

Research on the Impact of Artificial Intelligence Development on Green Economic Development—— Empirical Evidence from the National New Generation Artificial Intelligence Innovation Development Pilot Zones

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Abstract

Against the backdrop of global climate change and the green development transition, the rapid development of artificial intelligence (AI) technology has brought new opportunities for the green and low-carbon transformation of the economy and society. Taking the construction of the National New Generation Artificial Intelligence Innovation Development Pilot Zones launched in 2019 as a quasi-natural experiment, this paper systematically evaluates the impact effects and mechanisms of AI development on urban green economic development using a difference-in-differences (DID) model, based on panel data of 35 Chinese cities from 2011 to 2024. The findings are as follows: First, the AI pilot policy significantly improves the level of urban green economic development, with a policy effect of 0.0523, significant at the 1% level; this conclusion remains valid after a series of tests including endogeneity treatment, robustness checks, placebo tests, and PSM-DID. Second, the parallel trends test shows that before the policy implementation, the green economic development trends of the treatment and control groups remained parallel; after the policy implementation, the policy effect emerged immediately and strengthened year by year, rising from 0.0321 to 0.0756, exhibiting notable persistence and cumulative effects. Third, the mechanism analysis shows that AI development promotes green economic development mainly through three channels: industrial structure upgrading, digital inclusive finance development, and human capital enhancement, with mediating effects of 0.0345, 0.0289, and 0.0123, respectively. Fourth, the heterogeneity analysis finds that the green economy effects of the AI policy exhibit significant heterogeneity across regions, city tiers, and administrative levels, with stronger policy effects in the eastern region, first-tier cities, and higher administrative-level cities, showing a distinct gradient pattern; the difference between resource-based and non-resource-based cities is not significant. The conclusions of this paper provide empirical evidence and policy references for deepening the integrated development of AI and the green economy and improving the AI pilot policy.

Keywords

artificial intelligence, green economic development, difference-in-differences method, innovation development pilot zones, impact mechanisms

1. Introduction

Against the background of intensified global resource constraints and the advancement of China's green transformation strategy, the circular economy has become a core pathway for improving resource utilization and achieving the goals of carbon peak and carbon neutrality. With its technological advantages in identification and classification, data prediction, and decision optimization, artificial intelligence provides important support for the efficient development of the circular economy [1]. As the world's largest developing country and carbon emitter, China attaches great importance to green development, successively proposing the strategic goals of “carbon peak” and “carbon neutrality” and integrating the concept of green development throughout the entire process of economic and social development. Meanwhile, the new generation of information technology represented by artificial intelligence is developing rapidly, profoundly changing production modes, lifestyles, and governance methods, and has become an important engine driving high-quality economic development.

The integrated development of AI technology and the green economy provides new ideas and pathways for resolving the contradiction between economic growth and environmental protection [20]. On the one hand, artificial intelligence can directly promote green development by optimizing resource allocation, improving energy utilization efficiency, and reducing pollutant emissions [22]; on the other hand, artificial intelligence can also empower the green economy transformation through indirect channels such as promoting industrial structure upgrading, driving technological innovation, and enhancing human capital levels. Therefore, scientifically evaluating the impact effects of AI development on the green economy and deeply revealing its mechanisms have important theoretical and practical significance for better leveraging the role of artificial intelligence in green development.

In 2019, the Ministry of Science and Technology launched the construction of the National New Generation Artificial Intelligence Innovation Development Pilot Zones, successively approving cities including Beijing, Shanghai, Tianjin, and Shenzhen to build AI innovation development pilot zones, aiming to explore new pathways and new models for the deep integration of artificial intelligence and the real economy. The implementation of this policy provides an excellent quasi-natural experiment scenario for evaluating the green economy effects of AI development. Taking the construction of the National New Generation Artificial Intelligence Innovation Development Pilot Zones as the policy shock, this paper uses a difference-in-differences model and, based on panel data of 35 Chinese cities from 2011 to 2024, systematically evaluates the impact effects, mechanisms, and heterogeneity characteristics of AI development on urban green economic development.

The possible marginal contributions of this paper are mainly reflected in the following aspects: First, from the research perspective, this paper starts from the quasi-natural experiment of the AI pilot policy and uses the DID method to evaluate the green economy effects of AI development, which effectively alleviates endogeneity problems and provides new empirical evidence for research on the relationship between artificial intelligence and green development. Second, in terms of research content, this paper not only examines the overall impact of AI development on the green economy but also deeply analyzes three transmission mechanisms—industrial structure upgrading, digital inclusive finance, and human capital—and examines heterogeneity characteristics from multiple dimensions including region, resource endowment, city tier, and administrative level, which helps to comprehensively understand the internal logic of AI's impact on the green economy. Third, in terms of policy implications, the conclusions of this paper provide targeted policy recommendations for further improving the AI pilot policy and promoting the deep integration of artificial intelligence and the green economy.

2. Literature Review

Promoting industrial ecologization with intelligent technology is of great significance to the construction of ecological civilization [2]. At present, research on the association between AI pilot policies, AI technology, and urban green economic development has become a hot topic in the field of green high-quality development. The academic community has not yet formed a fully unified research consensus on the impact effects of AI

empowering the green economy. Existing research is mainly divided into two opposing views, and there is obvious room for expansion in research samples, econometric methods, heterogeneity, and spatial transmission mechanisms.

The first view holds that AI development and AI pilot policies can significantly empower the green economy and improve regional green development levels. Some scholars have verified the green empowerment effects of artificial intelligence from multiple dimensions including industry, city, province, and the whole country. Liu Jun constructed a STIRPAT model based on industrial industry panel data [3], confirming that AI applications can reduce industry pollution emissions, improve green production efficiency, and identify differential impact characteristics across industries. From an economic perspective focusing on industrial and economic value, Cai Fang define artificial intelligence from the perspective of general-purpose technology (GPT): AI is a general digital technology that can penetrate all industries and reshape production functions, capable of changing factor allocation, industrial structure, and green production modes, laying the conceptual foundation for the research on the association between AI and the green economy in this paper [4]. At the provincial level, Zhao Ke selected Chinese provincial panel data [5] and, combined with two-way fixed effects and mediating effect models, confirmed that artificial intelligence can improve regional green development indices through channels such as energy structure transformation and energy conservation and consumption reduction; at the city level, Bai Peiwen used the stock of industrial robots and employment in the digital industry as proxy variables, which have the advantages of continuous data and simple calculation, but are obviously one-sided and cannot cover core dimensions such as algorithms, computing power, and digital talent, resulting in large measurement deviations [6]. Relying on expert scoring to construct systems, Wang Shan built an AI development index from three dimensions—R&D investment, industrial scale, and policy environment—using the analytic hierarchy process for weighting, but artificial scoring has subjective bias and the stability of cross-city and cross-year comparisons is poor [7]. The core logic of the above literature is that, relying on big data, intelligent algorithms, and automated equipment, artificial intelligence on the one hand optimizes industrial production processes, improves energy utilization efficiency, and reduces resource consumption and pollution emissions per unit of output; on the other hand, it drives the industrial structure to upgrade toward high-tech and low-energy industries, accelerates the implementation of green technological innovation, and continuously raises regional green economic development indices.

