and the specific endogenous relationship needs to be further strengthened and clarified (Zhong et al., 2020). Hu et al. (2022) pointed out that the industrial structure refers to the composition and characteristics of a country or region's economic sector, and it also affects the direct path of using AI technology to improve the efficiency of the green economy. Technological innovations, such as the development of high-speed rail, indirectly stimulate the development of the green economy through the development of infrastructure services, and industrial structure plays a role in this path (Wang, Cheng, et al., 2023). Based on the analysis of mediating variables, industrial upgrading and transformation is one of the important factors in improving GEE. Rationalisation and high planning among industrial structures may bring about sustainable economic growth (Wang et al., 2022). In addition, industrial structure upgrading can effectively promote urban ecological efficiency, and this mediating variable has a partial positive intermediary effect in the direct path (Tang et al., 2020). Based on the spatial spillover effect, digitisation and green economic growth show a stable growth trend, and there is a significant mediating effect between the advanced industrial structure and the rationalisation of industrial structure. Zhu (2022) also proposed that there is a mediating effect between green economy, industrial structure upgrading, and technological innovation. From these, it can be assumed that an advanced and reasonable industrial structure can promote the GEE to a certain extent.

Understanding the mediating role of industrial structure planning and rationalisation can help identify sectors with the greatest potential to generate positive environmental outcomes through AI development. Accordingly, it can be assumed that advanced industrial structure (TS) and rationalised industrial structure (TI) play an intermediary role in the path of AI and GEE. The following hypotheses are put forward.

H2a: TS plays a mediating role in the direct path of AI to GEE.

H2b: TI plays a mediating role in the direct path of AI to GEE.

In recent years, the benefits of big data analysis and AI technology in the process of supply chain integration and their effects on environmental performance have gradually emerged. Benzidia et al. (2021) showed that the adoption of information technology has a positive impact on green supply chain collaboration, while the existence of moderating variables between these paths can strengthen the relationship between the two. For example, Zhao et al. (2020) believed that there is a significant endogenous relationship between foreign trade dependence, industrial structure rationalisation, advanced level, urbanisation level, and GEE. In order to promote green economic development and reduce energy consumption, Zhong et al. (2020) combined with the SBM estimation, found that the energy and economic benefits of urban agglomerations in the Yangtze River Delta region exhibit spatial agglomeration and economic dependence, while industrial structure and economic benefits are negatively correlated. Ma and Zhu (2022) believed that the digital economy effectively promotes high-quality linked radiation development and joint improvement of GEE in surrounding areas through spatial spillover effects. In other words, there is a spatial interaction effect between information technology represented by AI and regional GEE and economic dependence. The level of digitalisation has a positive spatial spillover effect on regional GEE. Moreover, the extent of this effect is better in the presence of economic distance. This suggests that there may be a moderating effect of economic dependence (Hao et al., 2023). To be more specific, the degree of dependence among economies reflects the degree of trade openness and economic radiation effects to a certain extent (Wang & Zheng, 2021). The higher the degree of economic dependence in a region, the closer the economic ties, and the more frequent the technology diffusion (Wang & He, 2019). Based on this, the present study aims to address this gap by examining the relationship between AI and GEE, conduct a hypothesis test on the specific endogenous relationship between AI and GEE economic dependence, and propose the following hypothesis:

H3: The economic dependence of a region moderates the relationship between AI and GEE.

METHODOLOGY

Research Framework

Based on the existing theoretical research and literature support, this study proposes the following theoretical framework to explore the impact of AI development on GEE and the endogenous relationship in the path, as shown in Figure 1.

