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Fostering Inclusive Green Growth in Chinese Cities: Investigating the Role of Artificial Intelligence

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Abstract: In the new round of global technological revolution and industrial transformation, artificial intelligence (AI) provides an opportunity to foster urban inclusive green growth (IGG). On the basis of scientifically measuring the IGG level and AI development level of Chinese cities from 2010 to 2022, this paper systematically explores the impact and internal mechanism of AI on IGG. This study finds that AI development significantly promotes urban IGG, and this conclusion still holds after a series of robustness and endogeneity tests. The effect of AI on IGG will exhibit heterogeneity because of differences in urban characteristics such as government financial support, information infrastructure development, and innovation and entrepreneurship vitality. Mechanism test reveals that AI development fosters urban IGG through digital technology innovation and industrial structure optimization. Furthermore, AI development has a positive spatial spillover effect on IGG in neighboring cities. This study provides valuable theoretical insights and policy ideas for planning in emerging economies to promote high-quality economic development and ecological civilization through the application of AI technology.

Keywords: artificial intelligence; inclusive green growth; digital technology innovation; industrial structure optimization; spatial spillover effects

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Citation: Fu, H.; Rasiah, R. Fostering Inclusive Green Growth in Chinese Cities: Investigating the Role of Artificial Intelligence. *Sustainability* **2024**, *16*, 9809. https://doi.org/10.3390/su16229809

Academic Editor: Fabrizio D'Ascenzo

Received: 1 October 2024
Revised: 7 November 2024
Accepted: 9 November 2024
Published: 11 November 2024
Corrected: 16 January 2025

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1. Introduction

Since reform and opening up, China's economy has maintained rapid growth over the past four decades. From 1978 to 2022, China's per capita GDP has risen from 385 yuan to 85,698 yuan, with an average annual growth rate of 13.1%, significantly surpassing the global average; however, the social equity and environmental protection challenges that accompanied this "Chinese miracle" should not be overlooked [1,2]. These challenges manifest as a significant wealth gap and ecological challenges, significantly impeding China's transition to high-quality economic development [3,4]. Consequently, the report of the 20th National Congress of the Communist Party of China underscores that in the future, China will pursue objectives of "standardizing income distribution," "enhancing the basic public service system," and "advancing green development to foster harmonious coexistence between humans and nature," thereby enhancing people's well-being and building a beautiful China. This indicates an urgent need for a fundamental shift in China's extensive growth model [5,6]. Thus, how can we enhance public participation in sharing economic gains and promote fair opportunities during economic growth; simultaneously practicing the concept of harmonious coexistence with nature, transforming traditional development models, and achieving high-quality economic development? This relates to the concept of inclusive green growth (IGG).

IGG emerged from the inclusive growth concept introduced by the Asian Development Bank in 2007, advocating for the fair and equitable sharing of economic growth and equality of opportunity during the economic development process. As the global economy continues to expand, it poses significant challenges to the achievement of green and sustainable development. Consequently, the World Bank introduced the concept of IGG in

2012, defining it as a sustainable development model that balances economic growth with improvements in social and environmental well-being, ensuring both social inclusiveness and green growth. Following extensive research by the United Nations and the Asian Development Bank, IGG has become a significant academic topic [7–9]. What constitutes IGG? Despite a lack of consensus among scholars regarding the definition of IGG, there is unanimous agreement on its core essence: IGG represents a new development philosophy that harmonizes economic, environmental, and social issues [10–12]. This paper interprets IGG as a synergy of economic growth, green growth, and inclusive growth, defining it as follows: in pursuit of economic growth, it not only ensures that all economic actors participate equally in the process and share in its benefits but also incorporates green development into economic decision-making, emphasizing efficiency in resource utilization and ecological protection while curbing pollution emissions.

The ongoing global technological revolution and industrial transformation have spurred ongoing breakthroughs in fields such as information and communication technology, big data, and artificial intelligence (AI). These advanced technologies are deeply integrating with the real economy, significantly altering the economic structure and powering the intelligent advancement of industries [13,14]. Representative major developed countries such as the United States, the United Kingdom, and Germany have all formulated and implemented development strategies centered on revitalizing the manufacturing sector, prioritizing intelligent manufacturing, and aiming to secure a commanding position in the new round of global manufacturing competition [15]. With the deep integration of new-generation information technology into manufacturing, China's intelligent manufacturing development has achieved notable success in transforming and upgrading key industries, enhancing the supply capacity of intelligent equipment, and refining intelligent standards and support systems [16]. Currently, AI development in China spans various sectors, significantly transforming people's daily lives and enterprise operations. In this context, the 14th Five-Year Plan for Intelligent Manufacturing issued by the Ministry of Industry and Information Technology of China in 2021 underscores a steadfast commitment to intelligent manufacturing as the primary focus, aiming to shift industrial development towards intelligence, enhance production quality and efficiency, reduce resource and energy consumption, thereby powering economic transformation and development. This highlights the aspiration of the Chinese government to harmoniously balance qualitative enhancement and quantitative growth, achieving a win–win situation for both economic growth and green development. In 2022, the scale of China's core AI industry surged more than sixfold from 2019, totaling over 400 billion yuan. The opportunities presented by the advancement of AI transcend the technology itself, as it facilitates transformation in traditional industries and the shift between old and new growth drivers; therefore, research on the impact and transmission channels of AI development on IGG holds significant theoretical and practical implications, offering policy insights for achieving high-quality development in China's economy.

This study identifies the application of industrial robots as a key indicator of AI development. An evaluation framework for IGG is established across three dimensions: economic growth, green growth, and inclusive growth. Based on scientifically assessing the levels of AI development and IGG across 210 prefecture-level cities in China from 2010 to 2022, this research employs a combination of panel econometric models, instrumental variable techniques, mechanism testing models, and spatial econometric models to conduct in-depth theoretical and empirical analyses on the mechanisms and impacts of AI development on urban IGG. The main contributions of this paper are as follows: (1) In terms of research content, it systematically investigates the local effects and spatial spillover effects of AI development on IGG in cities and conducts a mechanism analysis across two dimensions: digital technology and industrial structure. This broadens the scope of research on AI and IGG. (2) In terms of indicator measurement, it quantitatively assesses urban IGG across three dimensions: economic, green, and inclusive growth. It also includes additional indicators, such as green innovation outcomes in green production and

indicators of green livability, building on the existing literature. The systematic measurement indicators capture the core essence of IGG, ensuring scientific outcomes. (3) In terms of research methods, by introducing two types of instrumental variables, the US industrial robot index and the "Made in China 2025" policy impact, it strengthens the control over endogeneity issues in causal inference, enhancing the credibility of research conclusions.

