

Spatial Spillover Effects and Nonlinear Impact Intensity of Artificial Intelligence on Green Total Factor Productivity

Zhipeng Zhang *

School of Science, Shandong Jianzhu University, Jinan, 250000, China

*Corresponding Author: eltg567@gmail.com

ABSTRACT

This study focuses on the spatial evolution logic and heterogeneous impact intensity of artificial intelligence (AI) technology in driving green total factor productivity (GTFP). First, using spatial econometric models, the study confirms through global and local Moran's I indices that significant positive spatial autocorrelation and agglomeration characteristics exist in AI development levels across Chinese provinces. Empirical results show that AI not only significantly enhances local green TFP but also generates notable spatial spillovers through technology diffusion and diffusion effects, with positive coefficients for direct, spillover, and total effects. Subsequently, to more precisely measure variations in impact intensity, the study employed K-Means clustering to classify provincial samples into high, medium, and low development tiers. Dynamic GMM estimation was applied to address model endogeneity. Results indicate that AI exerts a sustained, positive influence on GTFP and its sub-dimension of green technology efficiency, with significant historical effects. However, at the sub-dimensional level, AI's direct impact on green technological progress has not yet exhibited statistically significant characteristics. Through comparisons of multiple regression models and lagged term treatments, this study confirms the robustness of the conclusions, providing quantitative support for analyzing AI's enabling mechanisms in the spatial dimension.

KEYWORDS

Spatial spillover effect; K-Means clustering; Dynamic GMM estimation

1. INTRODUCTION

Against the backdrop of global industrial low-carbon transformation and the deepening implementation of China's "dual carbon" strategy, artificial intelligence (AI)—as the core engine of the new technological revolution—has become a key pathway for enhancing green total factor productivity through its deep integration with green industries. Existing literature has extensively explored the driving factors of GTFP. Tang and Lan (2024) empirically tested the spatial effects of the digital economy on industrial GTFP growth, while Jia et al. (2024) discussed the differentiated contributions of structural and reform dividends to GTFP growth [1-2]. Additionally, factors such as green credit, green finance, and foreign direct investment (FDI) have been confirmed to significantly impact GTFP [3-7]. While Wang (2024) focused on the role of the digital economy and technological innovation, few studies have deeply deconstructed the specific enabling mechanism of AI, as a core new technology, on GTFP, particularly lacking a refined examination from the perspectives of spatial correlation and nonlinear intensity. However, the application of AI technologies often exhibits cross-regional mobility and diffusion, meaning its impact on green productivity extends beyond individual geographic units and manifests complex spatial correlations. While prior studies have acknowledged AI's productivity-boosting effects, most focus on linear analyses of direct impacts [8-10]. Few systematically examine spatial interaction effects across regions, and inter-provincial development

disparities are often addressed through subjective classifications, lacking nuanced deconstruction of impact intensities. The innovation of this section lies in first identifying AI spillover boundaries through a spatial econometric framework, then introducing a data-driven K-Means clustering algorithm to achieve objective, asymmetric classification of sample provinces. This is combined with a two-step dynamic GMM estimation to overcome endogeneity bias. The general research approach is as follows: the Moran's I index is used to analyze spatial correlation characteristics, and the spatial Durbin model (SDM) and its decomposed effect measure are employed to assess geographical spillover contributions. Subsequently, based on the clustering results, hierarchical regression is conducted for clusters of different levels. A dynamic panel model is used to deconstruct the differentiated driving logic of AI on green technology efficiency and technological progress. Finally, multidimensional robustness tests are implemented to ensure the scientific validity of the empirical conclusions.

2. SPATIAL EFFECT OF ARTIFICIAL INTELLIGENCE DEVELOPMENT ON GREEN TOTAL FACTOR PRODUCTIVITY

2.1. Spatial Correlation Analysis of Artificial Intelligence Development Level

2.1.1. Global Moran's I

As a highly universal innovation paradigm, artificial intelligence can generate spatio-temporal interaction effects. To analyze the spatial correlation of artificial intelligence development levels, Stata is used to calculate the global Moran's I of artificial intelligence development levels in 30 provinces of China from 2014 to 2023. The results show that the global Moran's I of artificial intelligence development levels in all provinces is greater than 0.22, and significant at the 1% level. From the time dimension, the artificial intelligence development level of provinces in China shows an overall upward trend from 2014 to 2023, with obvious positive spatial correlation.

2.1.2. Local Moran's I

The local Moran's I is used to investigate the spatial distribution of artificial intelligence development levels in provinces of China. Data from 2014, 2017, 2020, and 2023 are selected and incorporated into the geographic inverse distance spatial weight matrix. The results show that there are significant differences in the local Moran's I among different provinces and cities, and the spatial clustering results are shown in Figure 1.