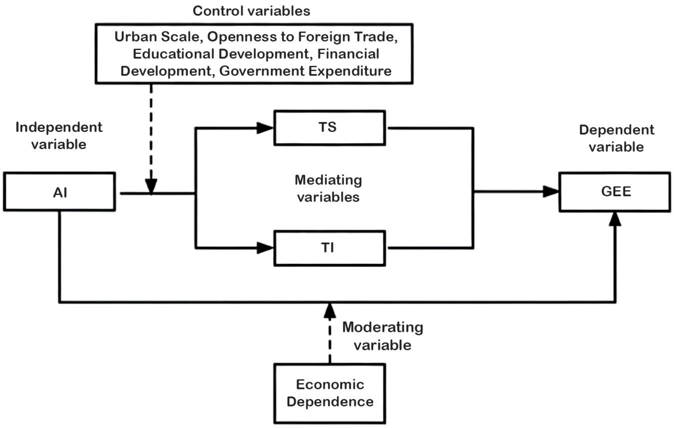

Figure 1. Research framework

Measurement of Variables

Dependent variable

Compared with the traditional model, the super-efficiency SBM model has outstanding performance in dealing with undesired output and determining the optimal decision-making unit of the boundary unit (Fu et al., 2023). This helps to more comprehensively reflect the GEE of the city, reduce model bias that may occur due to ignoring environmental costs, and thus alleviate the resulting endogeneity problems. Therefore, this study utilises a super-efficiency SBM model that incorporates non-desirable outputs to evaluate and measure the GEE of 11 cities in the Greater Bay Area. The specific calculation method for solving this problem is shown in Equation 1:

$$\min \rho = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}}{x_{ik}}}{\frac{1}{r_1+r_2}\left(\sum_{s=1}^{r_1}\frac{\bar{y}^d}{y^d_{sk}}+\sum_{q=1}^{r_2}\frac{\bar{y}^u}{y^u_{qk}}\right)}$$

$$s.t.\begin{cases}\bar{x} \geq \sum_{j=1,\neq k}^{n} x_{ij}\lambda_j;\ \bar{y}^d \leq \sum_{j=1,\neq k}^{n} y^d_{sj}\lambda_j \\ \bar{y}^u \geq \sum_{j=1,\neq k}^{n} y^u_{qj}\lambda_j;\ \bar{x} \geq x_k;\ \bar{y}^d \leq y^d_k;\ \bar{y}^u \geq y^u_k \\ \lambda_j \geq 0;\ i=1,2,\ldots,m;\ j=1,2,\ldots,n \\ s=1,2,\ldots,r_1;\ q=1,2,\ldots,r_2\end{cases} \tag{1}$$

Here, n is the number of decision-making units. Each decision-making unit has m kinds of inputs, r_1 types of expected outputs, and r_2 types of undesired outputs, where $n = 11$, $m = 3$, $r_1 = 1$, $r_2 = 1$. Meanwhile, x, yd, and yu are the elements in the corresponding input, desired output, and undesired output matrices, and ρ is the provincial GEE value. Input indicators include labour input expressed as the total number of employed persons at the end of the year; capital investment measured as the fixed asset investment stock of the whole society, calculated based on the perpetual inventory method; and energy input expressed as the electricity consumption of each city. Output indicators include the expected output of gross domestic product (GDP) in each urban area and the undesired output of industrial sulphur dioxide emissions in each city.

Table 1

Measuring indicators of GEE in the Guangdong-Hong Kong-Macao Greater Bay Area

First-level indicators	Second-level indicators	Variable description
Input indicators	Labour input	Number of employed persons at the end of the year (unit: 10,000 people)
	Capital input	Investment in fixed assets of the whole society (unit: 100 million yuan)
	Energy input	Power consumption (unit: 100 million kWh)
Expected output indicators	Economic output	Gross regional product (unit: 100 million yuan)
Unexpected output indicators	Environmental benefits	Sulphur dioxide emissions (unit: tons)

Mediating variable

TS is measured using the logarithm of the ratio of the output value of the tertiary industry to that of the secondary industry. This approach is intended to capture and reflect the transformation of the industrial structure from less advanced sectors to advanced sectors, indicating an upward transformation from low to high structural levels (Xu et al., 2022).

TI is calculated using the Theil index and then taking the logarithm (Zhang et al., 2020). The Theil index formula is as follows:

$$\mathrm{TL} = \sum_{i=1}^{n} (Y_i/Y) \ln (Y_i/L_i/Y/L) \tag{2}$$

Where Y represents the regional GDP, L represents the total employment at the close of the year, Y_i represents the production value of the i-th industry in the region, and L_i represents the total employment in the i-th industry in the region. The index measures the concentration of regional GDP across various industries, indicating the rationalisation of the industrial structure.

