Intelligence-Green Synergy: A New Pattern of Urban Green High-Quality Development Driven by Artificial Intelligence

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Abstract. As the underlying foundation of the new technological revolution, computer technology has become a core driver of urban green high-quality development integrated with artificial intelligence applications. Based on panel data of 282 Chinese prefecture-level cities from 2007 to 2023, this paper regards the pilot policy of the National New Generation Artificial Intelligence Innovation and Development Pilot Zone as a quasi-natural experiment, and employs a staggered DID model to explore the effect and mechanism of computer technology-driven AI on urban green high-quality development.The results show that advances in computer technology and AI significantly boost urban green high-quality development, which remains robust after parallel trend, PSM-DID and SUTVA tests. Mechanically, computer technology facilitates urban green transformation by promoting green innovation and industrial upgrading. Advancing the R&D and application of computer and AI technologies and embedding them into green innovation and industrial optimization is essential for promoting urban green high-quality development.

Keywords: Artificial intelligence; High-quality green development of cities; Green technological innovation; Industrial structure upgrading

1 Introduction

China's economic development is undergoing a critical transition to qualitative improvement. The past urbanization path relying on excessive resource input and environmental costs has resulted in low energy efficiency, restricting urban sustainable development. The 2025 Central Economic Work Conference arranged the acceleration of green and low-carbon transformation, providing guidance for low-carbon urban development.

Artificial intelligence, as a core driver of the new technological revolution, has become a key engine of urban high-quality development. The iterative upgrade of computing power and continuous model optimization provide foundational support for AI deployment, enabling its deep integration into green production. This mitigates the high

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energy consumption and emissions bottlenecks of traditional industries, fostering coordinated economic growth and ecological protection. This paper explores the mechanism and policy effects of AI–computer technology synergy on urban green high-quality development, verifies whether computer-enabled AI drives development, offering empirical evidence for intelligent green policy formulation.

2 Literature Review

2.1 The Relationship between Artificial Intelligence and Urban Green Development

Total factor productivity growth is the endogenous driver of long-term economic growth, and green transformation. AI supported by computer technology reshapes the aggregate production function, improves technical efficiency, and reduces energy consumption and carbon emissions, thereby directly enabling green growth. Accordingly, existing studies confirm that smart city construction and AI application exert a significant promotional effect on regional green high-quality development. Based on panel data spanning 2004–2020, the smart city pilot policy has been verified to effectively enhance urban green total factor productivity[1]. Further empirical evidence at the provincial and firm levels demonstrates that AI positively boosts total factor productivity[2]. Moreover, AI development optimized by computer algorithm can advance urban green high-quality development by improving carbon emission efficiency[3].

2.2 Influence Mechanism of Artificial Intelligence

In line with Neo-Schumpeterian growth theory, technological progress underpins long-run economic growth, and computer technology provides core computing power and algorithm for innovative AI applications, significantly improving innovation efficiency via machine learning and simulation algorithms. It accelerates the application of green technologies in clean energy, pollution control and circular economy, and increases R&D success rates[4]. Computer-based intelligent monitoring systems promote the green renovation of traditional production processes, upgrade production cleanliness and accelerate the intelligent deployment of emission-reduction technologies to improve industrial productivity[5].

Based on the industrial structure evolution theory, AI further facilitates green transformation via industrial structure upgrading. Through substitution and creation effects, AI reshapes labor markets and industrial ecology, promoting the advanced and green evolution of industrial structure[6]. Meanwhile, AI contributes to industrial rationalization by promoting industrial upgrading and restraining the deviation of industrial structure equilibrium[7]. Along with industrial optimization, enterprises achieve automated and low-carbon production, reducing resource waste and ecological damage[8].

3 Theoretical Mechanism and Research Hypotheses

3.1 Theoretical Model Setting

Based on Acemoglu & Restrepo[9], we assumes that the production function of final goods adopts CES form:

$$Y=\left(\int_{j\in\Omega} y_j^{\frac{\varepsilon-1}{\varepsilon}} dj\right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{1}$$

