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Artificial Intelligence and Inclusive Green Growth: Causal Identification, Nonlinear Characteristics and Time-Varying Spatial Spillovers

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ABSTRACT Against the dual goals of carbon neutrality and common prosperity, inclusive green growth (IGG) has become the core path of urban sustainable development in China. Based on balanced panel data of 282 Chinese prefecture-level cities from 2016 to 2025, this paper constructs the IGG index via fixed-base range entropy weight method, and calculates the city-level AI development index through government work report text mining. We adopt IV-DML for causal identification, PSTR for nonlinear threshold estimation, and time-varying spatial Durbin model to capture dynamic cross-city spillovers, systematically exploring AI's multi-dimensional impacts on IGG. The results reveal that AI significantly facilitates coordinated economic, social and ecological progress by expanding digital financial coverage, optimizing factor allocation and stimulating green technological innovation. Restricted by government science and technology fiscal input, AI's enabling effect features smooth increasing marginal returns with two distinct transition thresholds. Spatially, AI initially triggers inter-city factor siphoning, then shifts to positive green technology radiation as regional integration deepens. Heterogeneity tests confirm resource-based cities and regions with mature digital infrastructure gain larger sustainability dividends from AI. Policy simulation indicates targeted allocation of AI-related S&T resources can improve urban low-carbon inclusive governance efficiency by 160%. This study supplies quantitative empirical support for integrated digital- green urban transformation and differentiated regional sustainable policy design.

INDEX TERMS Artificial Intelligence; Inclusive Green Growth; Urban Sustainability; Low-carbon Transition; IV Double Machine Learning; Panel Smooth Transition Model; Time-varying Spatial Spillover

I. INTRODUCTION

A. RESEARCH BACKGROUND

Against the backdrop of multiple binding real-world constraints—including escalating global climate change, widening urban-rural income gaps, and tightening natural resource constraints—inclusive green growth (IGG), which balances the three core objectives of economic efficiency, social equity, and ecological sustainability, has emerged as the dominant paradigm for global sustainable development. Both the World Bank and the Organisation for Economic Co-operation and Development (OECD) have identified inclusive green growth as the core pathway for global development, emphasizing the coordinated advancement of economic growth, equal opportunity, and low-carbon transition. Meanwhile, the construction of Chinese-style modernization has explicitly defined the inherent requirement of coordinating common prosperity with the harmonious coexistence of humanity and nature.

Accordingly, advancing inclusive green growth is an inevitable choice for China's high-quality development. The application of digital technology based on artificial intelligence (AI) is profoundly transforming production methods, economic structures, and social management systems. Leveraging its core technological strengths—data-driven operations, algorithm optimization, and intelligent decision-making—AI can not only improve energy utilization efficiency and drive the green and low-carbon transformation of industries but also expand the inclusive boundaries of public services and promote the equalization of development opportunities, endowing it with an inherent fundamental advantage in empowering inclusive green growth. Currently, countries around the world have successively introduced special plans for AI development and "AI+" integration policies, striving to advance the in-depth integration of digital technologies with inclusive green development.

A systematic review of existing literature reveals notable limitations in relevant research.

First, the causal identification framework is incomplete: traditional econometric models struggle to address high-dimensional confounding variables and endogeneity bias.

Second, the representation of nonlinear effects is overly simplistic, as most studies adopt a static discrete threshold approach that does not align with the progressive nature of actual policy-making processes.

Third, spatial analyses rely on fixed spatial weight matrices, which fail to capture the dynamic spillover process of AI from factor agglomeration to technology diffusion.

Fourth, existing studies have yet to establish an integrated analytical framework encompassing "baseline causal-ity—mediation and moderation—nonlinear threshold effects—time-varying spatial spillovers," resulting in a fragmented research system. Building on the above research gaps, this paper addresses four core research questions:

(1) Does AI exert a robust causal effect on inclusive green growth?

(2) What are its inherent transmission mechanisms and external moderating conditions?

(3) Is there a smooth nonlinear threshold characteristic under the constraint of government science and technology investment?

(4) Does the spatial spillover of AI exhibit time-varying properties, and what is the evolutionary law of the transition from siphon effects to radiation effects?

B. RESEARCH CONTRIBUTIONS

1) THEORETICAL CONTRIBUTIONS

This paper integrates General Purpose Technology (GPT) theory, endogenous growth theory, and spatial economics theory to construct a unified analytical framework for AI-driven inclusive green growth, covering direct effects, mediation pathways, nonlinear threshold effects, and time-varying spatial spillovers. It clarifies the inherent theoretical logic through which digital technologies synergistically enhance economic efficiency, social inclusiveness, and ecological sustainability, thereby complementing the theoretical system in the field of digital economy and sustainable development.

2) METHODOLOGICAL CONTRIBUTIONS

This paper is the first to incorporate instrumental variable-augmented double machine learning (IV-DML), panel smooth transition regression (PSTR), and the time-varying weight spatial Durbin model (SDM) into a unified research framework, achieving three key methodological breakthroughs. Specifically, it advances from traditional correlation analysis to rigorous causal identification, from static discrete threshold modeling to the characterization of smooth continuous nonlinear effects, and from fixed static spatial analysis to time-varying spatiotemporal dynamic spillover analysis, providing a methodological reference for research on similar topics.