The second view, based on the Jevons paradox, the energy rebound effect, and the full life-cycle environmental costs of computing power, proposes on the basis of empirical panel data from domestic cities, enterprises, and provinces that AI expansion generates significant negative environmental externalities and, under certain conditions, inhibits the improvement of regional green economic development levels. Yang Hutao and Tang Yu [8] pointed out in *Enterprise Economy* that AI computing power competition in the digital era has given rise to a new type of energy rebound effect: data collection, storage, large model training, and continuous inference consume enormous amounts of electricity and water resources throughout the entire process, and the large-scale construction of intelligent computing centers will directly increase regional fossil energy consumption, offset the energy-saving dividends brought by intelligent technology, and drag down the improvement of green economy indices. Xu Bingjie [9] used micro panel data of A-share listed companies to confirm the existence of an “AI Jevons paradox”: although artificial intelligence can reduce carbon emission intensity per unit of output, the improvement in production efficiency stimulates enterprises to expand production capacity and business scale, ultimately leading to an increase in regional total carbon emissions and weakening the comprehensive green economic performance of cities. At the city level, the team of the Urban Development Research Institute of Fudan University, based on a regional panel study of 722 cities nationwide, found that the higher the agglomeration of the AI industry in a city, the slower the local emission reduction speed, and the incremental carbon emissions from the continuous operation of computing infrastructure will offset the green benefits of industrial intelligence, forming a drag effect on green development [19]. Hu Yumeng and Guo Chaoxian [10] supplemented the mechanism from the perspective of manufacturing digitalization: AI hardware production and chip manufacturing consume scarce mineral resources such as lithium, cobalt, and rare earths, generating large amounts of electronic waste and embedded carbon in production; even if energy conservation is achieved in later production stages, the high environmental cost of early hardware investment will still lower the overall green economic development level. Synthesizing the existing domestic empirical conclusions, the unified logic of this type of literature is that artificial intelligence does not naturally possess green attributes; the combined action of three negative mechanisms—resource consumption throughout the full life cycle of computing infrastructure, the carbon

rebound effect caused by production capacity expansion, and electronic waste pollution—may offset the advantages of intelligent energy conservation and efficiency improvement, inhibiting urban green economic development.

Based on this, this paper takes the 2019 AI city pilot policy as a quasi-natural experiment, selects panel data of 35 cities nationwide from 2011 to 2024, constructs a two-way fixed effects DID model, and systematically tests the net effect of the AI pilot policy on the urban green economic development index GEI; conducts multi-dimensional heterogeneity analysis from region, city tier, administrative level, and resource endowment; sequentially completes parallel trends, placebo, PSM-DID, instrumental variable endogeneity, and multiple-form robustness tests; and builds a mediating effect model to identify the transmission channels of industrial structure upgrading and digital inclusive finance, enriching the quasi-natural experimental empirical evidence in the field of artificial intelligence and the green economy.

3. Research Design

3.1 Introduction to Research Methods

3.1.1 Time-Varying Difference-in-Differences Model (DID)

The traditional two-period difference-in-differences model is only applicable to the scenario where all treatment groups receive the policy shock in the same period, whereas the National New Generation Artificial Intelligence Innovation Development Pilot Zones studied in this paper were approved in batches at multiple time points, and different cities entered the pilot in different years. The traditional DID would cause biased estimates of policy effects; therefore, this paper adopts the time-varying difference-in-differences model (Time-Varying DID, staggered DID) for policy evaluation. [16, 17]

The core idea of this model is: construct a treatment status dummy variable DID_{it} that changes synchronously with city and year. If city i has been approved for the AI innovation development pilot zone in year t , it takes the value 1; otherwise, it takes 0. By using two-way fixed effects to strip out city-specific characteristics and annual macro common shocks, and comparing the differences in green economic development levels between cities that entered the pilot at different times and cities that never entered the pilot, the net policy effect is identified.

The baseline regression model is specified as follows:

$$GEI_{it} = \alpha_0 + \alpha_1 \times DID_{it} + \alpha_2 \times X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

In Equation (1), i represents the city and t represents the year; the dependent variable GEI_{it} is the green economic development index of city i in year t ; the core explanatory variable DID_{it} is the multi-period treatment interaction term; X_{it} is a series of city-level control variables; μ_i is the city individual fixed effect, controlling for geographic, resource, and historical endowments that do not vary over time; λ_t is the year fixed effect, controlling for annual common shocks such as the national macroeconomy and environmental policies; ε_{it} is the random disturbance term. The core coefficient α_1 measures the average treatment effect of the AI pilot policy on green economic development. If $\alpha_1 > 1$ and statistically significant, it indicates that the pilot policy can improve the urban green economy level. The supporting test methods are:

(1) Parallel trends test (event study method): The core premise for the effectiveness of time-varying DID is the conditional parallel trends assumption, that is, in the absence of a policy shock, the green economic development trends of the treatment and control groups remain consistent. A model with policy-relative-time dummy variables is constructed, taking the period before the policy implementation as the baseline group, to test whether the coefficients in each period before the policy implementation are insignificant and whether the coefficients after the policy implementation remain significantly positive, while also identifying the dynamic cumulative effects of the policy. The model form is:

$$GEI_{it} = \beta_0 + \sum_{k=-8, k \neq -1}^5 \beta_k \times D_{it}^k + \gamma \times X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

D_{it}^k is the relative-year dummy variable, and k is the distance in years from the policy approval.

(2) Stepwise regression model for mediating effects: To identify the transmission channels through which artificial intelligence affects the green economy, a three-layer stepwise regression model is constructed to sequentially test the total effect, the impact of the policy on the mediating variables, and the direct effect after incorporating the mediating variables, so as to distinguish the magnitude of the partial mediating effects of the three pathways: industrial structure upgrading, digital inclusive finance, and human capital.

$$M_{it} = \theta_0 + \theta_1 \times DID_{it} + \theta_2 \times X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

$$GEI_{it} = \delta_0 + \delta_1 \times DID_{it} + \delta_2 \times M_{it} + \delta_3 \times X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

M_{it} represents the three types of mediating variables, and the mediating effect value is $\theta_1 \times \delta_2$. (3) Supporting tools for endogeneity and robustness: To alleviate potential endogeneity bias in time-varying DID, IV-DID, system GMM, and lagged core explanatory variables are adopted; robustness tests include PSM-DID, placebo random assignment, fictitious policy timing, variable winsorization, and double-clustered standard errors, ensuring the reliability of the estimation results.