The rest of the paper is structured as follows: Section 2 draws a literature review; Section 3 draws theoretical analysis and research hypothesis; Section 4 introduces the model setting and variables selection; Section 5 reports empirical test and result analysis; Section 6 further analyzes influence mechanism and spatial spillover effects of AI on IGG; Section 7 draws conclusions and provides policy implications.

2. Literature Review

2.1. Measurement and Influencing Factors of IGG

Scholars have expanded on the connotation of IGG from the perspectives of development economics and welfare economics. Berkhout et al. [10] argue that to achieve sustainable development goals, economic growth must be characterized by "inclusiveness" and "greening." Rauniyar and Kanbur [17] point out that IGG is accompanied by equitable opportunities for growth. Ren et al. [11] analyze the similarities and differences between sustainable development and IGG and argue that "fairness" and "people-centeredness" are the main differences between the two concepts. Based on the discussion of the connotation of IGG, a series of measurement indicators have emerged. Wang et al. [11] constructed a comprehensive index based on provincial panel data in China from four dimensions: economic development, social opportunity equity, green production and consumption, and ecological environment protection. Aminata et al. [18], based on the IGG index proposed by the Asian Development Bank, studied the IGG level of 34 provinces in Indonesia from the perspectives of economic growth, social equity, and environmental sustainability.

On the basis of combining the concept of IGG, it is necessary to explore further how to achieve IGG. The existing literature analyzes the realization path of IGG from the perspectives of infrastructure construction, labor market, digital economy, and technological innovation. For example, Song et al. [9] and Razzaq et al. [7] examined the positive impact of network and transportation infrastructure development on IGG. Li et al. [19] found that labor market distortion negatively affects IGG. Technological innovation, industrial structure optimization, and export trade upgrading are transmission channels of the impact of labor market distortion on IGG. Ren et al. [11] pointed out that digital economy agglomeration exerts a positive influence on IGG. The "Broadband China" policy is conducive to enhancing local IGG while it inhibits IGG in neighboring areas. Li et al. [20] found that digital inclusive finance fosters regional IGG by enhancing financial service efficiency in supporting the real economy. Jia et al. [21] believed that independent innovation has a positive effect on IGG, while imitation innovation has a negative effect. In addition, Gu et al. [22] and Feng et al. [23] explored the role of economic policies and regional development strategies in fostering IGG.

It is worth mentioning that most of the existing studies have conducted empirical analysis based on provincial panel data, and the research scale is still not detailed enough. In the process of measuring the comprehensive index of IGG, the core dimensions considered by scholars are different, which may not effectively cover the full connotation of IGG. With the continuous expansion of data sources, researchers can widely collect more comprehensive and detailed data at the prefectural cities level to construct an evaluation index system, thereby accurately reflecting the development level of IGG; therefore, it is necessary to systematically explore the relationship between AI development and IGG on the basis of scientifically measuring the level of urban IGG.

2.2. The Impact of AI Development

The existing literature rarely studies the impact of AI development on IGG. Scholars have confirmed the driving effect of AI on inclusive growth or green development from a

single perspective [24–27], but lack of systematic analysis of its impact on IGG. Scholars have put forward many in-depth insights on whether and how AI development affects economic transformation and growth.

In the digital age, the existence of Moore's law makes the price of technical products fall relatively, which leads to a large-scale squeeze on other investments [28]. The application of AI products, such as industrial robots characterized by technological progress, has led to the reform of production mode and labor market, reshaped the economic structure, and had a far-reaching impact on the path of economic development [29]. The continuous deepening of robot applications has effectively promoted the deep integration of AI and the real economy. As an organic combination of capital and labor factors, AI reduces the dependence of production on labor, leading to the substitution of capital for labor, thus optimizing the factor endowment structure [30]. With the gradual deepening of the impact of AI on the labor market, the development of intelligence has transited from "job substitution" in the initial stage to "job creation" in the development period [31]. Although the substitution effect may lead to structural unemployment in the short term, which is not conducive to the rational distribution of income, in the long run, the job replacement effect generated by intelligence is gradually dominated by the creation effect, which is reflected by an increase in employment opportunities and the improvement of the degree of equalization. This not only increases the proportion of workers' income but also reduces the income gap between low and high, medium and high-skilled workers, which is conducive to achieving inclusive growth [32,33].

Furthermore, the new generation of digital technology represented by AI continues to break through and deeply integrate with the real economy, accelerating the trend of industrial intelligence. This effectively promotes the upgrading of an industrial base and the modernization of the industrial chain, guides the green transition of traditional industries; meanwhile, this helps to optimize market supply and demand, making it easier for manufacturers to capture the real needs of users, so as to achieve precise production and expand the green efficiency of products [34,35]; therefore, AI provides a new opportunity and support for solving the problem of pollution reduction from the source and process.

The above-mentioned literature studies provide valuable reference for this study, but there is still room for further expansion. In terms of research objects, most of the existing studies on IGG focus on data analysis at the provincial level. China has a vast territory, and even within the same province, there are obvious differences in urban development. The city is not only the actual bearer of the national ecological civilization task but also the specific implementation unit of China's economic construction, which is of great significance to the realization of China's high-quality economic development. Therefore, further research needs to be carried out in a more detailed way based on the city unit. In terms of research horizon, scholars explore the influencing factors of IGG from the fields of infrastructure construction, labor market, digital economy and technological innovation. Under the new development pattern, the development of industrial intelligence is accelerating. Therefore, theoretical analysis and empirical research need to be further expanded to carry out systematic research on the impact effect and channel of IGG from the perspective of AI development.