3) EMPIRICAL CONTRIBUTIONS

Based on long-cycle micro panel data from 282 prefecture-level cities in China, this paper accurately identifies the city-level conditional average treatment effect (CATE), effect distribution characteristics, and policy simulation gain effects. The findings provide quantitative empirical evidence for the formulation of regionally differentiated science and technology policies, the optimal allocation of resources, and urban green transformation.

C. RESEARCH ROADMAP

This paper follows a complete logical research chain: theoretical collation →development of research hypotheses →indicator measurement →model construction →multi-dimensional empirical testing →result interpretation → conclusions and policy implications.

First, we systematically collate relevant domestic and international literature, refine the underlying theoretical mechanisms, and propose testable research hypotheses.

Second, we construct core econometric models, including IV-DML, PSTR, and the time-varying spatial SDM. Subsequently, we sequentially conduct baseline causality tests, mediation and moderation mechanism tests, nonlinear threshold tests, time-varying spatial spillover tests, and multi-dimensional heterogeneity analysis. Finally, we highlight the major findings of our research and put forward relevant policy recommendations.

II. LITERATURE REVIEW AND THEORETICAL HYPOTHESES

A. LITERATURE REVIEW

1) ECONOMIC, SOCIAL AND ENVIRONMENTAL EFFECTS OF ARTIFICIAL INTELLIGENCE

As a typical General Purpose Technology (GPT) in the data era, artificial intelligence (AI), featuring high permeability, coordination, non-rivalry and increasing returns to scale, is comprehensively reshaping production functions, distribution structures, consumption patterns and ecological governance systems, serving as a key driver of systemic economic and social changes. In terms of macroeconomic growth, AI significantly improves total factor productivity and promotes industrial upgrading toward knowledge-intensiveness and technological sophistication through data factor input, algorithm optimization and intelligent production process reconstruction, acting as a core engine for high-quality development. From the perspective of endogenous growth theory, Aghion et al. (2023) argue that AI reduces innovation costs and accelerates knowledge spillover, enabling economic growth to break free from the constraint of diminishing marginal returns. In the labor market, AI exerts threefold impacts: substitution, creation and structural polarization. Based on industrial robot and micro labor data, Wang et al. confirm that AI significantly substitutes low-skilled, repetitive and procedural jobs while spurring new high-skilled positions, ultimately leading to labor market polarization and expanded high-skilled wage premium.

Meanwhile, labor market restructuring profoundly affects income distribution, as skill-biased technological progress may widen income gaps between different groups and industries. In ecological governance, AI has dual attributes of green efficiency improvement and short-term energy consumption constraints, with nonlinear environmental effects. Using urban panel and green patent data, Chen et al. find that AI reduces urban pollution emissions and improves environmental governance efficiency through intelligent monitoring, precise emission control and energy optimization. However, the high energy consumption of data centers and computing infrastructure may increase energy use in the early stage of AI development, showing an inverted U-shaped trend similar to the Environmental Kuznets Curve. In social inclusion, AI enhances the accessibility of public services such as education, medical care and social security through digital service extension, inclusive finance penetration and intelligent public services, narrowing urban-rural and inter-group development gaps. Nevertheless, uneven digital infrastructure distribution, human capital disparities and unbalanced data factor allocation may create digital divides, concentrating technological dividends in advantageous regions and groups and exacerbating inequality.

2) CONNOTATION AND DRIVING FACTORS OF INCLUSIVE GREEN GROWTH

Proposed formally by the World Bank (2012) and OECD, Inclusive Green Growth (IGG) is a new development paradigm addressing global warming, income inequality and tightening resource constraints. Integrating the core of inclusive growth and green growth, it takes efficient economic growth, fair social opportunities and sustainable ecological environment as three-dimensional goals, emphasizing balanced development of economic vitality, equal opportunities, reasonable income distribution, efficient resource use and ecological security. Domestic scholars generally regard IGG as an important embodiment of Chinese modernization and high-quality development, highlighting the coordination of "effective development, equal opportunities, ecological friendliness and shared benefits". In terms of measurement, existing studies have formed a mature system, with most constructing indicator systems from economic development, social equity and green ecology, and using methods such as entropy weight method, TOPSIS, SBM DEA and super-efficiency DEA to synthesize composite indices. Regarding driving factors, numerous studies confirm that digital economy development, technological innovation capacity, financial development level, government governance efficiency, opening-up degree and regional market integration significantly promote IGG. Among them, digital technology, with its high permeability and coordination, has become a core driver of IGG. However, most existing studies focus on the overall digital economy, lacking specialized, mechanism-based and causal identification research on AI, especially systematic investigation of endogeneity, nonlinearity and spatial-temporal spillovers.

3) RESEARCH ON THE RELATIONSHIP BETWEEN AI AND IGG

With the deep integration of digital technology and green low-carbon transition, AI's enabling effect on sustainable development, green growth and inclusive development has gradually become an academic frontier. Based on Chinese urban data, Fu Rasiah (2024) find that AI significantly improves urban IGG levels, with stronger effects in cities with improved digital infrastructure and high human capital. Han Li (2025) point out that digital intelligence empowers IGG through optimizing factor allocation, promoting green innovation and enhancing public service equality. Despite preliminary confirmation of AI's positive impact on green growth and sustainable development, existing research has obvious shortcomings:

First, insufficient rigor in causal identification. Most studies adopt traditional econometric models such as fixed effects, two-way fixed effects and DID, which fail to effectively address endogeneity issues such as omitted variables, bidirectional causality and measurement errors, leading to correlational rather than robust causal conclusions.