Moderating variable

Based on the previous literature review and the proposed hypothesis 3, economic dependence may moderate the relationship between AI development and GEE. To be more specific, countries with highly interdependent economies can engage in international cooperation and knowledge sharing in technology-related fields to achieve sustainable development (Alami et al., 2023). For example, a country or region's adoption of a green economy driven by AI development could have ripple effects on global supply chains and affect the environmental performance of interconnected economies. The higher the regional economic dependence coefficient, the higher the economic correlation between the region and other regions (Qiang & Jian, 2020). The specific expression of the economic dependence model is as follows:

$$R_{ijt} = \sqrt{GDP_{it} N_{it} * GDP_{jt} N_{jt}} / KM^2 \tag{3}$$

$$R_{it} = \sum_{j=1}^{n} R_{ijt} \qquad j = 1, 2, \ldots, n \tag{4}$$

$$R_t = \sum_{j=1}^{n} \sum_{i=1}^{n} R_{ijt} \qquad \mathrm{i}, j = 1, 2, \ldots, n \tag{5}$$

Here, ij represents the region, KM represents the distance between regions, and t represents the measurement year. GDP represents the gross domestic product, N represents the urban population, R_{ijt} represents the economic dependence coefficient between region i and j in period t, R_{it} represents the cumulative economic dependence coefficient of region *i* in period *t*, and R_t represents the cumulative economic dependence of the entire region in period *t* coefficient. To better reflect the economic interdependence among the 11 cities within the Greater Bay Area, especially the economic interdependence between Guangdong Province and Hong Kong and Macau, and to give full play to the radiation and diffusion of the central city of the Bay Area to other cities in the Bay Area and other cities in Guangdong Province effect. In measuring the economic dependence coefficient of the GBA, relevant data from 11 cities in the Greater Bay Area between 2011 and 2021 were selected.

Control variable

To exclude other factors that may affect the causal relationship and improve the accuracy and reliability of the research results, this study introduces the following control variables:

1. City size (Den): Taking the population density of the area (10,000 people per square kilometre) as one of the control variables, the greater the population density, the greater the demand and consumption of resources (Chen et al., 2020). By controlling for city size, the impact of differences in city size is mitigated, allowing for a more accurate assessment of AI's impact on GEE.
2. Opening to the outside world (Ope): It is expressed as the proportion of total imports and exports to regional GDP, reflecting the region's dependence on external resources (Song et al., 2019). This variable may be related to GEE.
3. Educational development (Edu): Expressed by the teacher-student ratio in secondary schools, which is the number of secondary school students divided by the number of full-time teachers. Educational levels can affect innovation and technology adoption, which has implications for GEE (Lin & Zhu, 2019).
4. Financial development (Fin): It is measured by the total regional deposits and loans (10,000 yuan), which may relate to economic activities and resource allocation, thus affecting GEE.
5. Fiscal expenditure (Fis): Fiscal expenditure may affect environmental policies and resource use, expressed as the proportion of fiscal expenditure to regional GDP.
6. Industrial development (Ind): Introducing industrial development can mitigate the influence of industrial structural disparities on GEE. This research approach involves calculating the ratio of the tertiary industry's output value to that of the secondary industry (Zhao et al., 2020).

Core explanatory variable

In recent years, some studies have started to use patent data as proxy variables for AI technology innovation and application (Li, Song, et al., 2022). It is believed that patent data can effectively measure the efforts and investments made by firms in technological innovation during the sample period, reflecting their technological level and knowledge stock (Hou et al., 2023). Therefore, it is reasonable to use patent data to represent AI technology innovation and application. This study is based on the AI-related International Patent Classification (IPC) codes covered in the classification and reference relationship between Strategic Emerging Industries and International Patent Classification (2021) (Trial) published by the China National Intellectual Property Administration. The number of AI patent applications and patent grants for the 11 cities in the Guangdong-Hong Kong-Macao Greater Bay Area was manually collected using the patent retrieval system of the China National Intellectual Property Administration. This research represented AI using the proportion of AI patent applications to the total number of patent applications in the region and conducted robustness tests using the proportion of AI patent grants to the total number of patent grants in the region.