Where Ω denotes the set of industries,y_j represents the output of sector j, ε is the elasticity of substitution. The total output follows the Cobb-Douglas form: $y_j=\gamma^{-\gamma}(1-\gamma)^{-1}[E(T_j,M_j)]^{\gamma}x_j(T)^{1-\gamma}$, where $E(T_j,M_j)$ refers to the effective input of environmental resources, which is a function of technological innovation T_j and industrial structure M_j,satisfying $\partial E/\partial T>0$. $x_j(T)$ is the demand for intermediate good. Final goods producers pursue profit maximization, so the net output of final goods producers can be expressed as:

$$y_j=\frac{2-\gamma}{1-\gamma}E(T_j,M_j) \tag{2}$$

3.2 Influence Mechanism of Artificial Intelligence on Urban Green High-Quality Development

3.2.1 Artificial Intelligence and Technological Innovation.

Assume that the cost function of technological innovation C_k is correlated with the innovation success probability ρ . Following Aghion[10], $C_k=1-\left(1-\frac{\psi_k}{\lambda}\right)^{\frac{1}{\rho}}$, where ψ_k is the basic innovation efficiency parameter. Let A denote the development level of AI, and its influence on λ follows the Logistic function:

$$\lambda(A)=\frac{m}{1+\nu e^{-kA}} \tag{3}$$

In Equation (3), m is the theoretical upper limit of AI and k is the diffusion rate.set $\rho=\zeta\lambda^{\eta}T^{1-\eta}$.Differentiation of Equation (3) yields the impact of AI on technological innovation:

$$\frac{\partial T_j}{\partial A}=\frac{T}{(1-\eta)\lambda}\times\frac{\eta\ln(1-\frac{\psi_k}{\lambda})^{\eta}-\lambda\psi_k}{\ln(1-\frac{\psi_k}{\lambda})}\times\frac{mk}{1+\nu e^{-kA}} \tag{4}$$

3.2.2 Artificial Intelligence and Industrial Structure.

Industrial structure is measured by the output share of each sector in total output:

$$M_j=\left(\frac{P_j y_j}{P_Y Y}\right)^{\omega} \tag{5}$$

Differentiating Equation (5), the impact of artificial intelligence on industrial structure can be derived as:

$$\frac{\partial M_j}{\partial A}=\frac{M_j}{Y}\left(1-\frac{y_j}{Y}\frac{\varepsilon}{\varepsilon-1}\right)\frac{\partial y_j}{\partial T}\frac{\partial T}{\partial A} \tag{6}$$

3.2.3 Artificial Intelligence and Urban Green High-Quality Development. Therefore, urban green high-quality development is defined as the weighted sum of marginal output efficiency of environmental resource factors across the whole society:

$$U=\sum \left[\pi_j\times\frac{\partial y_j}{\partial E_j}\right] \tag{7}$$

In Equation (7), where π_j is the weight coefficient. Combining Equation (2) (7), differentiation obtains:

$$\frac{\partial U}{\partial A}=\sum \left[\pi_j\tau\lambda^{\tau}\frac{2-\gamma}{1-\gamma}\lambda^{\tau-1}(MT)^{\tau-1}U(E_j)^{\tau-1}\times\frac{mk}{1+ve^{-kA}}\times\frac{\partial U}{\partial E}\times\left(\frac{\partial M}{\partial\lambda}T+\frac{\partial T}{\partial\lambda}M\right)\right] \tag{8}$$

It can be seen from Equation (4) that $\partial T_j/\partial A>0$, and Equation (6) indicates $\partial M_j/\partial A>0$. All items in Equation (8) are positive, so $\partial U/\partial A>0$.

Based on the above theoretical derivation, three core research hypotheses are proposed:

H1: AI can significantly improve the level of urban green high-quality development.

H2: AI promotes urban green high-quality development by stimulating green technological innovation.

H3: AI advances urban green high-quality development by optimizing industrial structure.

4 Research Design

4.1 Empirical Model Construction

The enabling effect of AI on green high-quality development relies heavily on technological innovation supply, infrastructure support. The National New Generation Artificial Intelligence Innovation and Development Pilot Zone policy accelerates the R&D, transformation and application of AI via pilot layout, policy support, which provides a quasi-natural experiment for identifying the causal effect. This paper adopts the progressive DID model to evaluate the impact of artificial intelligence on urban green high-quality development.

$$green-dev_{cn}=\alpha_0+\alpha_1 AI_{cn}+\sum_{j=1}^{t}\phi_j X_{cn}+u_c+\lambda_n+\varepsilon_{cn} \tag{9}$$

Where green-dev$_{cn}$ denotes the green high-quality development level of city c in year n; the core explanatory variable represents AI_{cn}; a set of control variables are included X_{cn}; u_c and λ_n denote city fixed effects and year fixed effects respectively, and ε_{cn} is the random disturbance term.