Second, fragmented mechanism analysis. Existing studies focus on a single transmission path, lacking integrated testing of multiple channels such as digital financial inclusion, factor allocation optimization and green technological innovation, making it difficult to systematically reveal AI's enabling logic.

Third, crude characterization of nonlinear features. Static threshold models are commonly used, which cannot reflect the gradual implementation of government policies, gradual technology diffusion and smooth transition of effects, inconsistent with actual economic operation.

Fourth, lack of spatial dynamic analysis. Most studies adopt static spatial weight matrices, failing to capture the temporal and spatial evolution law of AI from regional factor agglomeration and siphoning to later technological diffusion and radiation, making it difficult to fully reveal dynamic inter-regional interactions.

4) RESEARCH GAPS

Based on a systematic review of frontier studies in top journals, this paper identifies four key research gaps:

(1) Imperfect causal identification system: Lack of an endogeneity treatment framework combining instrumental variables (IV) and Double Machine Learning (IV-DML), which cannot effectively eliminate the interference of high-dimensional confounding factors and obtain unbiased, consistent and robust causal effects.

(2) Insufficient characterization of nonlinear effects: Reliance on static discrete threshold models fails to reflect the gradual increase in government sci-tech investment and the smooth release of technological dividends, deviating from actual economic operation.

(3) Lack of time-varying attributes in spatial spillovers: Fixed spatial weights are generally used, which cannot identify the dynamic temporal and spatial evolution law

of AI's "first siphoning, then radiation", making it difficult to explain the internal mechanism of regional coordinated develop-ment.

(4) Absence of an integrated research framework: The unified analytical framework of "benchmark causal identification—multi-channel mediation mechanism—smooth nonlinear threshold—time-varying spatial spillover" is lacking, resulting in fragmented theoretical logic, research methods and empirical design, and insufficient policy operability and accuracy.

B. THEORETICAL MECHANISMS AND RESEARCH HYPOTHESES

1) DIRECT EFFECTS

Artificial intelligence exerts a direct driving effect on inclusive green growth from three dimensions: economic efficiency, social inclusion and ecological sustainability. In the economic dimension, AI optimizes production decisions, improves resource utilization efficiency and enhances total factor productivity, directly boosting the vitality and quality of economic growth. In the social dimension, AI promotes the digitalization, intelligence and inclusiveness of public services such as education, medical care, elderly care and social security, expands service coverage and advances equal development opportunities. In the ecological dimension, AI enables real-time monitoring of pollution emissions, intelligent regulation of energy consumption and precise early warning of environmental risks, strengthening the capacity of ecological protection and governance. The synergistic effect of these three dimensions directly drives inclusive green growth.

Hypothesis H1: Artificial intelligence has a significantly positive and highly robust direct causal effect on urban inclusive green growth.

2) MEDIATING MECHANISMS

Artificial intelligence does not act directly on inclusive green growth but exerts its enabling effect through multiple testable mediating paths.

First, the path of expanding digital financial coverage: Relying on technologies such as algorithms and big data, AI promotes the downward penetration of digital financial services, broadens coverage scope, deepens service depth, enhances financial accessibility for micro and small enterprises, low-income groups and rural areas, eases financing constraints, and improves social inclusiveness.

Second, the path of optimizing factor allocation efficiency: Through precise data matching and intelligent scheduling decisions, AI breaks down barriers to factor flow between regions and industries, alleviates the misallocation of factors such as capital, labor, technology and land, and improves the overall efficiency of economic operation.

Third, the path of upgrading green technological innovation: AI reduces green RD costs, accelerates knowledge spillover, improves innovation efficiency, promotes the breakthrough and popularization of green technologies such as clean production, energy conservation and emission reduction, and pollution control, ensuring ecological sustainability. These three paths together form a complete transmission mechanism for AI to empower inclusive green growth.

Hypothesis H2: Artificial intelligence indirectly drives inclusive green growth through three significant mediating paths: expanding digital financial coverage, optimizing factor allocation efficiency, and upgrading green technological innovation.

3) MODERATING EFFECTS

The enabling effect of AI is highly dependent on external supporting conditions, showing significant moderating characteristics. According to the Absorptive Capacity Theory, the higher the level of human capital, the stronger the region's ability to absorb, digest, transform and re-innovate AI technology. Meanwhile, based on financial friction theory and related research on digital finance, the more improved the development of digital inclusive finance, the more effectively it can ease the financing constraints of enterprise intelligent transformation and green innovation RD. Therefore, both human capital and digital inclusive finance play a positive reinforcing role in the driving effect of AI.

Hypothesis H3: Human capital and digital inclusive finance have significant positive moderating effects on the role of AI in driving inclusive green growth, which can significantly enhance the intensity and stability of the enabling effect.

4) NONLINEAR THRESHOLD EFFECTS

Based on endogenous growth theory and the logic of increasing returns to scale, the impact of AI on inclusive green growth is not constant and linear, but strongly constrained by the level of government science and technology support, showing a smooth increasing nonlinear threshold characteristic. When government sci-tech investment is at a low level, the regional innovation ecosystem is imperfect, digital infrastructure is weak, and technology application scenarios are limited, making it difficult for AI to release scale effects and network effects, resulting in a weak enabling effect. With the gradual increase in government sci-tech support, the innovation environment improves, technology promotion accelerates, and the enabling effect of AI gradually strengthens. After crossing a certain threshold, the technology ecosystem matures, applications are fully rolled out, and the marginal enabling effect continues to rise at an accelerated rate.