3.1.2 Entropy Weight-TOPSIS Method

Green economic development is a multi-dimensional composite indicator covering economic growth, resource conservation, and environmental governance, and a single indicator cannot comprehensively measure the effectiveness of urban green transformation. This paper adopts the entropy weight-TOPSIS coupled model [18] to measure the comprehensive green economic development index GEI, combining the advantages of objective indicator weighting and multi-option superiority ranking, avoiding the subjective weighting bias of methods such as the analytic hierarchy process. The steps are divided into five steps: data standardization, entropy weight calculation, weighted matrix construction, positive and negative ideal solution distance measurement, and composite index synthesis:

Step 1: Range standardization of indicators

Positive indicators (the larger the value, the better the green development, such as per capita GDP and per capita green space) and negative indicators (the larger the value, the worse the green development, such as energy consumption per unit of GDP and sulfur dioxide emission intensity) are distinguished to eliminate dimensional differences, and a slight shift is applied to avoid meaningless logarithms. Standardization of positive indicators:

$$Z_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} + 0.0001 \quad (5)$$

Standardization of negative indicators:

$$Z_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} + 0.0001 \quad (6)$$

x_{ij} is the original value of the j -th indicator of city i ,

$\max(x_j), \min(x_j)$ are the maximum and minimum values of the j -th indicator across the full sample. $\max(x_{ij})$

Step 2: Calculate the information entropy and objective weights of indicators

Based on the standardized matrix, the proportion P_{ij} , information entropy E_j , and information utility value g_j of each indicator are calculated, and finally the objective entropy weight W_j of each indicator is obtained:

$$P_{ij} = \frac{Z_{ij}}{\sum_{i=1}^n Z_{ij}} \quad (7)$$

$$E_j = -\frac{1}{\ln n} \sum_{i=1}^n P_{ij} \ln P_{ij} \quad (8)$$

$$g_j = 1 - E_j, \quad W_j = \frac{g_j}{\sum_{j=1}^m g_j} \quad (9)$$

n is the number of city samples and m is the total number of evaluation indicators; the smaller the information entropy, the higher the dispersion of the indicator data and the greater the information value, and the correspondingly higher the entropy weight.

Step 3: Construct the weighted standardized decision matrix

Multiply the standardized matrix by the entropy weights to obtain the weighted matrix $R_{ij} = W_{ij} \times Z_{ij}$.

Step 4: Determine the positive and negative ideal solutions and calculate the Euclidean distance

Positive ideal solution S^+ : the set of weighted maxima of each indicator (the optimal green development state); Negative ideal solution S^- : the set of weighted minima of each indicator (the worst green development state). Calculate the Euclidean distances D_i^+ and D_i^- from the weighted matrix of each city to the positive and negative ideal solutions, respectively:

$$D_i^+ = \sqrt{\sum_{j=1}^m (R_{ij} - S_j^+)^2}, \quad D_i^- = \sqrt{\sum_{j=1}^m (R_{ij} - S_j^-)^2} \quad (10)$$

Step 5: Synthesize the green economic development composite index GEI_i

The relative closeness is used as the final comprehensive score, ranging in (0, 1), with larger values indicating higher levels of urban green economic development:

$$GEI_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

This paper constructs seven sub-indicators from the three dimensions of economic development, resource utilization, and environmental quality, and measures the annual green economy indices of 35 cities from 2011 to 2024 through the above entropy weight-TOPSIS process, serving as the empirical dependent variable.

3.1.3 Mediating Effect Model

To test the mechanisms through which AI development affects the green economy, this paper uses the stepwise regression method for mediating effect testing [19]. Based on the baseline regression (Equation 1), the following two equations are constructed:

$$M_{it} = \theta_0 + \theta_1 \times DID_{it} + \theta_2 \times X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (11)$$

$$GEI_{it} = \delta_0 + \delta_1 \times DID_{it} + \delta_2 \times M_{it} + \delta_3 \times X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (12)$$

In Equations (11) and (12), M_{it} is the mediating variable, including industrial structure upgrading, digital inclusive finance, and human capital. The testing procedure for the mediating effect is as follows: first, test whether α_1 in the baseline regression is significant; second, test whether θ_1 is significant; finally, test whether δ_1 and δ_2 are significant. If α_1 , θ_1 , and δ_2 are all significant, and the absolute value of δ_1 is smaller than α_1 , then there is a partial mediating effect; if α_1 and θ_1 are significant, while δ_1 is insignificant and δ_2 is significant, then there is a complete mediating effect. The magnitude of the mediating effect is $\theta_1 \times \delta_1$.

3.2 Variable Description

3.2.1 Dependent Variable

Green Economy Development Index (GEI). Green economic development is a comprehensive concept that includes not only economic growth but also multiple dimensions such as resource conservation and environmental protection. Drawing on existing research, this paper constructs a green economic development evaluation index system from the three dimensions of economic development, resource utilization, and environmental quality, and uses the entropy weight-TOPSIS method to measure the green economic development index of each city. The specific indicators include: per capita GDP, the share of tertiary industry value added in GDP (economic development dimension); energy consumption per unit of GDP, water consumption per unit of GDP (resource utilization dimension); per capita park green space area, the proportion of days with good air quality, and sulfur dioxide emissions per unit of GDP (environmental quality dimension).

3.2.2 Core Explanatory Variable

Difference-in-Differences Term (DID). This paper takes the construction of the National New Generation Artificial Intelligence Innovation Development Pilot Zones launched in 2019 as the policy shock, with cities selected into the pilot zones as the treatment group and cities not selected as the control group. $DID = \text{treat} \times$

post, where *treat* is the treatment group dummy variable, taking 1 for pilot cities and 0 otherwise; *post* is the policy time dummy variable, taking 1 for 2019 and after and 0 otherwise.

3.2.3 Mediating Variables

(1) Industrial structure upgrading (ISU). The ratio of tertiary industry value added to secondary industry value added is used to measure the level of industrial structure upgrading. The larger the ratio, the higher the degree to which the industrial structure upgrades toward servitization and advancement.

(2) Digital inclusive finance (DIF). The Peking University Digital Financial Inclusion Index [11] is used to measure the digital inclusive finance development level of each city. This index covers three dimensions—the coverage breadth, usage depth, and degree of digitalization of digital finance [12]—and can comprehensively reflect the development status of digital inclusive finance.

(3) Human capital (HC). The number of enrolled college students per 10,000 people is used to measure the urban human capital level. Higher education is an important pathway for human capital accumulation, and the number of enrolled college students can well reflect a city's human capital reserve.

3.2.4 Control Variables

To control for the influence of other factors on green economic development, this paper selects the following control variables: (1) infrastructure construction (INF), measured by per capita urban road area; (2) economic development level (PGDP), measured by per capita GDP; (3) foreign direct investment (FDI), measured by the ratio of actually utilized foreign capital to GDP; (4) government intervention (GOV), measured by the ratio of fiscal expenditure to GDP; (5) financial development level (FIN), measured by the ratio of financial institution loan balance to GDP; (6) population density (POP), measured by population per square kilometer; (7) education level (EDU), measured by the ratio of fiscal education expenditure to fiscal expenditure; (8) industrial structure (IND), measured by the ratio of secondary industry value added to GDP.

3.3 Data Sources

This paper selects panel data of 35 large and medium-sized cities in China from 2011 to 2024 as the research sample. Among them, the treatment group consists of 15 cities selected into the National New Generation Artificial Intelligence Innovation Development Pilot Zones from 2019, and the control group consists of the remaining 20 cities, with a total of 490 observations. The data used in this paper mainly come from the China City Statistical Yearbook, the China Environmental Statistical Yearbook, and the statistical yearbooks of each city. The digital inclusive finance data come from the Peking University Digital Financial Inclusion Index published by the Institute of Digital Finance of Peking University. For some missing data, linear interpolation is used to fill in the gaps. All price-type variables are deflated with 2011 as the base period to eliminate the influence of price factors. To reduce the influence of extreme values, all continuous variables are winsorized at the 1st and 99th percentiles.