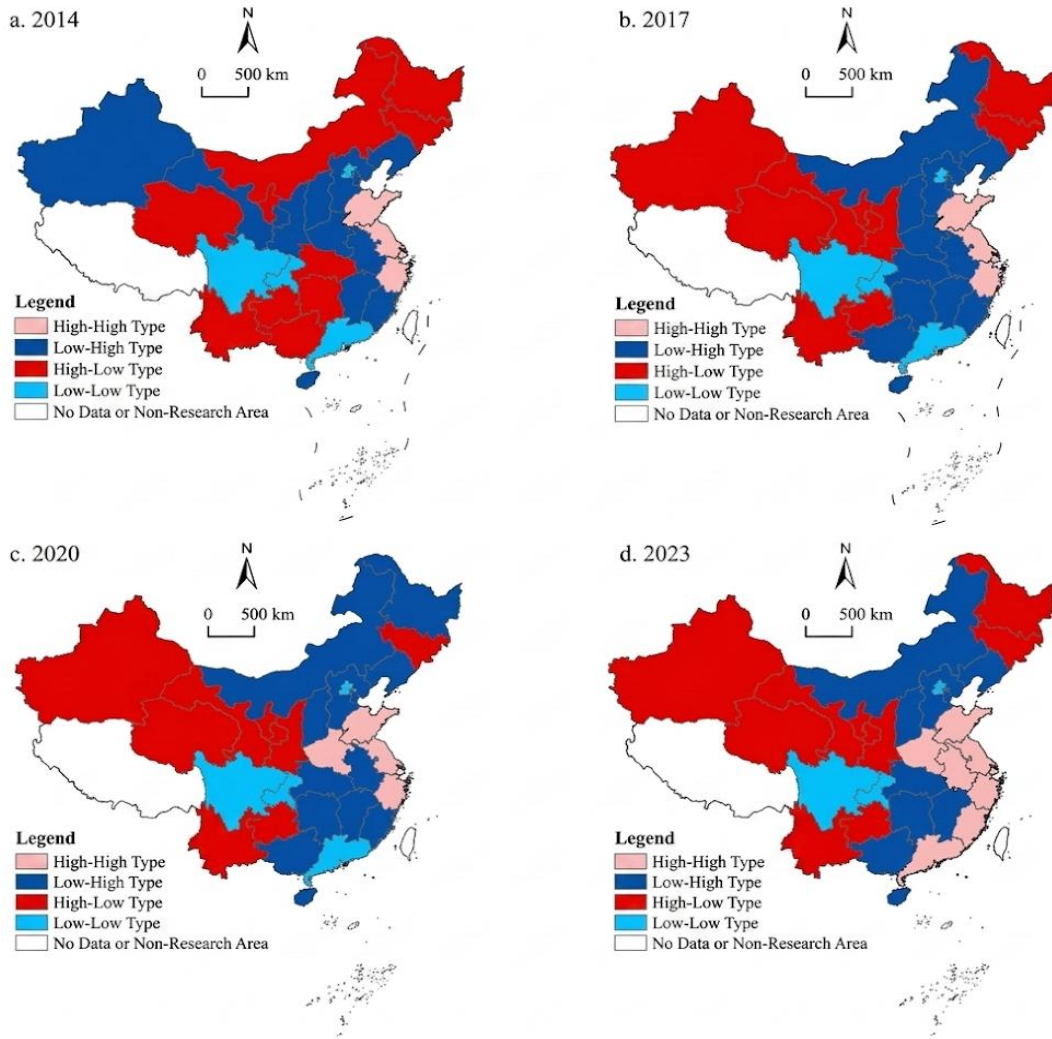


Figure 1. Spatial clustering results of artificial intelligence development level
(The figure was drawn by the author)

2.2. Spatial Econometric Model Setting

To examine the impact of artificial intelligence development on green total factor productivity, the baseline regression model is set as follows:

$$GTFP_{it} = \alpha + \beta AI_{it} + X'_{it}\gamma + \varepsilon_i + \lambda_t + \mu_{it} \quad (1)$$

Where: $GTFP_{it}$ is the explained variable green total factor productivity. Considering its general continuity, to reduce endogeneity and bias, $GTFP_{it-1}$, the lagged one-period term of green total factor productivity, is added to the model as an explanatory variable; X'_{it} represents a row vector of a series of control variables; β and γ are the estimated coefficients of the corresponding variables; α is the constant term; ε_i and λ_t represent city fixed effects and year fixed effects respectively; μ_{it} is the random disturbance term.

To explore the spatial effect of artificial intelligence development on green total factor productivity, this study constructs a spatial econometric model referring to the idea of Kuang Jinsong, Yang Kunyu [6] et al. The model settings are as follows:

$$GTFP_{it} = \rho GTFP_{it-1} + \beta AI_{it} + \phi X'_{it} + \alpha_i + \lambda_t + \mu_{it} \quad (2)$$

$$GTFP_{it} = \beta AI_{it} + X'_{it} \phi + \alpha_i + \lambda_t + \mu_{it}; \mu_{it} = \delta \mu_{it-1} + \varepsilon_{it} \quad (3)$$

$$GTFP_{it} = \rho GTFP_{it-1} + \beta_1 AI_{it} + \beta_2 AI_{it-1} + \phi X'_{it} + W'_{it} \xi + \alpha_i + \lambda_t + \mu_{it} \quad (4)$$

Equation (2) is the Spatial Autoregressive Model (SAR), Equation (3) is the Spatial Error Model (SEM), and Equation (4) is the Spatial Durbin Model (SDM). The Spatial Durbin Model (SDM) includes the following two spatial effect assumptions: ① Spatial spillover effects are caused by random shocks; ② The explained variable has spatial effects affecting other regions. β and ϕ are parameters to be estimated; ρ represents the estimated coefficient of the spatial lag term, which can reflect the spatial dependence of green total factor productivity among provinces; W'_{it} represents the spatial lag term of a series of control variables; ξ is the coefficient of the spatial lag term.