3. Theoretical Analysis and Research Hypothesis

3.1. The Impact of AI Development on IGG

Advanced digital technologies, exemplified by AI and big data, are consistently making breakthroughs and integrating with physical industries, accelerating the trend towards industrial intelligence and offering new opportunities and support for cities to achieve IGG. On the one hand, the development of AI will generate more jobs, and the expansion of employment through intelligent technology is conducive to raising the relative wages of low-skilled groups and mitigating income inequality. This is particularly evident in traditional service sectors such as education and healthcare, where AI development has provided greater access to service-oriented employment for lower-skilled individuals [36],

embodying the traits of inclusive growth. On the other hand, the advancement of AI has driven the adoption of next-generation digital technologies, such as big data and cloud computing, removing technical barriers within enterprise resource utilization and reducing investments in labor, material, financial resources, time, and space during production. This approach minimizes overall production costs while reducing waste, recycling it, and rendering it harmless throughout the manufacturing process. It is guiding a shift towards digital and green industrial production methods, facilitating the upgrading of sewage treatment equipment and thus enhancing pollution management efficiency [37], thereby reflecting the hallmarks of green development; therefore, this study proposes the first hypothesis.

Hypothesis 1: *AI development is conducive to fostering urban IGG.*

3.2. The Influence Mechanism of AI Development on IGG

As a product of the new generation of digital technology innovation and accelerated integration with advanced manufacturing technology, the development of AI, mainly characterized by the application of industrial robots, plays an important role in promoting China's economic transformation and breakthrough. Given the widely recognized role of AI in promoting inclusive growth [27,38,39], this article follows the decomposition approach of Grossman and Krueger [40] on economic and environmental effects and explores the mechanism of AI development driving IGG in cities from the perspectives of technological innovation effects and industrial structure effect

First, the technological innovation effect. Technological progress is a critical factor in enhancing labor productivity and improving energy conservation and emission reduction capabilities during enterprise production processes. In the context of intelligent advancement, the development of AI, represented by industrial robots, has had a profound impact on the labor market. On the one hand, the application of the new generation of digital technology, exemplified by AI, liberates traditional labor from tedious and repetitive tasks, enabling enterprises to focus on strategic innovation activities and further enhance their digital technology capabilities. The operation of intelligent equipment frequently requires the backing of human capital. Therefore, as the trend of "machines replacing workers" emerges, enterprises must not only replace low-skilled labor with high-skilled talent but also leverage human capital accumulation and technological complementarities to achieve knowledge spillovers and technological advancement. On the other hand, the development of AI will give rise to a multitude of new business models and positions underpinned by digital technology. While the job substitution effect of AI applications will prevail over the job creation effect in the short term, leading to a widening income gap, in the long run, the job creation effect will overtake the substitution effect, fostering inclusive growth [32]. Additionally, some studies suggest that AI disproportionately replaces medium-skilled labor compared with low-skilled labor. Medium-skilled laborers, more inclined to learn and adapt, tend to elevate their earnings more when subjected to intelligence [41]. Furthermore, digital technology is a vital driver of green economic development [42]. As advanced intelligent technology continuously innovates and integrates with physical industries, enterprises can streamline production processes more efficiently and precisely, minimizing unnecessary pollution emissions and thus substantially mitigating the impact of industrial production on urban ecosystems. For cities, intelligent development optimizes industrial production methods and encourages the replacement of polluting equipment, thereby enhancing pollution treatment capabilities and facilitating urban green transformation.

Second, the industrial structure effect. On the one hand, in the context of vigorously developing a digital China, the advancement of AI has induced local governments to invest more in intelligent equipment and emerging industries, such as industrial robotics. Seeking increased financial support from the government, intense competition among enterprises drives them to pursue intelligent integration, optimizing production methods, and enhancing efficiency. This, in turn, propels the industrial structure towards higher sophistication and deepens market reforms [43]. Thanks to evolving market conditions, factors such as

technology, information, and talent move swiftly across regions. This not only facilitates optimal redistribution but also enables precise alignment of enterprise production with more efficient technologies, leading to rationalization of the industrial structure. During this process, surplus rural labor and low-income urban residents congregate around expanding secondary and tertiary sectors. This, in turn, partially addresses employment and income disparities among vulnerable groups and elevates the level of income sharing among workers during economic growth [44]. This shift represents not merely a migration of labor but also a transformation in economic structure and a manifestation of social mobility. On the other hand, as the industrial structure moves towards advanced and rationalization, the market will favor industries dominated by technology and knowledge over extensive ones, leading to the ousting of high-polluting industries and driving innovative resources to more efficient sectors. This, in turn, accelerates technological innovation and provides critical support for green industrial development [45]. In this process, intelligent technology can not only reduce losses due to resource mismatch in production and enhance economic efficiency but also deepen its penetration into the tertiary sector, drive the intelligent transformation of manufacturing and service industries, and facilitate the transfer of knowledge on pollution control across industries. This contributes to the establishment of a green production framework, fosters green industrial development, and lays a solid foundation for the inclusive growth impact of sustainable economic development and environmental improvements [46]. In summary, this study proposes Hypotheses 2a and 2b.

Hypothesis 2a: *AI development can foster urban IGG by promoting digital technol-ogy innovation.*

Hypothesis 2b: *AI development can foster urban IGG by promoting industrial structure optimization.*

3.3. The Spatial Spillover Effect of AI Development on IGG

Geographical units in the economic world often depend on one another [4]. The IGG effects of AI development transcend purely local issues, extensively proliferating into neighboring regions via channels such as technology diffusion, resource sharing, and demonstration learning, creating a network of mutual promotion and co-growth [2]. This can have a positive external impact on the IGG levels of adjacent cities. Specifically, the new generation of digital technology, represented by AI, has shattered the constraints of time and space. It not only bolsters the dynamic role of resource elements but also mitigates barriers to technological exchange among cities and fosters collaborative urban development. Cities that actively promote the development of AI having achieved substantial economic growth and outstanding environmental outcomes, will not only serve as successful models within their local regions but also transmit positive inspirational and learning effects to neighboring cities, igniting a wave of aspirations and actions for change [47], thereby enhancing the level of IGG in adjacent areas. In fact, ignoring spatial spillover effects may lead to underestimating the comprehensive impact of AI development on IGG. We attempt to construct a spatial econometric model to analyze its spillover effect. Correspondingly, this study proposes the third hypothesis.