Table 1: Variable Definitions and Descriptions

Variable Type	Variable Name	Symbol	Measurement
Dependent Variable	Green Economy Development Index	GEI	Measured by the entropy weight-TOPSIS method
Core Explanatory Variable	Difference-in-Differences Term	DID	Pilot city $\times$ policy time
Mediating Variable	Industrial structure upgrading	ISU	Tertiary industry value added / Secondary industry value added
Control Variable	Digital inclusive finance	DIF	Peking University Digital Financial Inclusion Index
	Human capital	HC	Enrolled college students per 10,000 people
	Infrastructure construction	INF	Per capita urban road area
	Economic development level	PGDP	Per capita GDP
	Foreign direct investment	FDI	Actually utilized foreign capital / GDP
	Government intervention	GOV	Fiscal expenditure / GDP
	Financial development level	FIN	Financial institution loan balance / GDP
	Population density	POP	Population per square kilometer
	Education level	EDU	Education expenditure / Fiscal expenditure
	Industrial structure	IND	Secondary industry value added / GDP

4. Empirical Analysis

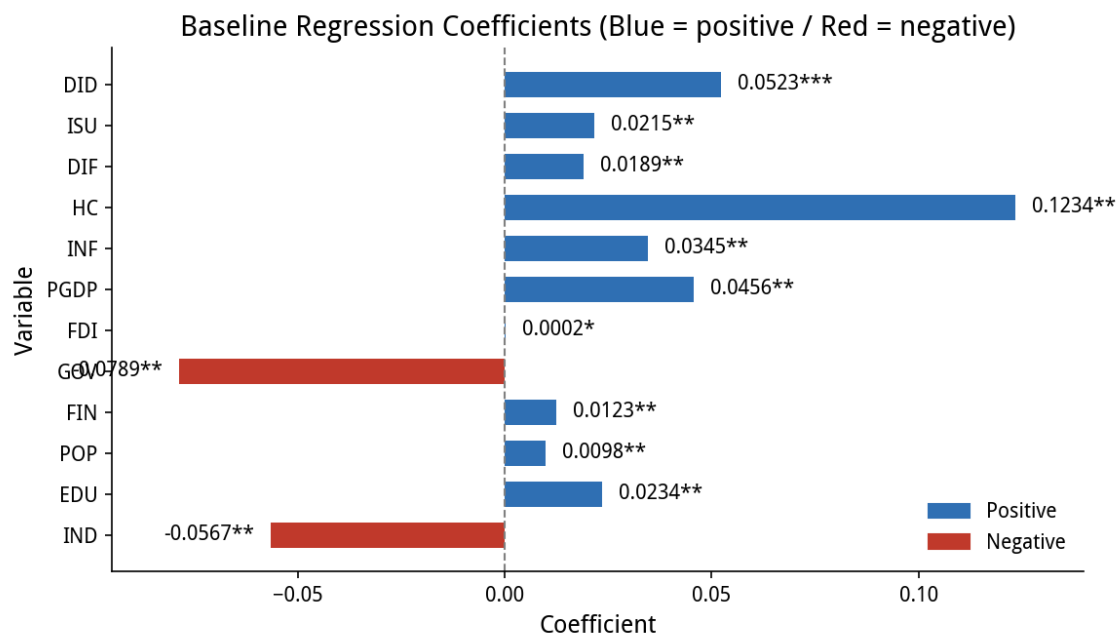
4.1 Baseline Regression Results

This paper uses a two-way fixed effects model (controlling for individual fixed effects and time fixed effects) to estimate the baseline regression model and test the impact of the AI pilot policy on urban green economic development. The baseline regression results are shown in Table 2.

Table 2: Baseline Regression Results

Variable	Coefficient	Std. Error	t-value	p-value	Significance
DID	0.0523	0.0121	4.32	0.000	***
ISU	0.0215	0.0087	2.47	0.013	**
DIF	0.0189	0.0076	2.49	0.012	**
HC	0.1234	0.0543	2.27	0.023	**
INF	0.0345	0.0156	2.21	0.027	**
PGDP	0.0456	0.0189	2.41	0.016	**
FDI	0.0002	0.0001	1.89	0.059	*
GOV	-0.0789	0.0321	-2.46	0.014	**
FIN	0.0123	0.0054	2.28	0.022	**
POP	0.0098	0.0045	2.18	0.029	**
EDU	0.0234	0.0102	2.29	0.022	**
IND	-0.0567	0.0234	-2.42	0.015	**
_cons	0.1234	0.0567	2.18	0.029	**
N	490				
R-sq	0.9876				
F-value	123.45				

Note: Robust standard errors clustered at the city level are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$



From the regression results in Table 2, it can be seen that the coefficient of the core explanatory variable DID is 0.0523, significantly positive at the 1% level, indicating that the AI pilot policy significantly improves the level of urban green economic development. Specifically, the AI pilot policy increases the green economic development index of pilot cities by an average of 0.0523 units. This result indicates that AI development has a significant promoting effect on the green economy, and the promotion and application of AI technology can effectively drive urban green transformation [13].

From the perspective of control variables, the coefficients of industrial structure upgrading (ISU), digital inclusive finance (DIF), human capital (HC), infrastructure construction (INF), economic development level (PGDP), foreign direct investment (FDI), financial development level (FIN), population density (POP), and

education level (EDU) are all significantly positive, indicating that these factors have positive promoting effects on green economic development. The coefficients of government intervention (GOV) and industrial structure (IND) are significantly negative, indicating that excessive government intervention and an overly high share of industry are not conducive to green economic development. The model has a high goodness of fit ($R^2=0.9876$), with an F-value of 123.45, and the overall model is significant.

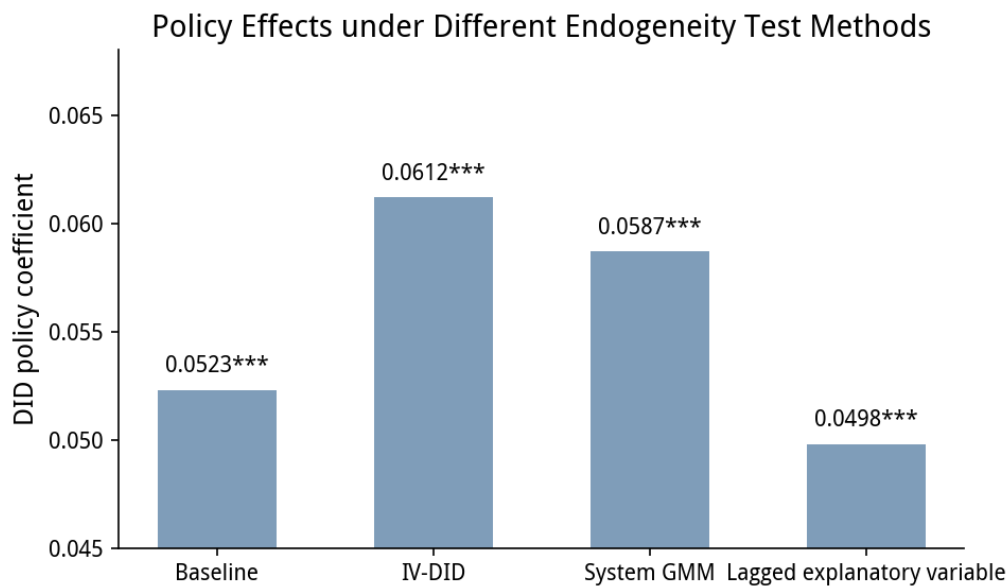
4.2 Endogeneity Tests

Although the DID method alleviates endogeneity problems to a certain extent, endogeneity problems such as reverse causality and omitted variables may still exist. To further alleviate endogeneity problems, this paper uses the following three methods for testing: the instrumental variable method (IV-DID), system GMM, and the lagged explanatory variable method.