2.3. Empirical Results of Spatial Effects

2.3.1. Test and Selection of Spatial Econometric Models

The positional difference of the spatial weight matrix determines the structural characteristics of the spatial econometric model, thus deriving various modeling forms. To select an appropriate model, it is necessary to identify its statistical adaptability through a systematic test process, and the specific process is shown in Figure 2:

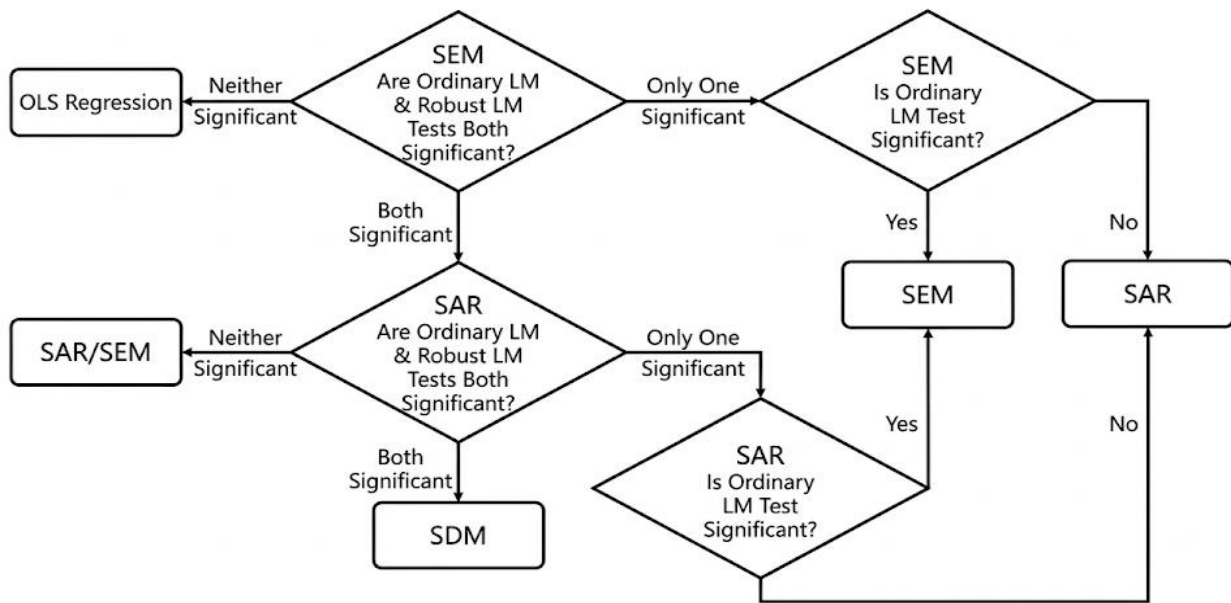


Figure 2. Flowchart of spatial econometric model selection

Among them, in the LM test, the statistics of the ordinary LM test and robust LM test for the spatial error model and spatial autoregressive model are both significantly 34.62 at the 1% significance level. This double significance usually points to more complex spatial interactions, so the Spatial Durbin Model is selected.

2.3.2. Spatial Econometric Results

Visualization maps, Moran's I and other measurement results show that GTFP and AI development levels have strong spatial agglomeration effects. This study preferably selects the geographic inverse distance matrix as the weight matrix of the Spatial Durbin Model. The results of its spatial econometric model are shown in the following figure 3 and figure 4:

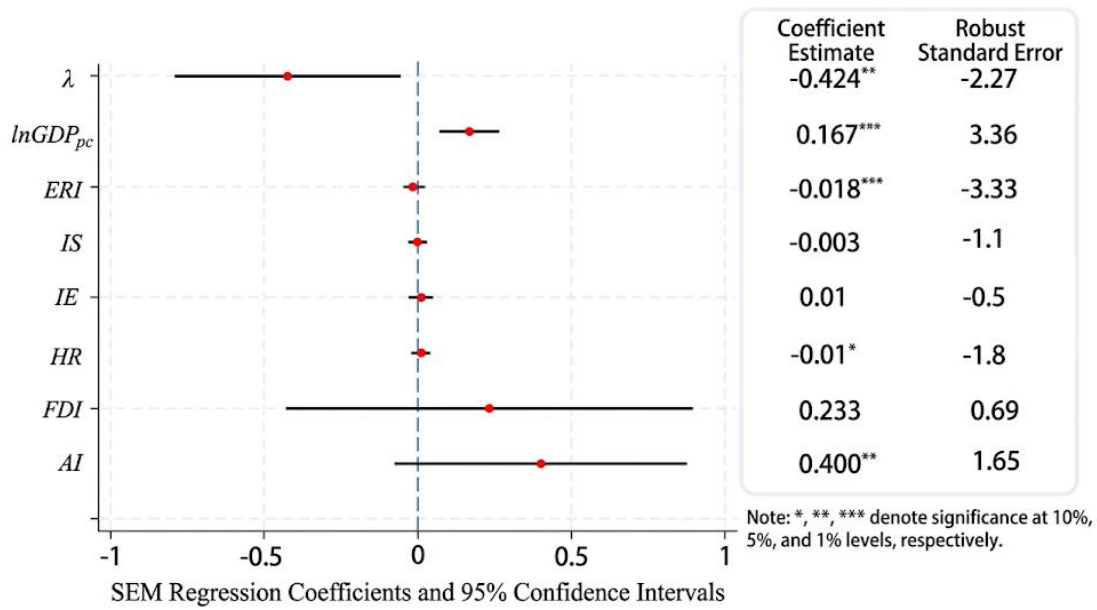


Figure 3. SEM regression coefficients and 95% confidence intervals

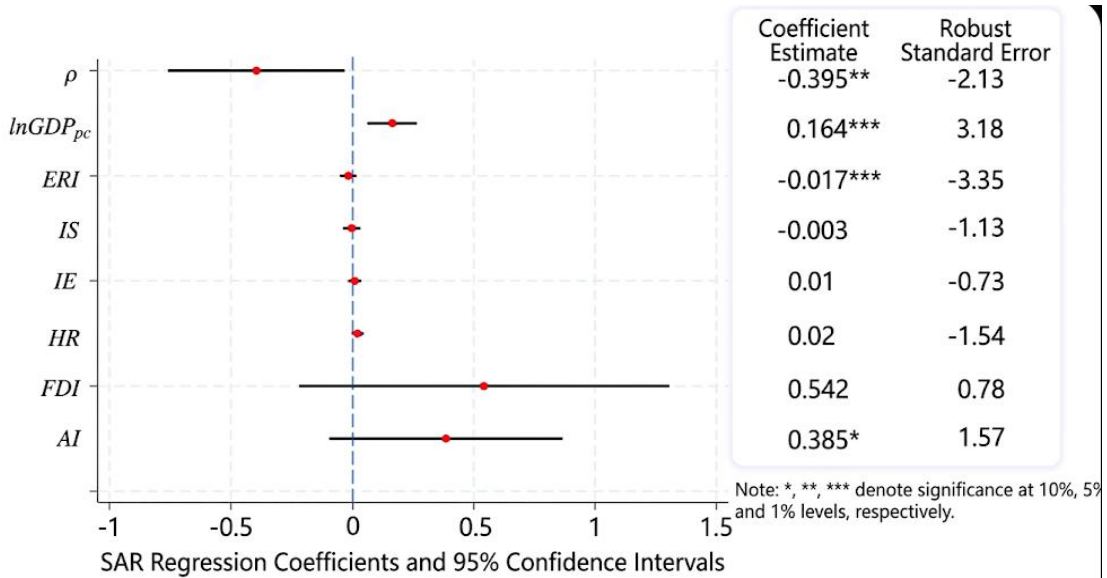


Figure 4. SAR regression coefficients and 95% confidence intervals

The study shows that the development of artificial intelligence has a significant promoting effect on green total factor productivity. The estimation results based on the SEM model and SAR model show that when the spatial spillover effect is not considered, the elastic coefficients of artificial intelligence are 0.400 and 0.385 respectively, confirming that it has a direct promoting effect on local green productivity. The spatial lag term coefficient of artificial intelligence development reaches 0.468, indicating that there is a cross-regional positive spillover effect of technology diffusion, that is, the progress of artificial intelligence in a province can effectively drive the improvement of green productivity in surrounding areas. SDM model regression results are shown in figure 5.

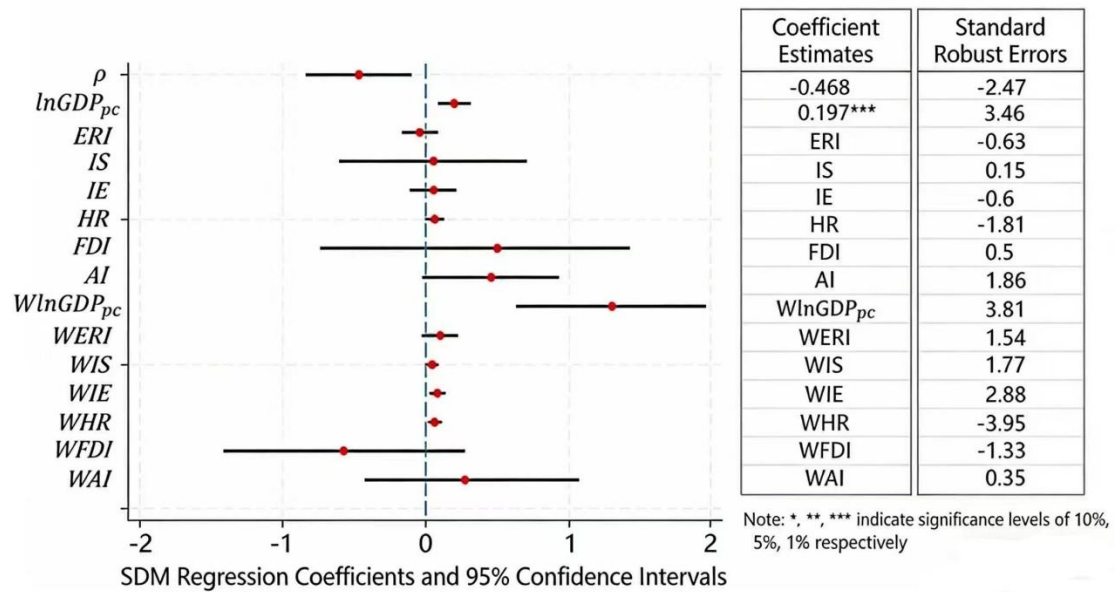


Figure 5. SDM model regression results

By incorporating spatial effects to construct the SDM model, this study calculates the direct effect, indirect effect (spatial spillover effect) and total effect of different influencing factors, and the results are shown in table 1.