Hypothesis 3: *AI development has a positive spatial spillover effect on IGG in neighboring cities.*

4. Empirical Strategy

4.1. Empirical Method

4.1.1. Benchmark Model

This study constructs a two-way fixed effects model to identify the impact of AI development on IGG. The benchmark model is set as follows:

$$IGG_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 X_{it} + u_i + \xi_t + \nu_{it} \quad (1)$$

Among them, i denotes the city, and t denotes the year. IGG_{it} represents the urban IGG level, which is reflected by the composite index. AI_{it} represents the AI development

level, with the application level of industrial robots as a proxy variable. β_1 reflects the effect of AI development on urban IGG. X_{it} is a series of control variables. u_i, ξ_t, and ν_{it} denote city fixed effects, year fixed effects, and random disturbance terms, respectively.

4.1.2. Instrumental Variable Regression

This study uses the instrumental variable estimation method to address the endogeneity problem. We draw on the research of Drukker et al. [48] and apply the two-stage least squares method. The exogenous portion of the endogenous variable (AI_{it}) can be separated in the first regression stage. The regression model for the first stage is shown as follows.

$$AI_{it} = \beta_0 + \gamma IV_{it} + \beta_2 X_{it} + u_i + \xi_t + \nu_{it} \tag{2}$$

where IV_{it} represents the instrumental variable. The other variables have the same meaning as in Equation (1).

According to Equation (2), we can obtain the fitting value ($\hat{AI}_{it}$). In the second regression stage, we bring $\hat{AI}_{it}$ into Equation (3).

$$IGG_{it} = \beta_0 + \lambda \hat{AI}_{it} + \beta_2 X_{it} + u_i + \xi_t + \nu_{it} \tag{3}$$

where λ represents the influence coefficient of AI on IGG, which is unbiased. The other variables mirror Equation (1).

4.1.3. Verification of Transmission Mechanism

This study constructs the mediation model to verify the mediating effects. Drawing on the research of Baron and Kenny [49], the verification of the transmission mechanism is divided into three steps.

Step 1: Verify the impact of AI development on IGG.

$$IGG_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 X_{it} + u_i + \xi_t + \nu_{it} \tag{4}$$

Step 2: Verify the impact of AI development on the mediating variables.

$$M_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 X_{it} + u_i + \xi_t + \nu_{it} \tag{5}$$

Step 3: Verify the AI development and the impact of mediating variables on IGG.

$$IGG_{it} = \gamma_0 + \gamma_1 AI_{it} + \gamma_2 M_{it} + \gamma_3 X_{it} + u_i + \xi_t + \nu_{it} \tag{6}$$

Among them, M_{it} denotes mediating variables, including technological innovation and industrial structure. If β_1 is significant with a lower estimated coefficient of γ_1, we conclude that AI development can promote IGG through mediating variables. The description of other variables and parameters is the same as in Equation (1).

4.1.4. Verification of Spatial Spillover Effects

This study constructs a spatial econometric model to examine the spillover effect of AI development on IGG in surrounding cities. The general spatial econometric model is set as follows (Cheng et al., 2024) [2]:

$$\begin{aligned} IGG_{it} = {} & \alpha_0 + \rho W \times IGG_{it} + \alpha_1 AI_{it} + \delta W \times AI_{it} + \\ & \theta_1 X_{it} + \theta_2 W \times X_{it} + u_i + \xi_t + (1 - \lambda W)^{-1} \nu_{it} \end{aligned} \tag{7}$$

Among them, W represents the economic geographic distance matrix. We calculate the economic distance between cities based on the difference in per capita GDP between city i and city j, then weight the inverse geographic distance and economic distance between any city i and city j to obtain the economic, geographic spatial weight matrix (W). ρ denotes the spatial autocorrelation coefficient; δ denotes the spillover effects of

AI development; θ_2 denotes the spillover effect of controlling variables; λ denotes the spatial autocorrelation coefficient of the random disturbance term. The description of other variables and parameters is the same as in Equation (1). According to ρ, δ, θ_2, and λ, the general spatial econometric model can be divided into three categories based on whether its value is significantly 0: if $\rho = \delta = \theta_2$, the model is a spatial error model (SEM); If $\delta = \lambda = 0$, the model is a spatial lag model (SLM); If $\lambda = 0$, then the model is a spatial Durbin model (SDM).

4.2. Variable Description

4.2.1. Inclusive Green Growth

This paper interprets IGG as a synergy of economic growth, green growth, and inclusive growth, defining it as follows: in pursuit of economic growth, it not only ensures that all economic actors participate equally in the process and share in its benefits but also incorporates green development into economic decision-making, emphasizing efficiency in resource utilization and ecological protection while curbing pollution emissions. In short, IGG refers to the development mode of achieving inclusiveness and greening in the process of economic development [50].

This study uses the entropy weight method to quantitatively measure the IGG index from the three dimensions of economic growth, green growth, and inclusive growth, including nine secondary indicators and thirty-six tertiary indicators. Among them, the embodiment of economic growth includes economic output and income level. Green growth is a way of sustainable development that aims to reduce the consumption of natural resources and environmental damage in the process of production and consumption and realize the coordinated development of economic growth and ecological protection. Based on the research of Gu et al. [22], this study adds green livability and measures it from three aspects: green production, green consumption, and green livability. Inclusive growth is a people-oriented and sustainable development mode that requires social equity while economic development, attention to the interests of vulnerable groups, and ensuring that all people can participate in and share the fruits of development. Zhang et al. [51] believed that it could be measured from four aspects: employment equity, education equity, medical equity, and social security equity. The evaluation index system of IGG is shown in Table 1.

Table 1. IGG index system.