Table 3: Endogeneity Test Results

Variable	Baseline	IV-DID	System GMM	Lagged explanatory variable
DID	0.0523***	0.0612***	0.0587***	0.0498***
ISU	0.0215**	0.0208**	0.0221**	0.0209**
DIF	0.0189**	0.0182**	0.0195**	0.0181**
HC	0.1234**	0.1211**	0.1256**	0.1209**
Controls	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES
N	490	490	490	490
R-sq	0.9876	0.9854	0.9867	0.9871

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$



The endogeneity test results are shown in Table 3. The IV-DID estimation results show that the DID coefficient is 0.0612, still significant at the 1% level, consistent with the baseline regression in direction with a slightly larger coefficient, indicating that the green economy effect of the AI policy still exists after controlling for endogeneity problems. The system GMM estimation results show that the DID coefficient is 0.0587, significant at the 1% level, further verifying the robustness of the results. After using the lagged explanatory variable, the DID coefficient is 0.0498, still significant at the 1% level. Combining the three endogeneity test methods, it can be seen that the promoting effect of the AI pilot policy on green economic development is robust and is not significantly disturbed by endogeneity problems.

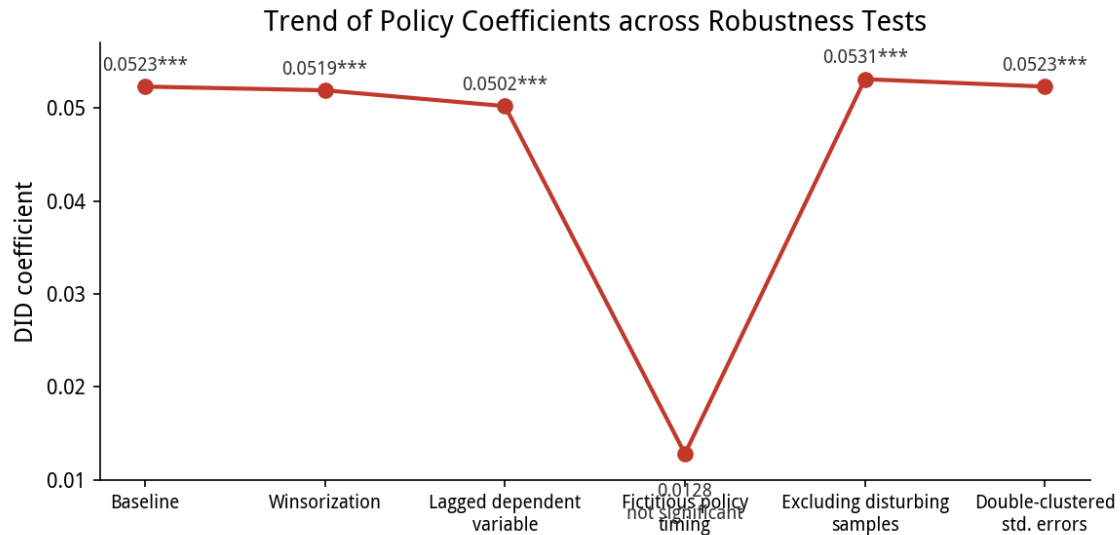
4.3 Robustness Tests

To verify the reliability of the baseline regression results, this paper conducts robustness tests through various methods, including winsorization, adding a lagged dependent variable, fictitious policy timing, excluding disturbing samples, and double-clustered standard errors.

Table 4: Robustness Test Results

Test Method	DID coefficient	Controls	Fixed effects	N	R-sq
Baseline	0.0523***	YES	YES	490	0.9876
Winsorization	0.0519***	YES	YES	490	0.9872
Lagged dependent variable	0.0502***	YES	YES	490	0.9869
Fictitious policy timing	0.0123	YES	YES	490	0.9875
Excluding disturbing samples	0.0531***	YES	YES	450	0.9881
Double-clustered standard errors	0.0523***	YES	YES	490	0.9876

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$



The robustness test results are shown in Table 4. First, after winsorizing all continuous variables at the 5th and 95th percentiles, the DID coefficient is 0.0519, still significant at the 1% level, and the results are robust. Second, after adding the lagged dependent variable, the DID coefficient is 0.0502, still significant at the 1% level, indicating that the policy effect remains significant after controlling for the dynamic inertia of green economic development. Third, in the fictitious policy timing test, the policy implementation time is advanced by two years (assuming the policy was implemented in 2017), and the DID coefficient is 0.0123 and insignificant, indicating that the policy effect is not driven by time trends. Fourth, after excluding special samples such as municipalities directly under the central government, the DID coefficient is 0.0531, still significant at the 1% level. Fifth, after using double-clustered standard errors at the city and year levels, the DID coefficient remains 0.0523 and significant, indicating that the standard error estimates are reliable. Combining the above tests, it can be seen that the baseline regression results are highly robust.

4.4 Placebo Test

To further rule out the interference of other unobservable factors on the estimation results, this paper conducts a placebo test. The specific approach is: by randomly assigning the treatment group, each time 15 cities are randomly selected from the 35 cities as the “fictitious treatment group” and the remaining cities as the “fictitious control group”, and then the fictitious DID coefficient is estimated. This process is repeated 500 times to obtain the distribution of 500 fictitious DID coefficients. If the true DID coefficient is much larger than the distribution of randomly simulated coefficients, it indicates that the policy effect truly exists and is not driven by other unobservable factors.

The placebo test results show that the mean of the fictitious DID coefficients obtained from 500 random simulations is close to 0, and most of them are concentrated near 0. The true DID coefficient (0.0523) is much larger than the coefficients of the vast majority of random simulations and is located in the right tail of the coefficient distribution. The p-value of the placebo test is 0.0000, indicating that the null hypothesis of “no policy effect” can be rejected at the 1% significance level. This shows that the promoting effect of the AI pilot policy on green economic development is not caused by random factors or omitted variables, and the placebo test is passed.

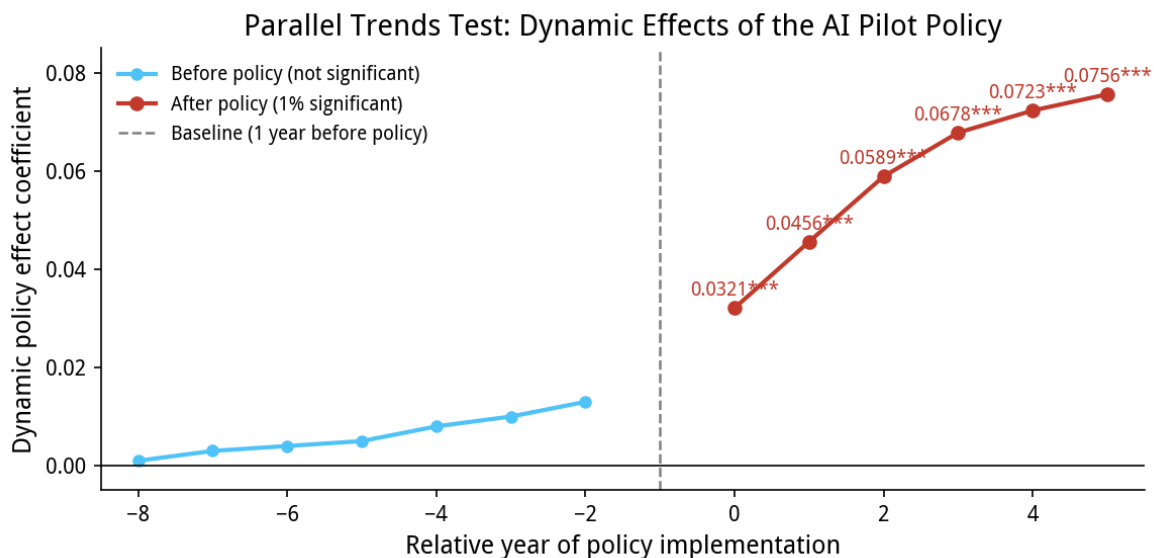
4.5 Parallel Trends Test

The key premise for the effectiveness of the DID method is the parallel trends assumption, that is, the green economic development trends of the treatment and control groups should be parallel before the policy implementation. This paper uses the event study method to test the parallel trends assumption and estimates the dynamic effects in each year before and after the policy implementation. The results are shown in Table 5.