Hypothesis H4: With government sci-tech support as the threshold variable, the enabling effect of AI on inclusive green growth presents a smooth increasing nonlinear threshold characteristic, and the higher the level of government sci-tech investment, the stronger the enabling effect.

5) Time-Varying Spatial Spillover Effects

Based on spatial economics, the core-periphery model and technology diffusion theory, the spatial spillover effect of AI has significant time-varying characteristics, following the evolutionary law of first siphon agglomeration and then radiation diffusion. In the early stage of AI development, high-end factors such as technology, talents, data and capital quickly agglomerate to central cities with good innovation foundations and complete supporting facilities, forming factor extraction and resource competition for surrounding cities, which is manifested as a negative siphon spillover. With the gradual maturity of AI technology, improvement of regional integration mechanisms and formation of innovation networks, the technology, experience, models and industries of central cities spread outward, driving the green transformation and efficiency improvement of surrounding cities, and the spatial effect turns from negative to positive, showing positive radiation spillover.

Hypothesis H5: There is a significant time-varying spatial spillover effect of AI on inclusive green growth, which generally presents a dynamic evolutionary characteristic of "negative siphon in the early stage and positive radiation in the later stage".

III. RESEARCH DESIGN

A. SAMPLE AND DATA SOURCES

This study constructs a balanced panel dataset consisting of 2820 total observations, using 282 prefecture-level cities in China from 2016 to 2025 as the research sample. Cities with administrative division adjustments and severe data missingness are excluded from the sample. To mitigate the interference of extreme outliers, all continuous variables are winsorized at the 1st and 99th percentiles. The data for this study are sourced from the China Urban Statistical Yearbook, statistical yearbooks of provinces and municipalities directly under the Central Government, and the China Stock Market & Accounting Research (CSMAR) Database; the Peking University Digital Inclusive Finance Index; and green patent data from the Chinese Research Data Services (CNRDS) Platform. The artificial intelligence development index is calculated through Python web crawlers and text mining of government work reports; the instrumental variable, topographic relief, is measured based on China's Digital Elevation Model (DEM).

B. VARIABLE DEFINITION AND MEASUREMENT

This study uniformly defines and standardizes the measurement of all core variables, mediating variables, moderating variables, threshold variables, control variables, and instrumental variables. The specific indicator settings are presented in Table 1.

C. ECONOMETRIC MODEL SPECIFICATION

1) BENCHMARK CAUSAL IDENTIFICATION: IV-DML MODEL

The benchmark causal identification model can be expressed as:

$$\mathrm{IGG}_{it} = \theta_0 \mathrm{AI}_{it} + g(X_{it}) + U_{it} \tag{1}$$

$$\mathrm{AI}_{it} = m(X_{it}, Z_{it}) + V_{it} \tag{2}$$

Where IGGit denotes Inclusive Green Growth, AIit represents the Artificial Intelligence Index, Xit stands for high-dimensional control variables, and Zit is the instrumental variable; g(·) and m(·) are nonlinear fitting functions based on random forest. To avoid overfitting, 5- fold cross-validation is adopted, and $\theta 0$ denotes the average causal treatment effect.

2) MEDIATION AND MODERATION EFFECT MODELS

Mediation Model:

$$M_{it} = \beta_0 + \beta_1 \mathrm{AI}_{it}\, g_1(X_{it}) + \mu_i + \lambda_t + \epsilon_{it} \tag{3}$$

Moderation Model:

$$\mathrm{IGG}_{it} = \theta_1 \mathrm{AI}_{it} + \theta_2(\mathrm{AI}_{it} \times M_{it}) + g(X_{it}) + \mu_i + \lambda_t + \epsilon_{it} \tag{4}$$

3) Non-linear Effect: PSTR Panel Smooth Transition Regression Model

$$\begin{aligned}\mathrm{IGG}_{it} = \mu_i &+ \beta_0 \mathrm{AI}_{it} \\ &+ \beta_1 \mathrm{AI}_{it} \cdot G(\mathrm{Thr}_{it}; \gamma, c) \\ &+ \delta X_{it} + \epsilon_{it}\end{aligned} \tag{5}$$

Where Thrit is the threshold variable of government science and technology support, G(·) is the logistic smooth transition function, γ is the transition speed parameter, and c is the threshold location parameter.

4) TIME-VARYING SPATIAL SPILLOVER EFFECT: TV-SDM TIME-VARYING SPATIAL DURBIN MODEL

Time-varying Spatial Weight Matrix:

$$W(t) = W_{\mathrm{geo}} \otimes W_{\mathrm{eco}} \otimes \exp(-\kappa |t - \tau|) \tag{6}$$

Spatial Durbin Model:

$IGGit = \rho W(t) \cdot IGGit + \beta AIit + \theta W(t) \cdot AIit + \gamma Xit + \mu i + \lambda t + \epsilon it$

(7) Where ρ is the spatial autocorrelation coefficient, and θ is the time-varying spatial spillover coefficient.