Data Collection

To deeply study the relationship between AI and GEE in regional development, this research will take the Guangdong-Hong Kong-Macao Greater Bay Area as a case study to analyse how to use AI to create GEE and the endogenous relationship of the path. As one of China's most dynamic and open economic engines, the Greater Bay Area is a national strategic priority for achieving high-quality development, as its pronounced economic diversity, significant environmental pressures, and high degree of economic interdependence provide a compelling microcosm to examine the interplay between AI, industrial structure, and GEE. Some scholars believe that the Greater Bay Area, as an emerging regional economy, is significant and representative in the development of the green economy (Lu et al., 2022; Zhou et al., 2018). Damania et al. (2003) believed that the construction of the Hong Kong-Zhuhai-Macao Bridge has promoted the urban integration of Greater Bay Area, and its location advantages and technology aggregation capabilities have laid a solid foundation for the green economy. In terms of differences in economic development, the radiation effect between bay areas and the differences in industrial structure may affect the impact of AI development on the GEE. Based on an in-depth analysis of the economic development status of the Greater Bay Area, this study will use regression techniques to construct a research framework exploring how AI can empower the development of the green economy in the Greater Bay Area. This study applies the theory of the economic dependence model to measure the level of economic dependence in Guangdong, Hong Kong, and Macao. A dummy variable multiple regression model is then constructed to empirically analyse the relationship between AI, economic dependence, industrial structure, and GEE. This study focuses on 11 cities in the Greater Bay Area, and the sample period is from 2011 to 2021. The AI patent data comes from the State Intellectual Property Office of China, while data for other variables are sourced from the World Bank database, the Statistical Yearbook of Guangdong Province, the Census and Statistics Department and Environmental Protection Department of the Hong Kong Special Administrative Region Government, and the Statistics and Census Service of the Macao Special Administrative Region Government. In this study, there may be certain data limitations and biases, such as sample time span restrictions and regional coverage limitations. To solve these problems, the interpolation method is used to estimate the missing data, and control variables are introduced in the model analysis to reduce the impact of bias. Table 2 provides an overview of the descriptive statistics for the variables.

Table 2

An overview of the descriptive statistics for the variables

Variable type	Variable name	Variable meaning	Sample size	Mean	Standard deviation	Minimum value	Maximum value
Dependent	Green economic efficiency	*GEE*	121	0.295	0.287	0.074	1.147
Independent	Artificial intelligence innovation	*AI*	121	0.019	0.020	0	0.108
Mediating	Advanced industrial structure	*TS*	121	0.514	1.120	−0.556	3.250
	Rationalised industrial structure	*TI*	121	−3.466	1.457	−9.579	−1.179
Moderating	Economic dependency	*ED*	121	0.712	0.427	0.173	1.835
Control	Urban scale	*Den*	121	4.098	5.576	0.267	21.400
	openness to foreign trade	*Ope*	121	0.976	0.714	0.153	3.671
	Education development	*Edu*	121	11.430	2.308	5.106	15
	Financial development	*Fin*	121	2.694	3.498	0.195	12.593
	Government expenditure	*Fis*	121	0.144	0.064	0.062	0.526

RESULTS

Baseline Regression

To examine the relationship between AI and GEE, a stepwise regression analysis is conducted to test the effect of GEE. Table 3 shows the regression results of the impact of AI on GEE, where the variance inflation factor (VIF) value of each explanatory variable in the model is significantly lower than 10, indicating no serious multicollinearity. Based on the results of the Hausman test and F test, the fixed effects model with both entity effects and time fixed effects is considered more appropriate. As shown in column (1) of Table 3, excluding control variables, the coefficient of AI is positive and significant at the 1% level, indicating that AI plays a positive role in improving GEE. After gradually introducing control variables, as shown in column (6), the AI coefficient remains significantly positive at the 1% level. Moreover, with the addition of each control variable, the goodness of fit of the model improves, suggesting that digital economic development indeed promotes GEE.

Among the control variables, population density and financial development significantly impact GEE. On the other hand, openness, education development, and fiscal expenditure have a significant negative impact on GEE.

Table 3

Baseline regression results of AI's impact on GEE

Variable	*GEE*					
	(1)	(2)	(3)	(4)	(5)	(6)
AI	10.088***	6.473***	6.290***	5.064***	3.648***	4.000***
	(8.57)	(6.17)	(5.95)	(4.61)	(3.54)	(4.07)
Den		0.026***	0.027***	0.027***	0.026***	0.034***
		(7.86)	(7.95)	(8.41)	(8.78)	(9.33)
Ope			0.030	0.023	−0.064**	−0.051*
			(1.23)	(0.96)	(−2.30)	(−1.93)
Edu				−0.037***	−0.040***	−0.040***
				(−3.01)	(−3.61)	(−3.80)
Fin					0.029***	0.028***
					(5.02)	(5.19)
Fis						−1.139***
						(−3.52)
Sample size	121	121	121	121	121	121
	0.402	0.620	0.625	0.655	0.722	0.751
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