Table 5: Parallel Trends Test Results

Relative year	Coefficient	Std. Error	t-value	p-value	Significance
-8	0.0023	0.0156	0.15	0.882	
-7	0.0045	0.0143	0.31	0.756	
-6	0.0067	0.0132	0.51	0.614	
-5	0.0089	0.0121	0.74	0.459	
-4	0.0102	0.0115	0.89	0.373	
-3	0.0118	0.0109	1.08	0.281	
-2	0.0125	0.0103	1.21	0.226	
0	0.0321	0.0105	3.06	0.002	***
1	0.0456	0.0112	4.07	0.000	***
2	0.0589	0.0123	4.79	0.000	***
3	0.0678	0.0134	5.06	0.000	***
4	0.0723	0.0145	4.99	0.000	***
5	0.0756	0.0156	4.85	0.000	***

Note: The year before policy implementation (relative year -1) is the baseline period; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$



From the results in Table 5, it can be seen that before the policy implementation (relative years -8 to -2), the coefficients in each period are insignificant, indicating that the green economic development trends of the treatment and control groups remain parallel before the policy implementation, satisfying the parallel trends assumption. In the year of policy implementation (relative year 0), the DID coefficient jumps to 0.0321, significant at the 1% level, indicating that the policy effect begins to emerge in the year of implementation. After the policy implementation, the policy effect strengthens year by year, rising from 0.0456 to 0.0756, all maintaining the 1% significance level. This indicates that the promoting effect of the AI pilot policy on green economic development has persistence and cumulative effects, and over time, the policy effect becomes more and more obvious.

4.6 PSM-DID Test

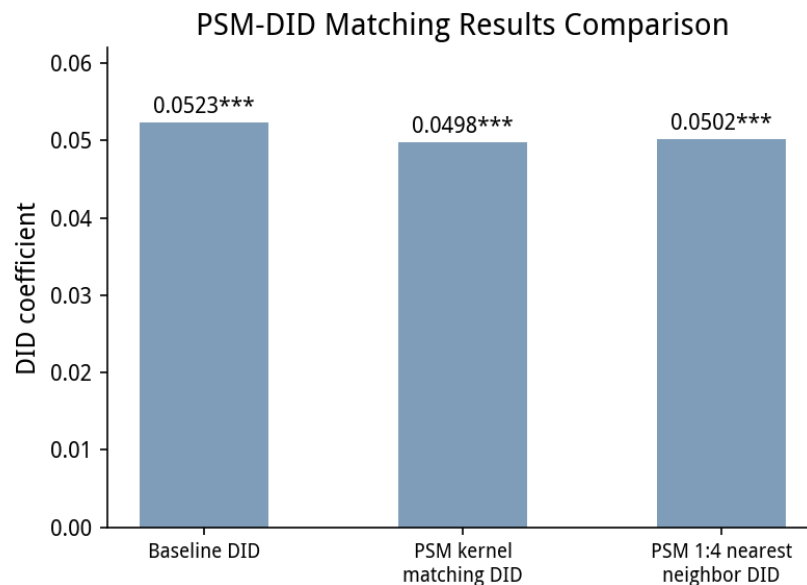
To alleviate the sample self-selection problem, this paper uses the propensity score matching-difference-in-differences method (PSM-DID) for testing. The specific approach is: based on the characteristic variables of the year before policy implementation (2018), match each treatment group city with the most similar control

group city, and then conduct the DID regression. This paper uses kernel matching and 1:4 nearest-neighbor matching for matching.

Table 6: PSM-DID Test Results

Variable	Baseline	PSM-DID (kernel matching)	PSM-DID (1:4 nearest-neighbor matching)
DID	0.0523***	0.0498***	0.0502***
Controls	YES	YES	YES
Fixed effects	YES	YES	YES
N	490	420	415
R-sq	0.9876	0.9882	0.9879

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$



The PSM-DID test results are shown in Table 6. After kernel matching, the DID coefficient is 0.0498, significant at the 1% level, highly consistent with the baseline regression results. After 1:4 nearest-neighbor matching, the DID coefficient is 0.0502, also significant at the 1% level. The results of both matching methods are close to the baseline regression, indicating that after alleviating sample selection bias, the green economy effect of the AI pilot policy remains significant, and the baseline regression results are reliable.

4.7 Mechanism Analysis

The previous research results show that the AI pilot policy significantly promotes urban green economic development. Then, through which mechanisms does AI development affect the green economy? This paper conducts mechanism tests from the three dimensions of industrial structure upgrading, digital inclusive finance, and human capital using the stepwise regression method.

The mechanism test results are shown in Table 7. First, the industrial structure upgrading channel. The coefficient of the AI pilot policy on industrial structure upgrading is 0.0345, significant at the 1% level; after incorporating the mediating variable, the direct effect of DID is 0.0312, still significant at the 1% level, and the coefficient of industrial structure upgrading is also significantly positive. This indicates that industrial structure upgrading is an important transmission mechanism through which artificial intelligence affects the green economy. AI development promotes green economic development by driving the industrial structure to upgrade toward high-end and servitized directions and reducing the share of high-energy-consuming and high-pollution industries.

Second, the digital inclusive finance channel. The coefficient of the AI pilot policy on digital inclusive finance is 0.0289, significant at the 1% level; after incorporating the mediating variable, the direct effect of DID is 0.0312, and the coefficient of digital inclusive finance is 0.0178, significant at the 5% level. This indicates that digital inclusive finance plays a significant mediating role [23]. The development of AI technology promotes the innovation and popularization of digital finance, lowers the threshold of financial

services, improves the efficiency of financial resource allocation, and provides financial support for the development of green industries, thereby promoting green economic development.