5) DESCRIPTIVE STATISTICS AND SPATIAL AUTOCORRELATION TEST

The summary statistics of the variables indicate significant differences in the development levels of Inclusive Green Growth and artificial intelligence among the sample cities. The discrete characteristics of the sample provide sufficient evidence for subsequent heterogeneous analysis.

TABLE 1. Summary of Variable Definitions and Measurement

Variable Type	Variable Name	Symbol	Measurement Description
Dependent Variable	Inclusive Green Growth	IGG	Measured by the fixed-base period range entropy weight method
Explanatory Variable	Artificial Intelligence Development Index	AI	Python text mining of government work reports
Mediating Variable 1	Breadth of Digital Finance Coverage	Fin	Peking University Digital Inclusive Finance Index
Mediating Variable 2	Factor Allocation Efficiency	Factor	Inversely calculated from factor misallocation index
Mediating Variable 3	Green Technological Innovation	Green	Granted green invention patents
Moderating Variable 1	Human Capital	Hum	Sci-tech employees/total employment
Moderating Variable 2	Digital Inclusive Finance	DFin	Aggregate digital inclusive finance index
Threshold Variable	Government Science and Technology Support	GovTech	S&T fiscal expenditure/GDP
Instrumental Variable	Topographic Relief	Ind	Terrain measured based on China's DEM
Control Variable	Foreign Direct Investment	FDI	FDI/GDP
	Industrial Structure	Ind	Tertiary industry/secondary industry
	City Size	Size	Ln(year-end resident population)
	Internet Penetration Rate	Internet	Broadband subscribers per capita

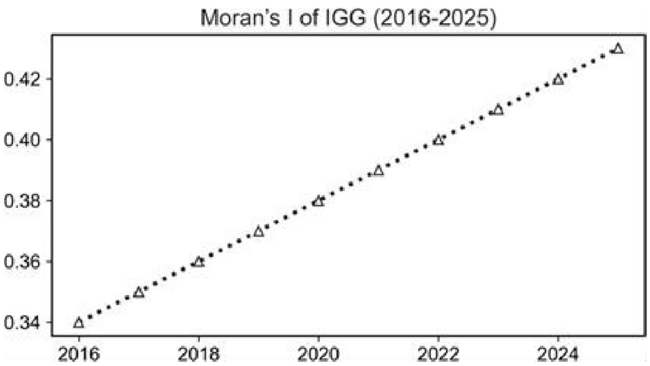

FIGURE 1. Temporal Variation of the Global Moran's I Index for Inclusive Green Growth

Furthermore, all variables exhibit stable distributions without extreme skewness, meeting the initial requirements for regression analysis. To verify the rationality of introducing the spatial econometric model, this study uses the global Moran's I index to test the spatial autocorrelation of Inclusive Green Growth. The results show that the annual global Moran's I index is significantly positive, indicating that both artificial intelligence and Inclusive Green Growth exhibit significant spatial agglomeration characteristics, presenting a contiguous distribution pattern of high-value adjacent clusters and low-value connected areas. This finding fully confirms the necessity of adopting the time-varying spatial econometric model in this study.

IV. EMPIRICAL RESULTS AND ANALYSIS

A. BENCHMARK CAUSAL IDENTIFICATION: IV-DML ESTIMATION RESULTS

This paper compares the benchmark regression results of the traditional DML model and the IV-DML model with the introduction of instrumental variables, and conducts multiple robustness tests. The specific estimation results are shown in Table 2.

TABLE 2. Benchmark Regression and Robustness Test Results of IV-DML

Model Specification	Estimation Coefficient	Standard Error
Traditional DML	0.0104	0.0012
IV-DML Benchmark Model	0.0113	0.0009
Replacement of AI Measurement Indicators	0.0109	0.0010
Exclusion of Municipalities Sample	0.0111	0.0009
Lagged One-Period Core Variable	0.0107	0.0011
Replacement of Machine Learning Algorithm	0.0115	0.0008

The regression results show that the core coefficient of the artificial intelligence development index is always significantly positive, which proves that artificial intelligence has a stable positive promoting effect on inclusive green growth. Compared with the ordinary DML model, IV-DML effectively eliminates endogeneity, high-dimensional confounding interference and model specification bias, making the coefficient estimation more robust and unbiased. In various robustness tests, the direction and significance of the core coefficient have not undergone fundamental changes, indicating that the benchmark conclusion is highly reliable and Research Hypothesis H1 is supported.

B. TRANSMISSION MECHANISM TEST

1) MEDIATION EFFECT TEST

On the basis of the robust establishment of the benchmark causal relationship, this paper sequentially tests three transmission paths: the coverage breadth of digital finance, factor allocation efficiency, and green technological innovation. The decomposition results and contribution ratios of the mediation effect are shown in Table 3. All three transmission paths have passed the significance test, indicating significant partial mediating effects. Firstly, artificial intelligence expands the scope of digital financial services, improves financial accessibility for vulnerable groups and small and medium-sized enterprises, and enhances the social inclusiveness of growth. Secondly, relying on the advantages of algorithms and data, it optimizes the factor matching