Influence Mechanisms

Building upon the baseline regression, the mediating role of industrial structure is examined to investigate the pathways through which AI affects GEE. The regression results are shown in Table 4, where column (1) represents the relevant results of the baseline regression. Regarding the upgrading of the industrial structure, as shown in columns (2) and (3) of Table 4, AI has a negative but not significant impact on the progress of the industrial structure, while the progress of the industrial structure has a significant negative impact on improving the GEE. Furthermore, the Sobel test examining the mediating effect of the advancement of industrial structure yields a Sobel value of 0.248, which is not statistically significant. This suggests that AI fails to promote the improvement of GEE through the advancement of industrial structure. This might be because the resource allocation effects and technological spillovers brought about by AI in traditional industries are stronger, resulting in enhanced efficiency in the allocation and utilisation of talent, technology, and capital in traditional industries without a significant shift towards more advanced industries.

Regarding the rationalisation of industrial structure, columns (4) and (5) of Table 4 show that AI has a negative and significant effect on the rationalisation of industrial structure, as evidenced by passing the significance test at the 10% level. Since the calculated Theil index for industrial structure rationalisation is a negative indicator, this suggests that AI contributes to the improvement of the rationalisation level of industrial structure. Moreover, the advancement of industrial structure has a significant negative impact on improving GEE, indicating that the rationalisation of industrial structure effectively enhances GEE. Furthermore, the Sobel test yields a Sobel value of 0.895, passing the significance test at the 1% level. The mediating effect of industrial structure rationalisation accounts for 22.38%. This indicates that AI can indeed promote the improvement of GEE by enhancing the level of industrial structure rationalisation.

Table 4

Test of influence mechanism

Variables	Baseline regression	Advanced industrial structure		Rationalised industrial structure	
	(1) *GEE*	(2) *TS*	(3) *GEE*	(4) *TI*	(5) *GEE*
AI	4.000***	−2.467	3.751**	−17.328*	3.105**
	(4.07)	(−0.62)	(3.17)	(−1.91)	(2.46)
TS			−0.101**		
			(−2.31)		
TI					−0.052***
					(−6.04)

(*continued*)

Table 4 *(continued)*

Variables	Baseline regression	Advanced industrial structure		Rationalised industrial structure	
	(1) *GEE*	(2) *TS*	(3) *GEE*	(4) *TI*	(5) *GEE*
Den	0.034***	0.123***	0.047***	−0.088***	0.030***
	(9.33)	(10.65)	(11.81)	(−4.88)	(6.02)
Ope	−0.051*	−0.067	−0.058**	−0.626***	−0.084***
	(−1.93)	(−1.77)	(−2.58)	(−7.49)	(−4.15)
Edu	−0.040***	0.123***	−0.028**	0.252**	−0.027***
	(−3.80)	(3.69)	(−2.58)	(2.26)	(−3.42)
Fin	0.028***	0.145***	0.043***	−0.004	0.028***
	(5.19)	(17.09)	(7.31)	(−0.10)	(3.51)
Fis	−1.139***	4.108***	−0.724	6.968***	−0.779
	(−3.52)	(4.24)	(−0.88)	(3.56)	(−1.22)
Fis	121	121	121	121	121
	0.751	0.882	0.770	0.373	0.790
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Sobel test	–	0.248		0.895**	
Mediating effect	–	0.248		0.895	
Proportion of mediating effect to total Effect	–	6.22%		22.38%	