Table 1. Spatial effects under the SDM model

Effect Type	Variable	Coefficient	Z Value
Direct Effect	AI	0.457*	1.80
	FDI	4.693	0.41
	HR	-0.001**	-2.36
	IE	-0.003	-1.03
	IS	-0.002	-0.18
	ERI	-0.006	-0.90
	$\ln GDP_{pc}$	0.175***	2.92
Indirect Effect (Spatial Spillover Effect)	AI	0.143*	1.76
	FDI	-8.364	-1.36
	HR	-0.002***	-3.59
	IE	0.001***	2.76
	IS	0.029*	1.91
	ERI	0.072	1.54
	$\ln GDP_{pc}$	0.850***	3.21
Total Effect	AI	0.600**	2.66
	FDI	-3.671	-1.22
	HR	-0.003***	-3.96
	IE	0.004***	2.59
	IS	0.031*	1.78
	ERI	0.065	1.26
	$\ln GDP_{pc}$	1.024***	4.02

Table 1 intuitively reflects the direct effect, spillover effect and total effect of provincial artificial intelligence development on green total factor productivity. Specifically:

The provincial artificial intelligence development level has significant direct effect, spatial spillover effect and total effect on green total factor productivity, with elastic coefficients of 0.457, 0.143 and 0.600 respectively. According to the results, during the observation period, the development of artificial intelligence not only promotes the development of local green productivity but also has a positive impact on surrounding areas. It can form positive spatial spillovers to surrounding provinces through technology penetration, technology diffusion and other ways, and promote the improvement of green total factor productivity in adjacent provinces.

The level of economic development has a significant positive spatial spillover effect on green total factor productivity. Economically developed areas have become the core engine for the improvement of green total factor productivity through technology diffusion, capital flow and consumption demonstration, and their radiation effect is far greater than the local effect. Human capital is significantly negative, showing a systematic inhibitory characteristic. This leads to the concentration of highly educated labor in non-green sectors such as the financial industry and semiconductor industry, and the prominent problem of insufficient environmental technology absorption capacity, which ultimately causes human capital to not be effectively transformed into green innovation momentum.

3. EMPIRICAL ANALYSIS BASED ON K-MEANS CLUSTERING AND DYNAMIC GMM ESTIMATION

To verify the impact intensity of artificial intelligence on green total factor productivity, it is necessary to consider not only the output and input of green productivity but also energy consumption and environmental pollution. Under the condition of mutual matching, it can promote the development of green total factor productivity by artificial intelligence; while under the condition of inconsistency, artificial intelligence may also cause the waste of resources. To explore the impact degree of artificial intelligence on green total factor productivity, this study combines K-Means clustering and two-step GMM estimation to conduct research. The specific models are as follows:

$$\ln\text{GTFP}_{it} = \alpha_1 + \alpha_2 \ln\text{GTFP}_{it-1} + \alpha_3 \ln\text{AI}_{it} + \alpha_4 \ln\text{IS}_{it} + \alpha_5 \ln\text{GDP}_{pc,it} + \alpha_6 \ln\text{ERI}_{it} + \alpha_7 \ln\text{IE}_{it} + \alpha_8 \ln\text{FDI}_{it} + \alpha_9 \ln\text{HR}_{it} + \varepsilon_{it} \quad (5)$$

$$\ln\text{MEC}_{it} = \alpha_1 + \alpha_2 \ln\text{MEC}_{it-1} + \alpha_3 \ln\text{AI}_{it} + \alpha_4 \ln\text{IS}_{it} + \alpha_5 \ln\text{GDP}_{pc,it} + \alpha_6 \ln\text{ERI}_{it} + \alpha_7 \ln\text{IE}_{it} + \alpha_8 \ln\text{FDI}_{it} + \alpha_9 \ln\text{HR}_{it} + \varepsilon_{it} \quad (6)$$

$$\ln\text{MTC}_{it} = \alpha_1 + \alpha_2 \ln\text{MTC}_{it-1} + \alpha_3 \ln\text{AI}_{it} + \alpha_4 \ln\text{IS}_{it} + \alpha_5 \ln\text{GDP}_{pc,it} + \alpha_6 \ln\text{ERI}_{it} + \alpha_7 \ln\text{IE}_{it} + \alpha_8 \ln\text{FDI}_{it} + \alpha_9 \ln\text{HR}_{it} + \varepsilon_{it} \quad (7)$$

Where: ε_{it} is the error term. MEC_{it} and MEC_{it-1} are green technology efficiency and its lagged one-period term respectively. MTC_{it} and MTC_{it-1} are green technological progress and its lagged one-period term respectively.

3.1. K-Means Clustering Analysis

To determine the impact degree of artificial intelligence on green total factor productivity, this study conducts K-Means clustering analysis on multiple variables such as the impact of 30 provinces in China. Through clustering, the core explanatory variables and explained variables are grouped, while retaining information diversity, improving estimation robustness, and reducing the problem of over-identification. The elbow method and silhouette coefficient method are used to determine the optimal number of clusters for the standardized data. As shown in Figure 6:

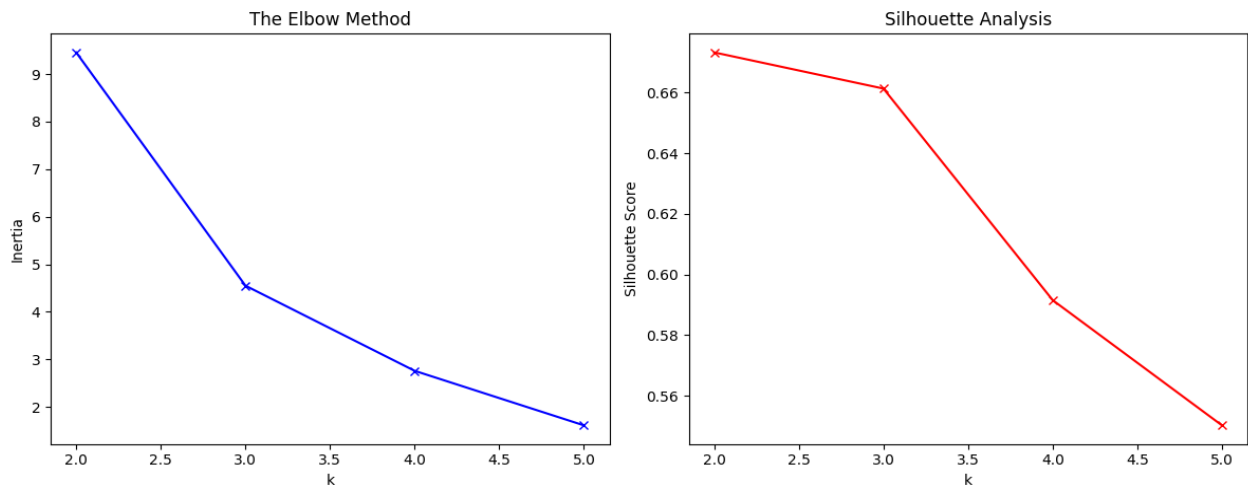


Figure 6. Determination of the optimal number of clusters

The final number of clusters is obtained as follows: First, the R&D investment in artificial intelligence and the leading level of green total factor productivity are higher than the significant level; second, the initial application of artificial intelligence, the level of green total factor production is medium and has not been fully released; third, traditional industries are dominant, artificial intelligence technology is relatively backward, and the growth of green total factor productivity is weak. The correlation distribution map of variables and the clustering grouping of each province are shown in figure 7 and figure 8:

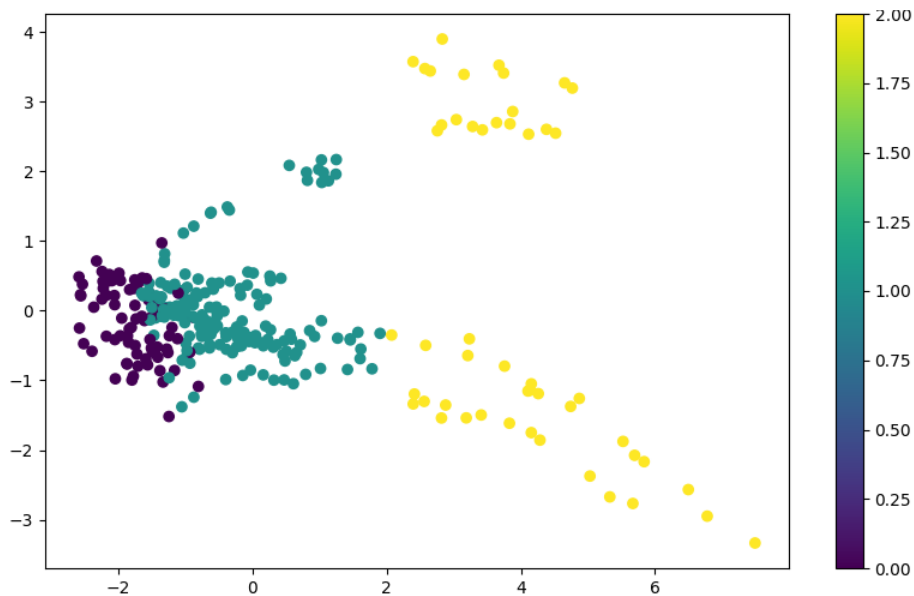


Figure 7. Correlation distribution map of variables

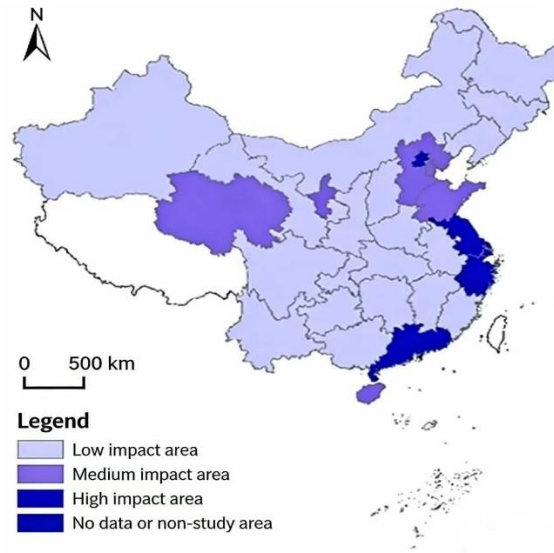


Figure 8. Clustering results of provinces

3.2. Dynamic GMM Estimation

This study adopts two-step system GMM estimation. Figure 9 shows the correlation and significance between artificial intelligence, green total factor productivity, and multiple economic and social related variables. To eliminate the heteroscedasticity problem existing in the short panel, the model is processed with robust standard errors. The regression results are shown in Table 2, where models (1), (2), and (3) are provinces with low, medium, and high levels of artificial intelligence development and green total factor productivity respectively.