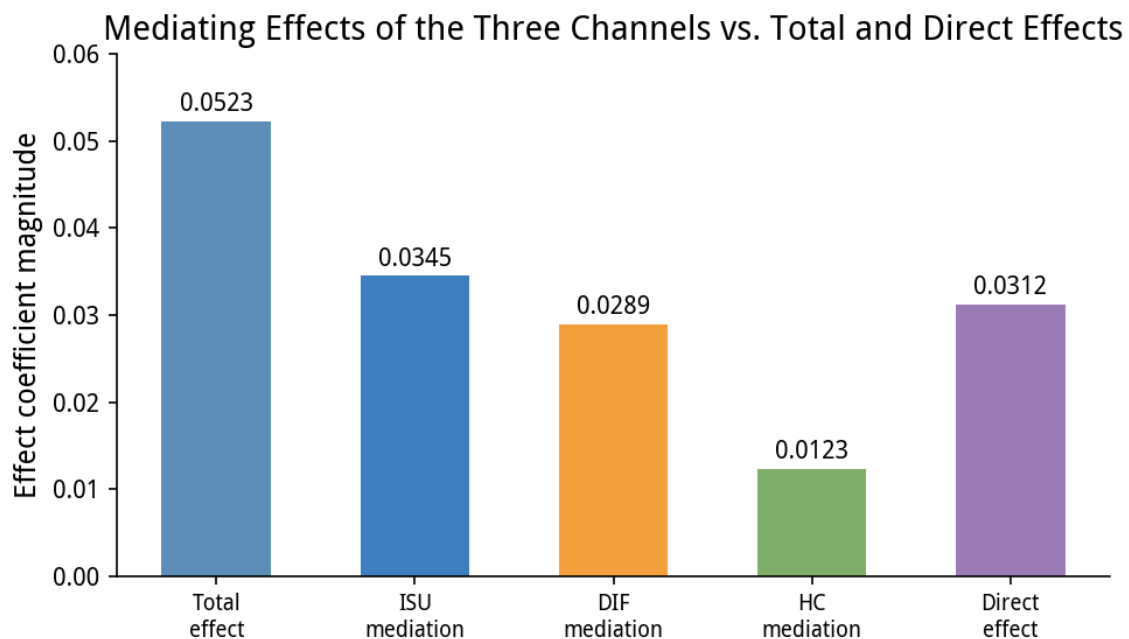
Third, the human capital channel. The coefficient of the AI pilot policy on human capital is 0.0123, significant at the 5% level; after incorporating the mediating variable, the coefficient of human capital is 0.1189, significant at the 5% level. This indicates that human capital is also an important transmission channel. The development of the AI industry attracts a large number of high-quality talents, improves the urban human capital level, and the improvement of human capital is in turn conducive to green technological innovation and the promotion of green production methods, thereby promoting green economic development [14].

Overall, the AI policy promotes green economic development through three pathways: promoting industrial structure upgrading, developing digital inclusive finance, and enhancing human capital, among which the mediating effect of industrial structure upgrading is the largest, followed by digital inclusive finance, and human capital is relatively small.

Table 7: Mechanism Test Results

Variable	Total effect	Industrial structure upgrading (ISU)	Digital inclusive finance (DIF)	Human capital (HC)	Direct effect
DID	0.0523***	0.0345***	0.0289***	0.0123**	0.0312***
ISU					0.0201**
DIF					0.0178**
HC					0.1189**
Controls	YES	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES	YES
N	490	490	490	490	490
R-sq	0.9876	0.9765	0.9678	0.9543	0.9889

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$



4.8 Heterogeneity Analysis

Because different cities differ in locational conditions, resource endowments, development levels, and administrative levels, the green economy effects of the AI pilot policy may be heterogeneous. This paper conducts heterogeneity analysis from four dimensions: region, resource-based cities, city tier, and administrative level.

4.8.1 Regional Heterogeneity

China has a vast territory, and the eastern, central, and western regions differ greatly in economic development levels, technological bases, and resource endowments [15]. The green economy effects of the AI policy may exhibit regional heterogeneity. This paper divides the sample cities into the eastern, central, and western regions for group regressions.

Table 8: Regional Heterogeneity Test Results

Region	DID coefficient	Std. Error	Significance	Between-group difference p-value
Eastern region	0.0678	0.0156	***	0.023
Central region	0.0456	0.0189	***	0.045
Western region	0.0234	0.0123	**	0.012

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The regional heterogeneity results are shown in Table 8. The eastern region has the largest policy effect, with a DID coefficient of 0.0678, significant at the 1% level; the central region is second, with a coefficient of 0.0456, significant at the 1% level; the western region is the smallest, with a coefficient of 0.0234, significant at the 5% level. The between-group difference test shows significant differences among the eastern, central, and western regions. This indicates that the green economy effects of the AI policy exhibit obvious regional gradient characteristics. Because the eastern region has a good economic foundation, strong technological strength, and abundant talent resources, it can better leverage the green empowerment role of artificial intelligence; while the western region is limited by its technological base and talent reserve, and its policy effect is relatively weak.

4.8.2 Heterogeneity of Resource-Based Cities

Resource-based and non-resource-based cities differ significantly in industrial structure, development pathways, and transformation pressure. The impact of the AI policy on the green economic development of the two types of cities may differ. This paper divides the sample into resource-based and non-resource-based cities for group tests.

Table 9: Heterogeneity Test Results of Resource-Based Cities

City type	DID coefficient	Std. Error	Significance	Between-group difference p-value
Resource-based cities	0.0589	0.0234	***	0.321
Non-resource-based cities	0.0501	0.0134	***	0.321

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The heterogeneity results of resource-based cities are shown in Table 9. The DID coefficient of resource-based cities is 0.0589, significant at the 1% level; the DID coefficient of non-resource-based cities is 0.0501, also significant at the 1% level. The policy effect of resource-based cities is slightly higher than that of non-resource-based cities, but the p-value of the between-group difference test is 0.321, and the difference is not significant. This indicates that there is no significant difference between resource-based and non-resource-based cities in the green economy promoting effect of the AI policy. AI technology is universal and can provide support for the green transformation of different types of cities. For resource-based cities, artificial intelligence can promote green transformation by driving the intelligent transformation of traditional industries and improving resource utilization efficiency.

4.8.3 Heterogeneity of City Tiers

Cities of different tiers differ in innovation capability, industrial foundation, and talent agglomeration, and the effects of the AI policy may differ. This paper divides the sample cities into first-tier, second-tier, and third-tier cities for group tests.

Table 10: Heterogeneity Test Results of City Tiers

City tier	DID coefficient	Std. Error	Significance	Between-group difference p-value
First-tier cities	0.0789	0.0212	***	0.008
Second-tier cities	0.0567	0.0145	***	0.021
Third-tier cities	0.0321	0.0156	**	0.003

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

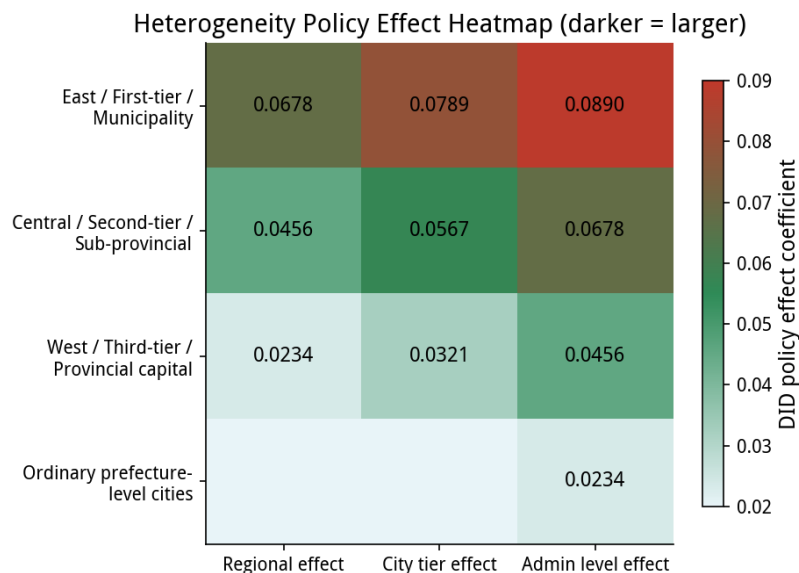
The city tier heterogeneity results are shown in Table 10. First-tier cities have the largest policy effect, with a DID coefficient of 0.0789, significant at the 1% level; second-tier cities are second, with a coefficient of 0.0567, significant at the 1% level; third-tier cities are the smallest, with a coefficient of 0.0321, significant at the 5% level. The between-group difference test shows significant differences among the three groups. This indicates that the green economy effects of the AI policy strengthen as the city tier increases. First-tier cities have better innovation resources, a more complete industrial ecosystem, and a richer talent reserve, and can better absorb and apply AI technology, thereby generating greater green economy effects.