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; t values in parentheses

Robustness Tests

To test the reliability of the impact of AI on GEE, a further robustness test was conducted, as shown in Table 5. To verify the robustness and consistency of the main research results of AI on GEE, specific robustness tests were conducted: different GEE measurement methods, variable substitution tests and two-tailed trimming (Wang, Sun, et al., 2024). First, different measurement methods for GEE were applied using the Global Malmquist-Luenberger (GML) index. The regression results in column (1) of Table 5 show that even if the measurement method of the dependent variable changes, the positive impact of AI on GEE is still significant at the 1% level. Even if the measurement method of the dependent variable is changed, the positive impact of AI on GEE is still significant, which proves the robustness of the results. Second, the core explanatory variable was replaced. The proportion of AI patent grants to total patent grants in the region was used as a replacement and the regression was re-estimated. The results in the second column of Table 5 indicate that even after substituting the core explanatory variable, AI continues to have a significant positive impact on GEE. Third, a change in sample size was considered. The sample data was trimmed two-tailed (1% level), which is usually used to test whether extreme values or outliers in the data distort the analysis results. The results in the third column of Table 5 reveal that after the trimming procedure, the positive effect of AI on GEE remains significant at the 1% level. This result shows that after removing extreme data, the positive impact of AI on GEE remains significant, indicating that the results are insensitive to potential outliers in the sample. These results demonstrate that AI has a significant promoting effect on GEE, and the regression results are robust to various tests and specifications.

Table 5

Robustness tests

Variables	(1) Alternative calculation method for GEE	(2) Replacing core independent variable: Proportion of AI patent grants	(3) Changing sample size: 1% trimming
AI	2.937***		5.174***
	(2.84)		(5.26)
AI_rep		4.730***	
		(3.31)	
Den	−0.012***	0.039***	0.031***
	(−3.04)	(10.60)	(9.78)
Ope	−0.100***	−0.074***	−0.065***
	(−3.28)	(−2.71)	(−2.99)
Edu	−0.025**	−0.039***	−0.046***
	(−2.15)	(−3.41)	(−4.69)
Fin	0.015**	0.028***	0.022***
	(2.51)	(4.89)	(4.79)
Fis	0.413	−0.932***	0.427
	(1.22)	(−2.82)	(1.24)
Ind	−0.013**	−0.001	−0.019***
	(−2.20)	(−0.22)	(−3.47)
Sample size	110	121	107
	0.290	0.739	0.844
Individual fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes

Moderation Effect

The results of the moderation effect indicate that the coefficient of the interaction term is 0.080, and it is significant at the 1% level, indicating the presence of a moderation effect of economic dependence (see Table 6). This suggests that economic dependence weakens the impact of AI on GEE.

One possible reason is that when the economic dependence is low, the regional economy faces a relatively stable production and operational environment, and the level of GEE among regions mainly reflects the comprehensive technological level of production efficiency and management. In this case, innovation in AI can effectively enhance regional GEE. Conversely, when the economic dependence is strong, there are more factors influencing GEE, and the mechanisms at play become more complex. Factors such as technology spillover effects or restricted technology imports may come into play. As a result, the role of AI innovation in promoting GEE is somewhat restrained.

Table 6

Test results of the moderating effect of economic dependence

GEE	Coefficient	Std. error	t	$p > \|t\|$
Ai	3.1896	0.898801	3.55	0.001
ED	−4.43E-06	2.10E-06	−2.11	0.037
Ai_ED	1.35E-09	2.56E-10	5.28	0
Us	0.034493	0.003322	10.38	0
Ope	−0.04298	0.027502	−1.56	0.121
Edu	−0.0372	0.009909	−3.75	0
Fin	0.028846	0.007056	4.09	0
Fis	−1.20224	0.362401	−3.32	0.001
cons	0.671264	0.146281	4.59	0

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$; t values in parentheses

DISCUSSION

The results of this study provide strong evidence supporting the critical role of AI in improving GEE. By optimising production processes, spurring innovation with environmental benefits, and fostering the integration of industries towards sustainable practices, AI contributes to a more resource-efficient and ecologically conscious economy. This study shows that AI promotes the improvement of GEE by enhancing the level of industrial structure rationalisation. This finding not only supports and extends the existing literature on the relationship between AI and GEE but also highlights AI's role in facilitating the concentration of resources in industries with higher productivity (Wang et al., 2025). This promotes the rationalisation of the industrial structure and shows that AI has a major role in shaping a more reasonable industrial structure. Specifically, by enhancing industrial structure rationalisation, AI's role extends beyond simple technological progress to reorganising and optimising resources for greater efficiency. Additionally, AI-driven data analytics plays a key role in identifying operational inefficiencies and facilitating the reorganisation of resources for optimal output. The analytical capabilities of AI enable industries to allocate resources efficiently, directing them to more productive sectors. This reallocation is manifested through AI-powered predictive maintenance in manufacturing, minimising equipment downtime, streamlining operations, and saving resources.