4.2 Variable Selection

1.Explained Variable: Urban green high-quality development (green-dev). Referring to Li&An[11], urban green total factor productivity is selected as the indicator, measured via the SBM model with undesirable outputs and the GML index. The specific evaluation indicators are shown in Table 1.

Table 1. Evaluation Indicator System

Primary Indicator	Secondary Indicator	Tertiary Indicator
Input Indicators	Labor Input	Urban year-end employed population (10,000 persons)
	Capital Input	Urban fixed asset capital stock (10,000 yuan)
	Energy Input	Annual urban electricity consumption (10,000 tons of standard coal)
Desirable Output	Economic Development	Urban gross domestic product
Undesirable Output	Pollution Emission	Industrial sulfur dioxide emissions (ton)
		Industrial wastewater emissions (10,000 tons)
		Industrial soot and dust emissions (ton)

2.Explanatory Variable: Artificial intelligence development level. This paper takes the National New Generation Artificial Intelligence Innovation and Development Pilot Zone policy as the proxy indicator. the Ministry of Science and Technology identified 18 demonstration cities during 2019–2022, aiming to lead integrated development of AI and computer technology. For treatment cities, the value is assigned 1 in the pilot year and subsequent years, and 0 in previous years; The control group are assigned 0. This paper excludes county-level cities and prefecture-level cities with severe data missing, and finally obtains 282 urban samples.

Keyword Frequency (AI_1). Keywords for computer algorithm optimization and machine learning are compiled to build a government AI support dictionary. Government work reports are preprocessed (stopword/invalid word filtering), and keyword frequencies are counted. AI_1 is constructed via TF-IDF:

$$AI\_1_{cn}=\sum_{h=1}^{H} \ln(1+n_{hcn})\times\ln\left(\frac{R_n}{1+r_{hn}}\right) \tag{10}$$

where n_{hcn} = frequency of keyword h in city c's report in year n; R_n = total reports in year n; r_{hn} reports containing keyword h in year n. $\ln(1+n_{hcn})$ denotes within-report intensity; $\ln\left(\frac{R_n}{1+r_{hn}}\right)$ denotes cross-sample discriminative power. Keywords frequent in few cities but rare overall get higher weights.

3.Control Variables: Referring to existing literature, the control variables include financial development level, educational expenditure, human capital, openness, scientific and technological expenditure, urbanization level and economic development level.

4.3 Data Source and Description

This paper employs panel data of 282 prefecture-level cities in China from 2007 to 2023, sourced from the China Urban Statistical Yearbook. To avoid estimation bias caused by outliers, all continuous variables are winsorized at the 1% level in both tails. The descriptive statistics of main variables are presented in Table 2.

Table 2. Descriptive Statistics of Main Variables

Type	Variable Name	Measurement Method	Symbol	Mean	Max	Min	Std.
Explained Variable	Urban Green High-Quality Development	Green total factor productivity	green-dev	0.333	1.017	0.145	0.136
Explanatory Variable	AI Development Level	AI pilot policy dummy variable	did	0.015	1	0	0.123
Control Variable	Economic Development	ln(per capita GDP)	Eco	10.610	12.045	8.410	0.701
	Financial Development	Year-end deposit and loan balance / GDP	Fin	2.480	6.874	0.896	1.186
	Urbanization Level	ln(population density)	Urb	5.718	7.459	2.328	0.943
	Educational Expenditure	Education expenditure / fiscal expenditure	Edu	0.179	0.283	0.087	0.041
	S&T Expenditure	S&T expenditure / fiscal expenditure	Sci	0.016	0.082	0.001	0.015
	Human Capital	Enrollment of university students / total population	Cap	0.018	0.117	0	0.024
	Openness	Total import and export volume / GDP	Open	0.183	1.670	0	0.286

5 Empirical Analysis and Discussion

5.1 Benchmark Test of AI Policy on Urban Green High-Quality Development

Table 3 reports the benchmark regression results of synergistic empowerment of AI and computer technology on urban green high-quality development. Columns (1) and (2) show that the coefficient of AI development level is significantly positive at the 1% level. This indicates that AI policy significantly improves urban green total factor productivity. We further employs a intensity DID to examine how pre-policy government support for computer algorithms shapes urban green high-quality development. We interact did dummy with the algorithm optimization keyword index AI_1 to construct the intensity term did×AI_1. As shown in Columns (3) (4), the coefficient is significantly positive at the 1% level. This indicates that, among pilot cities, a higher frequency of computer algorithm-related keywords in government work reports reflects greater policy emphasis on algorithmic optimization, strengthening the effect of AI on green high-quality development.