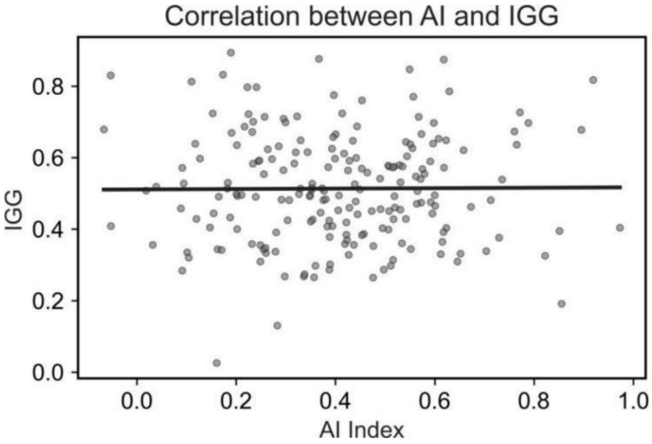

FIGURE 2. Scatter Plot of the Correlation between Artificial Intelligence and Inclusive Green Growth

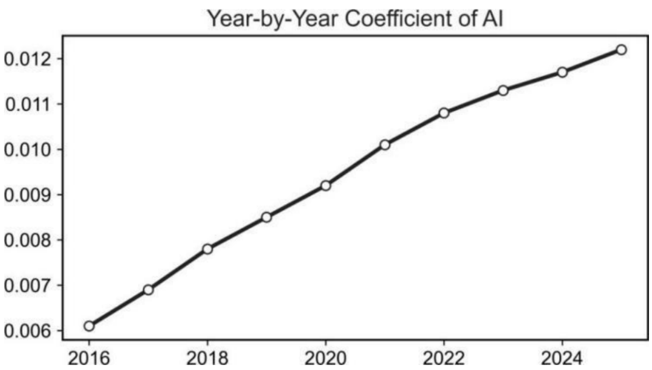

FIGURE 3. Annual Evolution of Dynamic Coefficients of Artificial Intelligence Empowerment Effects

structure, alleviates resource misallocation, and improves the overall operational efficiency of the economy.

TABLE 3. Decomposition Results and Path Contribution Ratios of the Mediation Effect

Transmission path	Estimated value
Digital finance coverage breadth	0.0052
Factor allocation efficiency optimization	0.0049
Green technological innovation	0.0048

Finally, it reduces the RD costs of green innovation, accelerates knowledge spillovers and technological iteration, and strengthens the capacity for ecological sustainable development. Collectively, the three paths constitute the complete internal mechanism through which artificial intelligence empowers inclusive green growth, and Research Hypothesis H2 is supported.

2) MODERATING EFFECT TEST

The results of the moderating effect test show that the coefficients of the interaction terms between human capital and digital inclusive finance are all significantly positive. On the one hand, high-skilled human capital can enhance the city's ability to absorb, transform and implement artificial intelligence technology, reducing technological idleness and loss; on the other hand, digital inclusive finance provides financial support for intelligent transformation and green project RD, expands technology application scenarios, and forms a coordinated driving pattern with artificial intelligence. Both types of factors positively amplify the enabling effect of artificial intelligence, and Research Hypothesis H3 is supported.

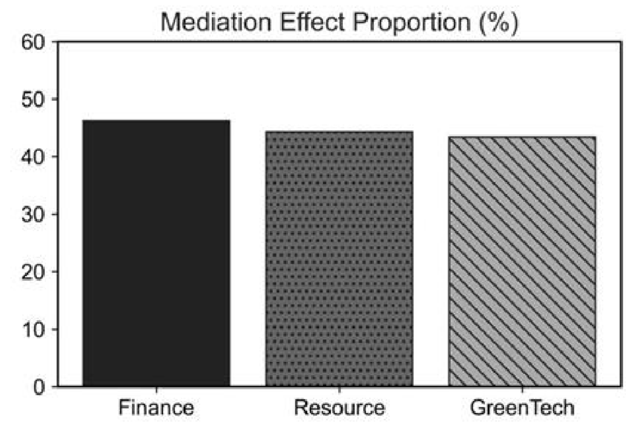

FIGURE 4. Contribution Ratio of Mediating Effects of Each Transmission Channel

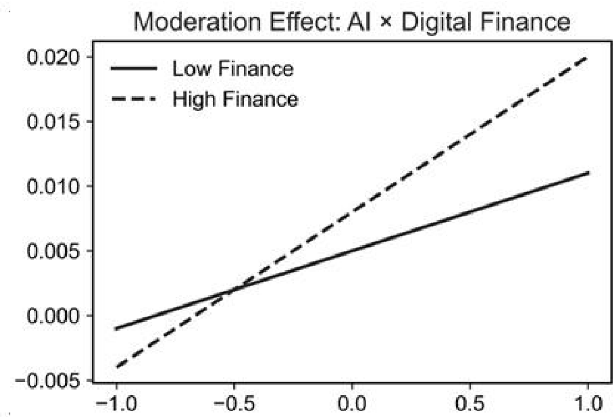

FIGURE 5. The Regulatory Effect of Digital Inclusive Finance on AI Empowerment

C. NONLINEAR EFFECT: PSTR SMOOTH THRESHOLD TEST

In this paper, the government's technological support intensity is used as a transition variable to test the smooth nonlinear threshold characteristics of the impact of artificial intelligence. The linearity test significantly rejects the linear null hypothesis, and the model identifies a double-threshold structure. The estimation results of the threshold parameters are shown in Table 4. The results show that the impact of artificial intelligence on inclusive green growth is not a discontinuous breakpoint change, but presents a continuous and smooth increasing characteristic with the