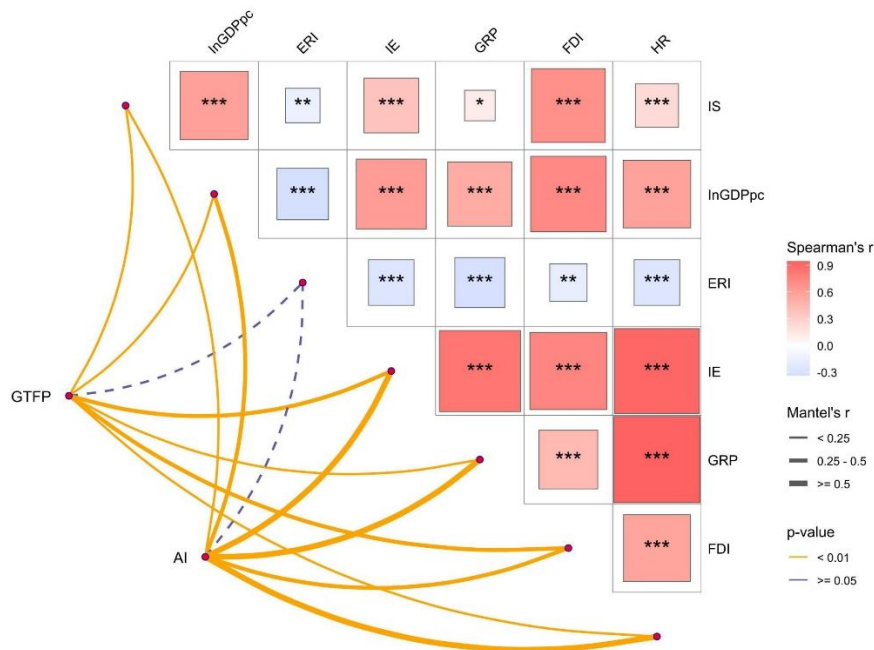


Figure 9. Variable correlation butterfly chart

Both the AR (2) and Hansen tests in models (1) to (4) accept the null hypothesis, indicating that the model has no second-order autocorrelation and the instrumental variables are valid. In models (1) to (4), the coefficients of the lagged one-period green total factor productivity and artificial intelligence are always significantly positive, and this impact is relatively stable, that is, the historical effect has a continuous impact on the current value.

Artificial intelligence has a significant positive impact on GTFP in models (1), (2), and (3), meaning that the development of artificial intelligence can promote the improvement of green total factor productivity, but the impact intensity varies. In model (3), the coefficient is 0.092***, and for each 1% increase, the green total factor productivity will increase by 0.092%. Artificial intelligence helps provinces achieve the reduction, recycling, and harmless treatment of waste, further reducing environmental costs; the increase in government financial investment in artificial intelligence R&D encourages enterprises and scientific research institutions to carry out technological research on the integration of artificial intelligence and green development, and improves the industry-university-research cooperation mechanism to accelerate the transformation and implementation of scientific research achievements.

Models (4) and (5) in the table take green technology efficiency and green technological progress as explained variables respectively. In model (4), the coefficient of artificial intelligence is positive, with a value of 0.015, but not significant. In model (5), the coefficient of artificial intelligence is negative, indicating that artificial intelligence has no significant impact on green technological progress, but foreign investment has a positive impact on the green technology level at the 5% significant level. GMM estimation results are shown in table 2.

Table 2. GMM estimation results

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
	GTFP	GTFP	GTFP	MEC	MTC
lnGTFP(-1)	0.452*** (8.604)	0.455*** (9.999)	0.414*** (7.69)	-	-
lnMEC(-1)	-	-	-	0.015 (0.648)	-
lnMTC(-1)	-	-	-	-	-0.263 (-0.787)
lnAI	0.297*** (10.333)	0.047* (1.662)	0.092*** (2.79)	0.02*** (0.598)	-0.003 (-0.029)
lnIS	-0.004 (-0.203)	0.203** (2.187)	0.028 (0.31)	-0.125* (-1.742)	0.386* (1.681)
lnGDP _{pc}	-0.110** (-2.515)	-1.780 (-0.91)	0.023* (0.51)	-0.002 (-0.048)	0.098 (0.606)
lnERI	-0.005 (-0.153)	-0.925 (-1.01)	-0.006 (-0.38)	-0.017 (-0.833)	-0.074 (-1.622)
lnIE	0.002 (0.248)	-0.014 (-0.969)	0.009 (0.59)	-0.005 (-0.122)	-0.072 (-0.808)
lnFDI	0.001 (0.038)	0.800 (0.92)	-0.112 (-2.59)	-0.02 (-0.321)	0.159** (2.095)
lnHR	0.010 (0.456)	-1.074 (-0.95)	0.0223* (1.09)	0.019 (0.41)	-0.057 (-1.197)
C	0.966*** (18.412)	0.304 (0.772)	1.9578 (2.61)	1.811*** (2.702)	-3.377 (-1.438)
AR(2)	-0.99 (0.322)	-0.97 (0.331)	-0.96 (0.335)	-0.99 (0.323)	-0.71 (0.478)
Hansen	1.59 (0.207)	26.88 (0.108)	23.51 (0.216)	17.2 (0.441)	29.18 (0.033)

Note: *, **, and *** indicate significance levels of 10%, 5%, and 1% respectively. The values in parentheses are robust standard errors. The same below.