Table 3. Benchmark Regression Results

Variable	(1)	(2)	(3)	(4)
	green-dev			
did	0.200***	0.196***		
	(0.044)	(0.043)		
did×AI_1			0.061***	0.061***
			(0.015)	(0.014)
Control Variables	NO	YES	NO	YES
Year Fixed Effects	YES	YES	YES	YES
City Fixed Effects	YES	YES	YES	YES
Observations	4794	4794	4794	4794
R^2	0.148	0.049	0.211	0.218

Note:*,**,*** denote significance at the 10%,5%,1% levels respectively. Robust standard errors are reported in parentheses. The same applies below.

5.2 Robustness Tests

5.2.1 Parallel Trend Test.

This paper adopts the event study approach to conduct the parallel trend test. The results are shown in Fig. 1. Before policy implementation, the estimated coefficients fluctuate around zero, implying no statistically significant difference in green total factor productivity between pilot and non-pilot cities. After implementation, a notable divergence emerges between the two groups. The parallel trend assumption is thus satisfied. Moreover, the coefficient magnitude gradually increases over time, suggesting the policy effect strengthens continuously.

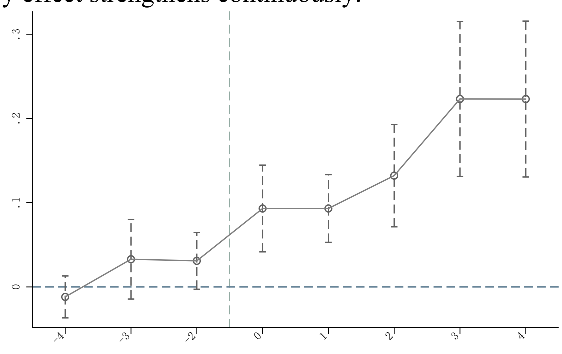

Fig. 1. Parallel Trend Test

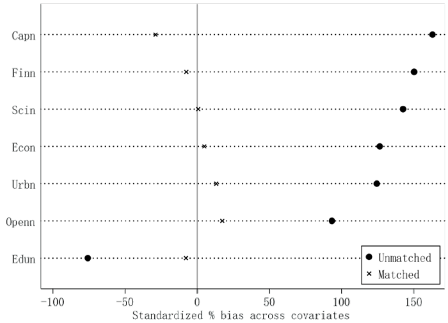

Fig. 2. Standardized Differences Before and After Matching

5.2.2 PSM-DID.

To address non-random pilot selection, mitigate self-selection bias arising from differences in inherent endowments like digital infrastructure, this paper employs PSM-DID method to enhance the reliability of regression results. We adopt 1:2 nearest neighbor matching and kernel matching (Fig. 2). identifies that the standardized mean differences of control variables decrease substantially after matching. The DID regression is re-estimated based on the matched sample. As shown in Columns (1)–(2) of Table 4, the DID coefficient remains significantly positive at the 1% level, verifying the robustness of the benchmark results.

Table 4. Robustness Test Results

Variable	Kernel Matching (1)	1:2 Nearest Neighbor Matching (2)	green-dev (3)	green-dev (4)
did	0.218*** (0.0442)	0.172*** (0.0438)	0.199*** (0.044)	0.198*** (0.044)
Control Variables	YES	YES	NO	YES
Province effects	NO	NO	YES	YES
Province×Year	NO	NO	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Observations	4794	605	4794	4794

5.2.3 Controlling Provincial and Province-Year Interactive Fixed Effects.

Provincial disparities in digital infrastructure and fiscal endowments may bias causal identification. This paper introduces provincial fixed effects to absorb cross-provincial endowment differences, and province-year interaction effects to control time-varying policy and industrial variations across provinces. As shown in Columns (3)–(4) of Table 4, the main findings remain significantly positive after adding these fixed effects.

5.2.4 SUTVA Test.

SUTVA is a prerequisite for valid DID, which excludes spillover effects and expectation effects.