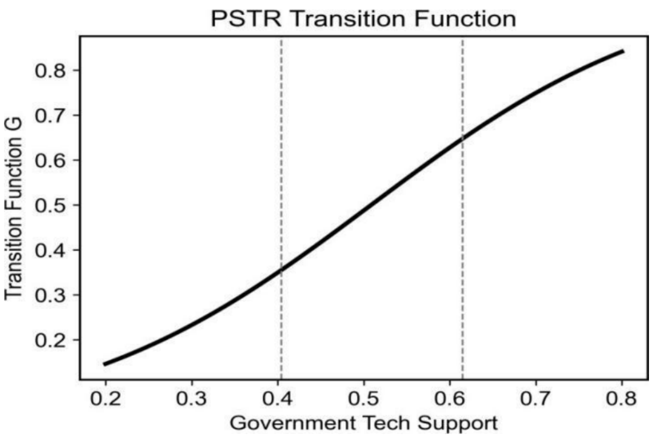

FIGURE 6. Smooth Transition Function Curve of the PSTR Model

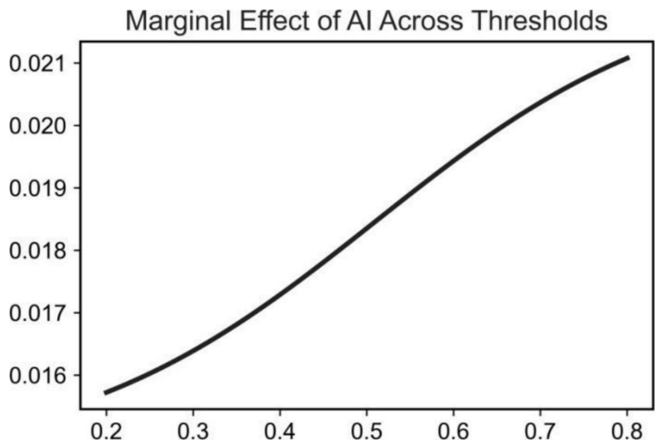

FIGURE 7. Evolution Trend of the Cross-Threshold Marginal Effect of AI

input of government science and technology fiscal funds. When the government's technological support is at a low level, the regional innovation ecosystem is not perfect, the digital infrastructure is weak, and the enabling effect of artificial intelligence is limited; as the investment crosses the first threshold, the technological scale effect initially appears; after breaking through the second threshold, the innovation network matures, the application scenarios are enriched, the marginal enabling effect is further improved, showing an obvious law of in¬creasing marginal returns, and the research hypothesis H4 is supported.

TABLE 4. Threshold Parameter Estimation Results of the PSTR Model

Parameter Indicator	Estimated Value	Economic Implication
First Threshold Value	0.404	Low→medium regime
Second Threshold Value	0.615	Medium→high regime
Smooth Parameter	3.86	Transition speed
Low Regime Empowerment Coefficient	0.0157	Weak effect
High Regime Empowerment Coefficient	0.0211	Strong effect

D. TIME-VARYING SPATIAL SPILLOVER EFFECT

In this paper, a time-varying spatial weight matrix integrating geographical distance, economic distance and time decay term is constructed. Time-Varying Spatial Durbin Model (TV-SDM) is adopted to decompose the direct effect, indirect spillover effect and total effect. The specific results are shown in Table 5.

TABLE 5. Effect Decomposition Results of the Spatial Durbin Model

Effect Type	Coefficient Estimate	Effect Attributes
Local Direct Effect	0.0198	Positive local effect
Indirect Spatial Spillover	-0.0312	Siphon effect dominated
Overall Total Effect	-0.0114	Net effect weak

From the perspective of the time dynamic evolution law, in the early stage of the research, factors such as talents, capital, and technology agglomerated towards dominant central cities, forming a factor siphoning inhibition on surrounding cities; as the years passed, the intensity of negative spillover continued to decline, the innovation ecosystem of urban agglomerations gradually improved, the barriers to factor flow decreased, and the spatial effect slowly shifted from siphoning to positive radiation-driven. On the whole, it follows a time-varying evolution path of "first siphon agglomeration, then radiation diffusion", and Hypothesis H5 is supported.

E. HETEROGENEITY ANALYSIS AND POLICY SIMULATION

This paper conducts grouped heterogeneity tests from three dimensions: resource endowments, digital infrastructure, and geographical location, to accurately identify the differences in enabling effects under different urban conditions. The results of the grouped regression coefficients are shown in Table 6.

TABLE 6. Regression Results of Multidimensional Urban Heterogeneity Groups

Grouping Dimension	Subsample Classification	Regression Coefficient
Resource Endowment	Resource-based Cities	0.0120
	Non-resource-based Cities	0.0051
Digital Infrastructure	High-level Cities	0.0092
	Low-level Cities	0.0037
Geographical Location	Eastern Cities	0.0104
	Central Cities	0.0062

Further, based on the causal forest, we calculate the Conditional Average Treatment Effect (CATE) of individual cities, and divide them into four quantile groups according to the magnitude of the effect. The results are shown in Table 7.