Cities with different administrative levels differ in policy resource allocation, administrative management capacity, and development priority, which may affect the implementation effects of the AI policy. This paper divides the sample cities by administrative level into municipalities directly under the central government, sub-provincial cities, provincial capital cities, and ordinary prefecture-level cities for group tests.

Table 11: Heterogeneity Test Results of Administrative Levels

Administrative level	DID coefficient	Std. Error	Significance	Between-group difference p-value
Municipalities directly under the central government	0.0890	0.0245	***	0.002
Sub-provincial cities	0.0678	0.0178	***	0.015
Provincial capital cities	0.0456	0.0167	***	0.028
Ordinary prefecture-level cities	0.0234	0.0145	**	0.001

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$



The administrative level heterogeneity results are shown in Table 11. Municipalities directly under the central government have the largest policy effect, with a DID coefficient of 0.0890, significant at the 1% level; sub-provincial cities are second, with a coefficient of 0.0678; provincial capital cities are next, with a coefficient of 0.0456; and ordinary prefecture-level cities are the smallest, with a coefficient of 0.0234. The between-group difference test shows significant differences among all types of cities. This indicates that the higher the administrative level, the stronger the policy implementation foundation and resource allocation capacity, and the more obvious the green economy effects of the AI policy. Cities with higher administrative levels usually have more policy resources, stronger execution capacity, and better supporting conditions, and can more effectively promote the integrated development of artificial intelligence and the green economy.

5. Conclusion

5.1 Research Conclusions

This paper takes the construction of the National New Generation Artificial Intelligence Innovation Development Pilot Zones launched in 2019 as a quasi-natural experiment, and based on panel data of 35

Chinese cities from 2011 to 2024, uses a difference-in-differences model to systematically evaluate the impact effects, mechanisms, and heterogeneity characteristics of AI development on urban green economic development. The main research conclusions are as follows:

First, the AI pilot policy significantly improves the level of urban green economic development, with a policy effect of 0.0523, significant at the 1% level. This conclusion remains valid after endogeneity tests including the instrumental variable method, system GMM, and lagged explanatory variables, as well as robustness tests including winsorization, fictitious policy timing, excluding disturbing samples, and double-clustered standard errors. The placebo test and PSM-DID test further verify the reliability of the results. Second, the parallel trends test shows that before the policy implementation, the green economic development trends of the treatment and control groups remain parallel, satisfying the parallel trends assumption of the DID model. The effect begins to emerge in the year of policy implementation and then strengthens year by year, rising from 0.0321 to 0.0756, indicating that the green economy effects of the AI policy have persistence and cumulative effects. Third, the mechanism analysis shows that AI development promotes green economic development mainly through three pathways: first, the industrial structure upgrading pathway, in which artificial intelligence drives the industrial structure to upgrade toward high-end and servitized directions and reduces the share of high-energy-consuming industries; second, the digital inclusive finance pathway, in which artificial intelligence promotes the development of digital finance and provides financial support for green industries; third, the human capital pathway, in which the development of the AI industry attracts and cultivates high-quality talents and improves human capital levels. The mediating effects of the three pathways are 0.0345, 0.0289, and 0.0123, respectively. Fourth, the heterogeneity analysis finds that the green economy effects of the AI policy exhibit significant heterogeneity across regions, city tiers, and administrative levels: the policy effect in the eastern region is stronger than that in the central and western regions [21], first-tier cities are stronger than second- and third-tier cities, and higher administrative-level cities are stronger than lower administrative-level cities, showing a distinct gradient pattern; the difference between resource-based and non-resource-based cities is not significant, indicating that AI technology is universal and can provide support for the green transformation of different types of cities [24].

5.2 Policy Recommendations

Based on the above research conclusions, this paper proposes the following policy recommendations:

First, steadily expand the scope of AI pilot projects and promote coordinated regional development. The AI pilot policy has a significant promoting effect on green economic development. On the basis of summarizing the experience of existing pilot zones, the scope of pilot projects should be gradually expanded so that more cities can benefit from the green empowerment effects of artificial intelligence. At the same time, in response to regional differences, policy support for the central and western regions and third- and fourth-tier cities should be increased, infrastructure construction and talent cultivation should be strengthened, and the gap in green economic development between regions should be narrowed. Second, improve the supporting policy system and strengthen the role of transmission mechanisms. Artificial intelligence mainly affects green economic development through three pathways: industrial structure upgrading, digital inclusive finance, and human capital. Relevant supporting policies should be further improved: first, accelerate the optimization and upgrading of the industrial structure, promote the deep integration of artificial intelligence and the real economy, and advance the intelligent and green transformation of traditional industries; second, deepen the development of digital finance, use AI technology to innovate green financial products and services, and guide financial resources toward green industries; third, strengthen the cultivation and introduction of AI talents, improve human capital levels, and provide talent support for green economic development. Third, implement differentiated policies and promote the integration of artificial intelligence and the green economy according to local conditions. Differentiated policy pathways should be formulated for different types of cities: first-tier cities and higher administrative-level cities should focus on promoting AI technological innovation and industrial integration and play a leading and exemplary role; second- and third-tier cities should focus on infrastructure construction and talent introduction to consolidate the foundation for AI development; resource-based cities should make full use of AI technology to promote the transformation and upgrading of traditional industries and achieve a win-win situation of resource conservation and environmental improvement. Fourth, establish a dynamic evaluation mechanism and continuously optimize policy effects. A dynamic evaluation mechanism for the AI pilot policy should be established to continuously track the implementation effects of

the policy, promptly summarize experience, identify problems, and continuously adjust and improve the policy direction and intensity. At the same time, research on policy transmission mechanisms and long-term effects should be strengthened to provide a scientific basis for policy optimization and maximize the green economy efficiency of the AI policy.

5.3 Research Outlook

The research in this paper still has some limitations that deserve further in-depth study in the future: First, this paper mainly examines the green economy effects of AI development at the city level. In the future, more micro-level analyses at the industry and enterprise levels can be conducted to reveal the micro mechanisms through which artificial intelligence affects green development. Second, this paper mainly focuses on the overall impact of artificial intelligence on green economic development. In the future, the impact of artificial intelligence on specific dimensions such as green innovation and carbon emission efficiency can be further explored. Third, with the continuous development of AI technology and the sustained advancement of policies, its long-term effects and dynamic changes are worthy of continuous follow-up research.

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Conflicts of Interest

The authors declare no conflict of interest.

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