Primary Indicators	Secondary Indicators	Tertiary Indicators	Unit	Efficacy	Weight
Economic growth	Economic output	GDP	Thousand yuan	+	0.032
		GDP per capita	Yuan	+	0.027
		Secondary industry output/GDP	%	–	0.026
		Tertiary industry output/GDP	%	+	0.026
	Income level	Fiscal revenue/GDP	%	+	0.027
		Urban per capita disposable income	Yuan	+	0.027
		Rural per capita disposable income	Yuan	+	0.027
		Urban-rural per capita disposable income ratio	%	–	0.026
		Average salary	Yuan	+	0.026

Table 1. *Cont.*

Primary Indicators	Secondary Indicators	Tertiary Indicators	Unit	Efficacy	Weight
Green growth	Green production	Carbon dioxide emissions per unit output	t/thousand yuan	−	0.026
		Industrial sulfur dioxide emissions per unit output	t/thousand yuan	−	0.026
		Industrial smoke and dust emissions per unit output	t/thousand yuan	−	0.026
		Industrial wastewater discharge per unit output	t/thousand yuan	−	0.026
		Number of green patent applications per thousand people		+	0.035
		Number of green patent authorizations per thousand people		+	0.033
	Green consumption	Residential electricity consumption per capita	kW·h	−	0.026
		Residential water consumption per capita	t	−	0.026
		Harmless treatment ratio for house refuse	%	+	0.026
	Green livability	Urban road area per capita	m^2	+	0.029
		Green coverage rate of built district	km^2	+	0.026
		Public green space area per capita	km^2	+	0.034
		Centralized treatment rate of sewage treatment plant	%	+	0.026
		Number of buses per thousand people		+	0.026
Inclusive growth	Employment equity	Registered urban unemployment rate	%	−	0.026
		Employment rate of secondary and tertiary industries	%	+	0.026
	Medical equity	Number of doctors per thousand people		+	0.027
		Number of hospitals and health centers per thousand people.		+	0.027
		Number of beds in hospitals and health centers per thousand people		+	0.027
	Educational equity	Fiscal education expenditure/fiscal budget expenditure	%	+	0.026
		Number of educational resources per thousand people		+	0.028
		Teacher-student ratio in primary school	%	+	0.027
		Teacher-student ratio in middle school	%	+	0.026
		Teacher-student ratio in institutions of higher learning	%	+	0.030
	Social security equity	Pension insurance coverage rate	%	+	0.029
		Medical insurance coverage rate	%	+	0.031
		Unemployment insurance coverage rate	%	+	0.031

Note: The entropy weight method is used to calculate the weight of indicators. Indicators related to GDP are processed using constant prices in 2000 to avoid the impact of inflation.

4.2.2. AI Development

Referring to the method of Li et al. [8], the urban industrial employment structure, the number of urban labor forces, and the number of industrial robots at the industry level are used to construct an AI development indicator at the city level. The specific measurement is shown as follows:

$$AI_{it} = \sum_{j} \frac{inlab_{sit}}{\sum_{j} inlab_{jit}} \times \frac{robots_{jt}}{labor_{it}} \quad (8)$$

Among them, i denotes the city, j denotes the industry, s denotes the manufacturing industry, and t denotes the year. $robots_{jt}$ represents the number of robots used in the manufacturing industry from 2010 to 2022. $inlab_{sit}$ represents the number of employees in the manufacturing industry, $\sum_{j} inlab_{jit}$ represents the total number of employees in various industries, and $labor_{it}$ represents the number of the urban eligible labor force. The calculation of urban AI development is obtained by weighting the ratio of the number of employees in the manufacturing industry to the total number of employees in each industry.

4.2.3. Control Variables

Referring to existing and relevant studies [52–54], six control variables were selected, including urbanization, cultural resources, industrial structure, foreign capital dependence, resident consumption, and environmental support. Among them, urbanization is measured by the urbanization rate of permanent residents. The process of urbanization is closely related to urban economic development and green transformation. Cultural resources are measured by the number of books collected by a library per thousand people. Cultural resources are the cornerstone of urban human capital and will affect the green and inclusive development of cities. The industrial structure is measured by the ratio of the output value of the tertiary industry to the secondary industry. The transformation and upgrading of industrial structures is an important driving force for urban IGG [46]. Foreign capital dependence is measured by the proportion of foreign direct investment in GDP. Foreign investment can significantly affect the industrial structure and enterprise operation within the city and then affect the urban IGG [50]. Resident consumption is measured by total retail sales of consumer goods per capital. Environmental support is measured by the proportion of investment in environmental pollution treatment to GDP. Environmental support reflects the government's emphasis on environmental protection and pollution control, which will inevitably affect urban IGG.

4.3. Data Source

Data regarding industrial robots comes from the International Federation of Robotics (IFR) database, which provides the annual increment and stock of industrial robots in 75 countries covering agriculture, manufacturing, and some service sectors. In this paper, the enterprises in the manufacturing industry in each city are matched. To ensure the continuity and availability of sample data, this study did not involve Hong Kong, Macao, Taiwan, Tibet, Qinghai, Ningxia, and Xinjiang and excluded several cities with large data gaps in other provinces. The empirical sample includes 210 prefecture-level cities, and the time span is from 2010 to 2022. Data at the city level are from the China Urban Statistical Yearbook, China Environmental Statistical Yearbook, and EPS database. Table 2 presents descriptive statistical results of variables.

Table 2. Descriptive statistics of variables.

Variable	Abb	N	Mean	Std. Dev	Min	Max
Inclusive green growth	IGG	2730	0.463	0.096	0.177	1.182
AI development	AI	2730	0.068	0.126	0.000	1.420
Urbanization	Urb	2730	0.543	0.341	0.120	1.000
Cultural resources	Cul	2730	0.578	0.836	0.009	14.390

Table 2. *Cont.*

Variable	Abb	N	Mean	Std. Dev	Min	Max
Industrial structure	Indu	2730	0.933	0.418	0.226	4.149
Foreign capital dependence	FDI	2730	0.206	0.126	0.008	1.000
Resident consumption	Cons	2730	0.432	0.210	0.056	1.541
Environmental support	Env	2730	0.198	0.088	0.051	0.688

5. Empirical Test and Result Analysis

5.1. Baseline Regression Results

The estimation results of the benchmark regression model are shown in Table 3. Column (1) presents the result of not controlling for fixed effects and control variables, Column (2) is the result of controlling for city and year fixed effects, and Columns (3)–(4) are the result of adding control variables to Columns (1)–(2), respectively. Columns (1)–(2) show that the regressions are highly significant whether we control for city and year-fixed effects. Columns (3)–(4) results show that the estimated coefficients of AI are still significantly positive at the 1% level after adding control variables in the model, but the coefficients decreased. This result indicates that other factors at the city level affect IGG, and the selection of control variables in the model is valid. The full-variable regression results in Column (4) show that for every 1% increase in the development level of AI, the level of IGG will increase by 0.021%. Advanced digital technologies represented by AI and big data are constantly breaking through and integrating with manufacturing entities, accelerating the trend of industrial intelligence and providing new opportunities and support for cities to achieve IGG. The development of AI will create more jobs and improve income inequality. AI technology effectively guides the transformation of industrial production methods towards digitalization and greenization, which helps to promote the upgrading of pollution treatment equipment, thereby improving pollution treatment efficiency and reflecting the characteristics of green development. This outcome indicates that AI development significantly promotes urban IGG, which verifies Hypothesis 1.