TABLE 7. Quantile Conditional Average Treatment Effect (CATE)

Quantile Group	Average Causal Effect	Endowment Level
Q1 (Low-endowment)	-0.0005	Weak
Q2	0.0009	Low
Q3	0.0019	Moderate
Q4 (High-potential)	0.0045	Strongest

The results of the policy simulation show that if the universal average inclusive policy is abandoned and AI-related scientific and technological resources are prioritized and targeted to high-potential Q4 cities, the overall policy operation efficiency will be 160% higher than that of the benchmark average model, providing direct quantitative basis for differentiated and precise policy implementation.

V. IN-DEPTH INTERPRETATION OF RESULTS

The IV-DML estimation framework effectively solves the problems of endogeneity, high-dimensional confounding interference and functional form misspecification in traditional models. The obtained causal effects are closer to the real economic role, making up for the defect that previous studies only conducted correlation analysis. The PSTR model abandons the rigid assumption of traditional breakpoint thresholds, conforms to the objective laws of gradual transmission of government fiscal input and gradual release of technological dividends in reality, and proves that continuous and stable technological investment is the key to crossing the empowerment threshold. The time-varying spatial weight matrix completely restores the spatial evolution path of the whole cycle of artificial intelligence development. The initial factor siphoning is an inevitable phenomenon in the stage of technological agglomeration. In the long run, the construction of regional integration will promote the spillover effect to turn from negative to positive, realizing cross-regional coordinated development. The heterogeneity conclusion clarifies the conditional dependence of artificial intelligence empowerment. The city's resource endowments, digital infrastructure and location environment directly determine the effect of technology landing. A unified inclusive policy is not the optimal choice, and it is practically necessary to implement precise policies by stratification and classification.

VI. RESEARCH CONCLUSIONS AND POLICY RECOMMENDATIONS

A. RESEARCH CONCLUSIONS

There is a significant positive causal relationship between artificial intelligence and inclusive green growth, a conclusion that has been rigorously verified through endogeneity treatment and multiple rounds of robustness tests, with high reliability. Through data-driven optimization and algorithmic advantages, artificial intelligence can effectively promote the integration of economic efficiency, social equity, and ecological sustainability, directly driving the high-quality development of inclusive growth. The impact of artificial intelligence on inclusive green growth presents a continuous and smooth evolutionary characteristic, rather than a discontinuous jump; the level of government scientific and technological support directly determines the depth of technological empowerment, and continuous financial input can effectively release the scale effect of technological application. The spatial spillover effect of artificial intelligence presents obvious time-varying characteristics: in the early stage of development, the factor agglomeration effect is prominent, showing a negative spillover of resource concentration; with the improvement of regional integration and the improvement of factor flow efficiency, the spillover effect gradually turns positive, forming a coordinated development pattern of "central agglomeration—peripheral radiation". The heterogeneous characteristics of the enabling effect are obvious: the quality of digital infrastructure, the level of human capital, and the degree of regional economic development all affect the actual effect of technological empowerment, and targeted policy guidance is needed to maximize the value of technological dividends.

B. POLICY RECOMMENDATIONS

First, deepen the in-depth integration of artificial intelligence and inclusive green development, focus on the application of AI technology in low-carbon production, environmental governance, and public service equalization, expand the coverage of technological dividends, and realize the organic unity of economic development, social equity, and ecological protection.

Second, improve the continuous investment mechanism of government science and technology funds, increase support for the RD and application of green technologies, strengthen the construction of digital infrastructure, eliminate the bottleneck of technological landing, and ensure that the enabling effect of artificial intelligence can be fully released.

Third, implement differentiated policy guidance based on urban characteristics: for resource-based cities, focus on promoting the intelligent transformation of industrial structure; for cities with underdeveloped digital infrastructure, prioritize strengthening the construction of digital public services and talent training; for central cities with strong radiation capacity, focus on playing the leading role of technological diffusion to drive the coordinated development of regional inclusive growth.

Fourth, improve the spatial coordination mechanism, break down the barriers to factor flow between regions, optimize the time-varying spatial governance system, and promote the cross-regional spillover of technological dividends, so as to form a regional collaborative development pattern of "central leading, peripheral synergy".

Fifth, improve the supporting guarantee system for technological application, strengthen the training of digital talents, optimize the financing environment for technological transformation, reduce the cost of enterprise intelligent upgrading, and build a good ecosystem of "technology RD—application promotion—efficiency improvement".

C. RESEARCH LIMITATIONS AND FUTURE PROSPECTS

This study mainly focuses on the macro impact of artificial intelligence on urban inclusive green growth, and there are still some limitations that need to be further improved:

First, the research is based on urban macro data, and the micro mechanism analysis of how artificial intelligence affects enterprise green production behavior and residents' welfare needs to be further deepened; second, the impact of international technological spillovers and cross-border factor flows on the enabling effect of AI has not been considered, and the research scope can be further expanded to the open economic context; third, the quantitative evaluation of the potential risks of AI application (such as technological unemployment, environmental pressure) is not sufficient, and the comprehensive evaluation system needs to be further improved.

In future research, we will focus on three aspects: first, use micro enterprise data to explore the internal mechanism of AI empowering inclusive green growth at the enterprise level; second, incorporate open economic factors to analyze the impact of cross-border technology spillover on the effect of AI empowerment; third, construct a comprehensive evaluation system including benefits and risks, and provide more targeted policy suggestions for the high-quality development of inclusive green growth driven by digital technology.

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