3.3. Robustness Test

3.3.1. Result Analysis and Presentation Based on Different Regression Models

The least squares estimation (OLS), fixed effect model (FE), and random effect model (RE) are used for regression again. The results are shown in models (6), (7), and (8) in the following table.

3.3.2. Lagged One-Period of Core Explanatory Variable

Considering the time-lag dynamic effect of the current change in artificial intelligence development level on green total factor productivity, the core explanatory variable is lagged by one period. This reduces the possible two-way causal relationship between artificial intelligence and green total factor productivity, and alleviates the endogeneity problem to a certain extent. The lagged one-period data

factor is consistent with the current logarithm of artificial intelligence, indicating that the data factor not only plays a role in the current period but also improves the development level of green total factor productivity through intertemporal impact, further enhancing the robustness and reliability of the conclusion. Robustness test results are shown in table 3.

Table 3. Robustness test results

Variable	(6) FE	(7) RE	(8) OLS	(9) GTFP
lnGTFP(-1)	-	-	-	0.415*** (-7.629)
lnMEC(-1)	-0.441*** (-7.740)	-0.462*** (-7.629)	-0.399*** (-3.141)	-
lnMTC(-1)	0.100* (-1.663)	0.075 (-1.166)	0.056 (-0.447)	-
lnAI(-1)	-	-	-	0.079** (2.165)
lnAI	0.046*** (-0.78)	0.117** (-2.166)	0.568*** (-13.527)	0.095*** (-2.777)
lnIS	0.464* (-1.708)	0.358 (-1.563)	0.342** (-1.971)	0.032 (-0.348)
lnGDP _{pc}	0.227 (-1.558)	0.643*** (-6.596)	0.311*** (-3.908)	0.008 (-0.182)
lnERI	-0.007 (-0.243)	-0.047* (-1.714)	-0.196*** (-5.228)	-0.009 (-0.749)
lnIE	-0.084* (-1.891)	-0.100** (-2.325)	-0.136** (-2.071)	0.015 (-1.235)
lnFDI	0.936*** (-3.121)	0.113 (-0.877)	-0.382*** (-3.827)	-0.112*** (-4.206)
lnHR	0.035 (-1.003)	0.060* (-1.724)	0.148** (-2.272)	0.025 (-1.126)

4. CONCLUSIONS

This study systematically reveals the geographic evolution patterns and intensity characteristics of AI-driven green TFP by integrating spatial econometric models, clustering algorithms, and dynamic panel analysis. Findings confirm that AI not only accelerates local green development but also promotes interregional collaborative transformation through significant spatial spillover effects. Additionally, K-Means clustering-based empirical grouping confirms AI's central role in enhancing green technology efficiency. However, this study has certain limitations: the spatial weight matrix is primarily based on geographic location, offering a relatively simplistic portrayal of complex dimensions such as economic linkages. Furthermore, while dynamic GMM mitigates endogeneity, it remains insufficient for analyzing subtle dynamic interactions within clustered groups. Future research should focus on constructing multidimensional nested spatial weight matrices to more precisely capture spillover pathways. It should also explore, at the micro-firm level, how AI drives breakthroughs in green technological progress through data utilization and technological iteration. This will provide decision-making references for formulating more precise, differentiated regional AI policies.

REFERENCES

- [1] Tang W, Lan Q. Research On Digital Economy And Green Total Factor Productivity Growth Of China'S Industry And Spatial Effects [J]. The Singapore Economic Review, 2024, 70(07).
- [2] Jia W, Wu S, Yang Y, et al. Growth of Green Total Factor Productivity in China: "Structural Dividend" or "Reform Dividend"? [J]. Growth and Change, 2024, 55(4): e12736-e12736.
- [3] Zhang C, Wang Z, Li Y, et al. Can green credit policy with dual-carbon targets make highly polluting enterprises "green": A micro-analysis of total factor productivity growth [J]. Journal of environmental management, 2024, 367121981.
- [4] Pan Z, Hu Y, Xu R. China's foreign direct investment: driving green growth or seeking pollution havens? Based on the perspective of green total factor productivity [J]. Frontiers in Environmental Science, 2024, 121389876-1389876.
- [5] Feng C, Zhong S, Wang M. How can green finance promote the transformation of China's economic growth momentum? A perspective from internal structures of green total-factor productivity [J]. Research in International Business and Finance, 2024, 70(PA):102356-.
- [6] Yuhuan W. Retraction Note: Digital Economy, Technical Innovation and China's Green Total Factor Productivity Growth [J]. International Journal of Computational Intelligence Systems, 2024, 17(1).

- [7] Gao D, Zhou X, Mo X, et al. Unlocking sustainable growth: exploring the catalytic role of green finance in firms' green total factor productivity [J]. *Environmental science and pollution research international*, 2024, 31(10):14762-14774.
- [8] Weiteng S, Haoran G, Junyao B. Green total factor productivity growth and its driving forces in China's fisheries sector [J]. *Frontiers in Sustainable Food Systems*, 2023, 7.
- [9] Fang L, Ning L. RETRACTED: The threshold effect test of human capital on the growth of agricultural green total factor productivity: Evidence from China [J]. *International Journal of Electrical Engineering & Education*, 2023, 60(1_suppl):3944-3958.
- [10] Yanlin S, Yuwei T, Ge L. Economic growth targets and green total factor productivity: evidence from China [J]. *Journal of Environmental Planning and Management*, 2023, 66(10):2090-2106.