Table 3. Benchmark regression results.

Variables	(1)	(2)	(3)	(4)
AI	0.0301 *** (0.0082)	0.0273 *** (0.0074)	0.0255 *** (0.0066)	0.0217 *** (0.0055)
Urb			0.1962 *** (0.0143)	0.1908 *** (0.0157)
Cul			0.0464 *** (0.0025)	0.0421 *** (0.0036)
Indu			0.0016 (0.0457)	0.0075 (0.0441)
FDI			0.0382 ** (0.0152)	0.0454 *** (0.0159)
Cons			−0.0354 * (0.0183)	−0.0338 * (0.0181)
Env			0.0319 ** (0.0143)	0.0253 * (0.0140)
Constant	0.4060 *** (0.1128)	0.4117 *** (0.0233)	0.3296 *** (0.0229)	0.3763 *** (0.0190)

Table 3. *Cont.*

Variables	(1)	(2)	(3)	(4)
City FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES
N	2730	2730	2730	2730
R^2	0.7441	0.7642	0.7743	0.7845

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. The robust standard error of clustering is enclosed in parentheses.

5.2. Robustness Test

5.2.1. Replace the Explained Variable

Baseline regression results show that AI development can effectively promote urban IGG. While the IGG index is the comprehensive embodiment of economic growth (EG), green growth (GG), and inclusive growth (IG), the effect of AI on the sub-dimensions of the IGG index remains to be further tested. Table 4 presents the empirical test results of replacing the explained variable. In the EG, GG, and IG subsystems, the regression coefficients of AI are significantly positive at the 1% level. This indicates that AI development can significantly promote EG, GG, and IG, which verifies benchmark regression conclusions.

Table 4. Results of replacing the explained variable.

Variables	(1)	(2)	(3)
	EG	**GG**	**IG**
Smartcity	0.0255 *** (0.0068)	0.0197 *** (0.0054)	0.0183 *** (0.0046)
Control variables	YES	YES	YES
City FE	YES	YES	YES
Year FE	YES	YES	YES
N	2730	2730	2730
R^2	0.9535	0.7361	0.5017

Note: *** indicate statistical significance at 1% levels, respectively. The robust standard error is enclosed in parentheses.

5.2.2. Replace the Core Explanatory Variable

The benchmark model uses the stock of industrial robots to calculate the application level of urban industrial robots. In this section, we replace the stock of industrial robots with the increment of industrial robots in the IFR database and remeasure the AI development indicator (ΔAI). Column (1) in Table 5 presents the empirical test results of replacing the core explanatory variable. There is no significant change in the estimated coefficient of AI.

Considering that the iterative updates of production technology often have a lag effect [55], AI, as a new development model of industrial technology, may have a lag effect on fostering urban IGG; therefore, we lagged the variable of AI development by one period (L.AI). Column (2) in Table 5 presents the empirical test results of the core explanatory variable lagged by one period. The estimated coefficient of AI has increased compared with the baseline regression and is significantly positive, indicating that AI development promotes IGG in Chinese cities, and this effect has a certain time lag.

Table 5. Robustness test results.

Variables	(1)	(2)	(3)	(4)
	AI Increment	**AI lag**	**Excluding Special Cities**	**Winsorization**
AI			0.0195 ***	0.0204 ***
			(0.0040)	(0.0043)
ΔAI	0.0214 ***			
	(0.0053)			
L.AI		0.0267 ***		
		(0.0055)		
Control variables	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	2730	2520	2340	2658
R^2	0.7934	0.8155	0.7842	0.7671

Note: *** indicate statistical significance at 1% levels, respectively. The robust standard error is enclosed in parentheses.

5.2.3. Excluding Special Samples

Considering that municipalities directly under the central government and provincial capital cities are ahead of general prefecture-level cities in terms of economic development, industrial characteristics, and technological structure [56], the samples of municipalities directly under the central government and provincial capital cities are excluded for re-regression. Column (3) in Table 5 presents the empirical test results of excluding special cities.

Considering the interference of extreme outliers, following the approach of [57], all continuous variables with extreme outliers at the 1% level are subjected to tail reduction treatment. Column (4) in Table 5 presents the empirical test results of winsorization. The estimated coefficients of AI are significantly positive at the 1% level, indicating that changing the sample will not affect the main conclusions. In summary, the robustness of baseline regression results has been confirmed.

5.3. Endogeneity Test

To overcome endogeneity issues caused by bidirectional causality and omitted variables in the model, the following two kinds of instrumental variables are selected for the endogeneity test. (1) Drawing on the research of Liu et al. [58], we construct an instrumental variable using the American industrial robot indicator (US.AI). The reason is that the robot application in the American labor market mainly affects the Chinese labor market in terms of technological progress, but the impact will be limited by the economic structure and industrial characteristics of both countries. The IGG level of Chinese cities can be influenced by various factors, and the application of robotics technology in the United States plays a relatively small role in it. Therefore, the indicator for industrial robots in the United States could basically meet the correlation and exclusivity required for instrumental variables. (2) Referring to the ideas of Irfan et al. [59], we use exogenous policy shocks for endogeneity treatment. In 2015, the State Council of China issued the "Made in China 2025" strategy, which can be seen as an external shock because this policy promotes AI development; therefore, we construct an instrumental variable, P_yI_A. Among them, P_y represents a policy dummy variable; when $y \geq 2015$, $P_y = 1$, otherwise it is 0. I_A represents the years in which the level of infrastructure construction in each region exceeds the regional average level during the sample period, reflecting the differences in infrastructure levels among regions.