Table 5. SUTVA Test Results

Variable	Spillover Effect (1) green-dev	(2) green-dev	Expectation Effect (3) green-dev	(4) green-dev	(5) green-dev
did_neighbor	0.007 (0.017)	0.03 (0.017)			
did			0.196^{***} (0.043)	0.196^{***} (0.043)	0.196^{***} (0.043)
did × $PreYear^1$			0.017 (0.012)	0.017 (0.013)	0.018 (0.013)
did × $PreYear^2$				0.009 (0.011)	0.009 (0.012)
did × $PreYear^3$					0.005 (0.014)
Control Variables	NO	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
City Fixed Effects	YES	YES	YES	YES	YES
R^2	0.6734	0.6786	0.7000	0.7001	0.7001
Observations	4794	4794	4794	4794	4794

For spillover effect, we construct a dummy variable did_neighbor based on adjacent pilot cities. For expectation effect, referring to Fang et al[12], we introduce interaction terms of the core policy variable with three pre-period dummy variables: did×PreYear1, did×PreYear2, did×PreYear3.As shown inTable 5, the coefficients of did_neighbor, did×PreYear1, did×PreYear2, did×PreYear3 are all statistically insignificant. It suggests that the promotional effect of AI policy on local green development is barely disturbed by cross-regional spillover and policy expectation effects, which confirms the validity of SUTVA.

5.3 Mechanism Analysis

Green technological innovation is the core driver of urban green productivity improvement and provides technical support for green high-quality development. Referring to Song et al·[13], we adopt green invention patent applications per ten thousand people to measure green technological innovation. Columns (1)–(2) in Table 6 show that AI exerts a significantly positive effect on green technological innovation at the 1% level, indicating that AI strongly supports green innovation and thereby facilitates urban green development. Further, Column (3) shows that did×AI_1's coefficient is significantly positive at the 1% level, indicating that a higher frequency of computer optimization-related expressions in government reports strengthens the pilot policy's promotion of green technological innovation.

As a key driver of green total factor productivity, industrial structure upgrading reshapes the economic paradigm. It substitutes high-pollution sectors with low-carbon, high efficiency industries, which enhances factor allocation efficiency and reduces emission. Following Lü et al[14], we measure industrial structure upgrading by the ratio of tertiary to secondary industry added value. Columns (3)–(4) in Table 6 show that AI significantly promotes industrial structure upgrading at the 10% level, consolidating the industrial foundation for urban green development. Further, Column (6) shows that did×AI_1' coefficient is significantly positive at the 10% level, implying that a higher frequency of computer optimization-related expressions in government reports effectively guides factors toward the tertiary sectors, promoting industrial structure upgrading.

Table 6. Mechanism Test Results

Variable	invention_std				Indn	
	(1)	(2)	(3)	(4)	(5)	(6)
did	0.290*** (0.038)	0.247*** (0.033)		0.303** (0.129)	0.260* (0.138)	
did×AI_1			0.229*** (0.032)			0.078* (0.047)
Control Variables	NO	YES	YES	NO	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
City Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	4794	4794	4794	4794	4794	4794
R^2	0.324	0.282	0.415	0.249	0.453	0.558

6 Conclusions and Policy Implications

To capture the opportunities brought by the AI industry, this paper adopts the difference-in-differences method to systematically investigate the impact and underlying mechanisms of artificial intelligence on urban green high-quality development, based on panel data of 282 Chinese cities from 2007 to 2023, and taking the National New Generation Artificial Intelligence Innovation and Development Pilot Zone policy as a quasi-natural experiment. The main conclusions are as follows. First, AI policy significantly boosts urban green high-quality development. The iterative upgrade of computing power and continuous model provide foundational support for AI deployment, enabling its deep integration into green production. This mitigates the high energy consumption and emissions bottlenecks of traditional industries, fostering coordinated economic growth and ecological protection. Second, mechanism tests verify that AI promotes urban green high-quality development by stimulating green technological innovation and accelerating industrial structure upgrading.

Based on the above findings, this paper puts forward policy suggestions. First, strengthen the leading role of green technological innovation. Break through key generic and core bottleneck technologies, improve the industry–university–research collaborative innovation mechanism, and accelerate the transformation of innovative achievements. It is also essential to protect intellectual property rights, set up special funds to support green patent research, and build a linkage between technological innovation and social development. Second, take industrial structure optimization as the starting point. Governments should use fiscal resources to foster modern service industries and high-tech industries. Preferential policies and financial support should encourage enterprises to increase R&D investment in high-tech fields such as AI, guide the urban construction toward green and high-quality transformation. Third, prioritize green computing infrastructure, optimize data center energy use, and support smart green applications. Deploy intelligent control systems across industry, construction, and energy sectors to precisely manage emissions and resource consumption.

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