The results of this study demonstrate that economic dependence plays a mediating role between AI and GEE paths. While AI undeniably increases the efficiency of the green economy, the degree of economic dependence within a country determines the magnitude of this impact (Wang, Sun, et al., 2023). Countries that rely heavily on specific industries have had mixed success in harnessing the benefits of AI for sustainable transformation. For example, economies that are highly dependent on the fossil fuel industry may face challenges in adopting AI-based renewable energy solutions due to economic and infrastructural constraints. According to this, the interaction term between AI and GEE is used to evaluate the moderating relationship between economic dependence. This highlights that the degree of economic diversification and the level of development of regional economic linkages are key factors affecting the potential of AI to promote GEE. In other words, AI could promote positive changes, but a country's economic structure and the degree of trade dependence of a region can also affect the impact mechanism of these variables to some extent.

Implications

This research has important implications for academia, policymakers, and industry. First, this study contributes to the literature by providing empirical evidence on the impact of AI development on GEE. It highlights the significant role of AI in regional economic development, an area that is still being further explored in the context of sustainable development. This study underscores the importance of technological development. Governments should formulate policies to support AI technology applications in key industries, particularly those that enhance resource utilisation efficiency and ecological benefits. This includes supporting innovative systems and mechanisms for technology research and development to boost green economic growth and potential.

Secondly, research on the intermediary effect of industrial structure provides strong support for industry development strategies and sustainable practices. In optimising industrial structure adjustment, it is possible to encourage the diversification of economic structure and reduce dependence on a single industry, thereby enhancing the potential of AI technology to promote GEE.

Finally, by revealing the moderating role of economic interdependence, this study reveals the significant role of economic interdependence and economic radiation effects in accelerating AI to improve GEE. Increasing investment in AI-related infrastructure, especially in renewable energy and efficient energy use technology, is one of the main potential paths for the future green economy. For example, governments and industries should promote cooperation between multinational companies, academia and research institutions, develop corresponding policies to attract foreign investment, and support initiatives to promote regional job creation, skills development, and sustainable green development.

Furthermore, this study makes several distinct contributions. First, it moves beyond the direct link to construct an integrated framework that simultaneously examines the mediating role of industrial structure (both rationalisation and advancement) and the moderating effect of regional economic dependence in the AI-GEE relationship, uncovering the underlying transmission mechanisms. Second, it provides novel empirical evidence from the highly integrated yet economically diverse context of the Guangdong-Hong Kong-Macao Greater Bay Area, a strategic region where the interplay of technology, industrial transformation, and regional interdependence is particularly pronounced. Third, it employs a robust methodological approach, utilising a super-efficiency SBM model to accurately measure GEE and leveraging AI patent data for a more precise assessment of technological innovation. By doing so, this research not only validates AI's positive role but also delineates the specific conditions and pathways through which it enhances GEE, offering nuanced insights for regional policy and sustainable development strategies.

CONCLUSION

This study explores the key role of AI in improving the efficiency of the green economy, especially in the context of the Guangdong-Hong Kong-Macao Greater Bay Area. The results show that AI significantly enhances the green economy by optimising production processes, fostering environmentally friendly innovation, and driving the integration of sustainable practices in industries. In addition, economic dependence plays a moderating role between AI and GEE, indicating that countries with high dependence on certain specific industries face greater challenges in promoting sustainable transformation through AI.

Although the research has achieved significant empirical results, including the positive effect of AI on GEE, the mediating effect of industrial structure, and the moderating effect of economic dependence, there are still some factors and limitations that deserve attention and improvement. First, as the Guangdong-Hong Kong-Macao Greater Bay Area comprises only 11 cities, the findings may not fully represent the situation in other regions or countries. In addition, a potential limitation is that this study mainly focuses on the direct relationship between AI and GEE, ignoring other potential factors, such as policy dynamics. With the rapid development of AI, the sample data is likely to expand, making it worthwhile to conduct further empirical research using newer, larger, and more extensive data. Specifically, the sample range and time span can be expanded, and further analysis can be conducted from multiple dimensions such as policy and market. Moreover, while this offers valuable regional-level insights, it does not explore the potential heterogeneity of effects across different types of cities. Investigating these heterogeneities represents a critical and fruitful direction for future research, as it could yield more targeted and context-specific policy recommendations.

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