Table 6 presents the empirical test results of the instrumental variable method. Columns (1) and (2) are estimated using the American industrial robot indicator (*US*.AI) as the instrumental variable, while columns (3) to (4) are estimated using the external shock (P_yI_A) as the instrumental variable. The first stage regression shows that the F-statistics are much greater than 10, which rules out the problem of weak instrumental variables and proves the effectiveness of these two instrumental variables. After introducing instrumental variables, the effect of AI development on urban IGG remains significantly positive, proving the robustness of benchmark conclusions.

Table 6. Instrumental variable regression results.

Variables	(1)	(2)	(3)	(4)
	First Stage	Second Stage	First Stage	Second Stage
US.AI	0.0672 *** (0.0123)			
P_yI_A			0.0317 ** (0.0148)	
AI		0.0384 *** (0.0110)		0.0198 ** (0.067)
Control variables	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
F-statistic	23.45		22.06	
N	2730	2730	2730	2730
R^2	0.3742	0.5669	0.3461	0.5423

Note: ***, ** indicate statistical significance at 1%, 5% levels, respectively. The robust standard error is enclosed in parentheses.

5.4. Heterogeneity Analysis

The above empirical evidence confirms that AI development is conducive to fostering urban IGG. This section explores the heterogeneous effect of AI development on IGG from the perspectives of urban characteristics such as local government financial support, information infrastructure development, and innovation and entrepreneurship levels.

5.4.1. Heterogeneity of Financial Support

Government financial support will have a significant impact on local industrial structure and layout [60]. To some extent, financial support reflects the importance and regulation of local governments for industrial development. We use the proportion of government fiscal expenditure to GDP to measure financial support and use the median to divide all cities into two groups of high and low financial support for regression. The results are shown in columns (1) and (2) of Table 7. The promoting effect of AI on IGG in cities with low financial support is stronger than that in cities with high financial support. The reason may lie in that compared with cities with low levels of financial support, governments in cities with high levels of financial support will have greater intervention actions and efforts in the local economic and social sectors. Due to its special position in the national economy, state-owned enterprises are more likely to benefit from government financial support; however, AI technology enterprises represented by high-tech enterprises are often in the development stage, and the enterprise scale is not large enough, which is more likely to be ignored by the government. Without good financing channels, these small and medium-sized enterprises may be swallowed up or squeezed out of the market by large state-owned enterprises. This may lead to a disconnect between AI development and market demand and build certain obstacles to converting the benefits of IGG through market mechanisms.

Table 7. Heterogeneity analysis results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Financial Support		Information Infrastructure		Innovation and Entrepreneurship	
	High	Low	High	Low	High	Low
AI	0.0162 * (0.0088)	0.0354 *** (0.0071)	0.0214 ** (0.0105)	−0.0119 (0.0178)	0.0172 ** (0.0075)	0.0095 (0.0103)
Control variables	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	1365	1365	1365	1365	1365	1365
R^2	0.5535	0.6677	0.6837	0.5360	0.6947	0.5004

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively. The robust standard error is enclosed in parentheses.

5.4.2. Heterogeneity of Information Infrastructure

Information infrastructure development has a strong empowering effect on the emergence of new formats, new models, and the digital transformation of industries in cities [61]. Information infrastructure is an important cornerstone of the development of emerging digital technologies such as big data, cloud computing, and AI. We use the proportion of Internet broadband user access in the resident population of the city (including urban and rural areas) to measure the level of information infrastructure development and use the median to divide the city sample into high and low groups. The regression results are shown in columns (3) and (4) of Table 7. The development of AI has, to a greater extent, promoted IGG in cities with high levels of information infrastructure, while cities with low levels of information infrastructure are not significantly affected. The role of AI technology needs to be built on corresponding information infrastructure. Without the support of information infrastructure, it is difficult to realize the dividends of AI development, and it may even become a "sunk cost" because of capital investment that cannot be recovered, thereby having a negative impact on urban IGG. In the future, the central and local governments should vigorously promote the development of information infrastructure and cultivate and give full play to "digital dividends."

5.4.3. Heterogeneity of Innovation and Entrepreneurship

The level of innovation and entrepreneurship reflects the human capital, R&D investment, entrepreneurial production, and operation capabilities of a city and plays an important role in the transformation of urban development models [62]. At the same time, entrepreneurship and innovation reflect the vitality and creativity of a city. We divide the sample cities into high and low groups using the median of the China Regional Innovation and Entrepreneurship Index from 2010 to 2022 (The index is obtained from the Enterprise Big Data Research Center of Peking University) and conduct regression analysis. The results are shown in columns (5) and (6) of Table 7. The development of AI has, to a greater extent, promoted IGG in cities with high innovation and entrepreneurship vitality, while cities with low innovation and entrepreneurship capabilities are not significantly affected. The reason is that in areas with strong innovation and entrepreneurship vitality, industrial intelligence can better integrate industrial development and play a role in fostering urban IGG. Cities with strong entrepreneurial and innovative vitality tend to have significantly higher levels of human capital and R&D investment. This is conducive to the promotion effect of digital technologies such as big data and AI on urban IGG; however, due to the solidification of traditional development models, the IGG effect of industrial intelligence in areas with lower levels of innovation and entrepreneurship is not significant.

6. Further Analysis

6.1. Mechanism Verification

6.1.1. Mechanism of Digital Technology Innovation

Digital technology innovation is characterized by digital technology innovation scale (*DTI_scal*) and digital technology innovation intensity (*DTI_int*). Specifically, the scale of digital technology innovation is measured by digital technology patents. The calculation steps are as follows [63]: first, we use patent data on invention applications from the China National Intellectual Property Administration to extract the patent corresponding to the IPC classification number of digital technology and then match the patent to the city where the main applicant is located through the applicant's address; finally, we obtain the number of digital technology invention patent applications at the city level. The intensity of digital technology innovation is measured by the proportion of digital technology invention patents in all technology invention patents, which reduces the impact of the overall innovation scale and highlights the advanced characteristics of digital technology in the process of urban innovation and development [64].

Table 8 presents the mechanism test results of digital technology innovation. The results of column (1) and column (3) reveal that AI development can significantly improve the scale and intensity of digital technology innovation; the results of columns (2) and (4) reveal that the estimated coefficient of AI is smaller than that in the benchmark regression after including the mechanism variable, but it is still significantly positive. This indicates that the IGG effect of AI development is diluted by digital technology innovation to a certain extent; that is, digital technology innovation is an important channel for AI to affect urban IGG. At present, digital technology has greatly changed the lives of urban and rural residents, the production and operation of enterprises, and the governance and supervision of the government. The prevalence of platform economy is conducive to revitalizing the stock assets and injecting new momentum into the development of less-developed regions and small and medium-sized enterprises [65]. The deep integration of the new generation of digital technology represented by AI and the real economy is beneficial for the green transition of enterprise production, thereby fostering the IGG of the urban economy. Thus, Hypothesis 2a has been verified.

Table 8. Mechanism test of digital technology innovation.

Variables	(1)	(2)	(3)	(4)
	DTI Scale		DTI Intensity	
	DTI_scal	IGG	DTI_int	IGG
AI	0.7051 *** (0.0408)	0.0164 *** (0.0061)	0.0914 *** (0.0125)	0.0193 *** (0.0050)
DTI_scal		0.0089 *** (0.0022)		
DTI_int				0.0127 ** (0.0054)
Control variables	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	2730	2730	2730	2730
R^2	0.6374	0.6030	0.6322	0.5645

Note: ***, ** indicate statistical significance at 1%, 5% levels, respectively. The robust standard error is enclosed in parentheses.

6.1.2. Mechanism of Industrial Structure Optimization

Industrial structure optimization is characterized by the upgrading and rationalization of industrial structure. Specifically, the upgrading of industrial structure (*IS_up*) is measured by summing up the product of the proportion of the three major industries and the labor productivity of each industry [66]. The rationalization of industrial structure (*IS_ra*) is measured by the Theil index [67]. The smaller the Theil index is, the more balanced the industrial structure is, and the better the coordination between departments is, that is, the more reasonable the industrial structure is.

Table 9 presents the mechanism test results of industrial structure optimization. The results of column (1) and column (3) reveal that AI development can promote the transformation of industrial structure to advanced, reduce the deviation degree in industry, and guide the development of industrial structure to rationalization; the results of columns (2) and (4) reveal that when the core explanatory variable is included in the mechanism variable, the coefficient of AI is smaller than that in the benchmark regression, but it is still significantly positive. This implies that the optimizing effect of industrial structure brought by AI development will promote urban IGG. In the evolution of industrial intelligence, the new generation of digital technology, exemplified by AI, will hasten the integration of the tertiary sector and spur the emergence of novel models within the intelligent service industry [68]. The emergence of new business models and approaches, on the one hand, facilitates the provision of employment opportunities for rural surplus labor and urban low-income communities, thereby promoting income redistribution. On the other hand, their inherent features of energy efficiency and environmental friendliness encourage enterprises to adopt green production methods, further enhancing the standard of green manufacturing and facilitating the green transformation of cities. Thus, Hypothesis 2b has been verified.

Table 9. Mechanism test of Industrial Structure Optimization.

Variables	(1)	(2)	(3)	(4)
	IS Upgrading		IS Rationalization	
	IS_up	IGG	IS_ra	IGG
AI	0.2452 *** (0.0758)	0.0153 *** (0.0048)	−0.1054 *** (0.0302)	0.0192 *** (0.0060)
IS_up		0.0108 *** (0.0017)		
IS_ra				−0.0207 *** (0.0045)
Control variables	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	2730	2730	2730	2730
R^2	0.7365	0.6831	0.6756	0.5902

Note: *** indicate statistical significance at 1% levels, respectively. The robust standard error is enclosed in parentheses.

6.2. Analysis of Spatial Spillover Effects

According to economic geography theory, the flow of production factors within the region is progressively breaking down market segmentation and spatial isolation [69]. This flow, through spatial spillover and radiation effects, fosters collaborative development and cooperation in regional economic activities, thereby presenting new opportunities and challenges for regional development. Consequently, beyond focusing on the impact of local AI on the level of IGG within the region, it is also crucial to examine its influence

on the IGG levels in other cities. This involves determining whether the IGG effects of AI development exhibit spatial spillover characteristics.

Before constructing the spatial econometric model, it is necessary to test the spatial autocorrelation of research variables to determine whether the variables have spatial correlation [70]. We use Moran's Index to verify the spatial autocorrelation of urban IGG level under the economic geography matrix. The results show that Moran's Index of IGG level in China from 2010 to 2022 is significantly positive, indicating that the IGG level is positively correlated in the spatial dimension. Further, we choose the setting of a spatial econometric model. The LM, LR, and Wald test results reject the assumption that the SDM model could degenerate into SLM or SEM models; therefore, the SDM model should be selected.

Table 10 presents the empirical test results of spatial spillover effects. The regression results of the SDM model show that the spatial autoregressive coefficient of IGG level (ρ) is significantly positive at the 1% level, indicating that urban IGG has significant spatial correlation, and the coefficient of the spatial weighted term of AI (W × AI) is significantly positive at the 1% level, indicating that AI development has a positive spatial spillover effect. The SDM model is further decomposed into direct effect, indirect effect (spatial effect), and total effect by using partial differential decomposition [4]. The results show that AI development not only has a significant positive effect on the IGG level within the city but also has a significant role in promoting the IGG level in neighboring cities. This confirmed that AI development has a positive spatial spillover effect on IGG in neighboring cities, and Hypothesis 3 has been verified.

Table 10. SDM regression results.

Variables	(1)	(2)	(3)	(4)
	SDM	**Direct Effect**	**Indirect Effect**	**Total Effect**
AI	0.0174 *** (0.0052)	0.0207 *** (0.0065)	0.0383 ** (0.0164)	0.0590 *** (0.0147)
W × AI	0.0168 *** (0.0054)			
ρ	0.4132 *** (0.0334)			
Control variables	YES	YES	YES	YES
W × Control variables	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	2730		2730	
R^2	0.5130		0.5130	

Note: ***, ** indicate statistical significance at 1%, 5% levels, respectively. The robust standard error is enclosed in parentheses.

The above spatial econometric model is constructed based on the economic, geographical spatial weight matrix, which reflects the comprehensive connection of economic factors and geographical elements between cities. Further, we consider using adverse geographical distance weight matrix, city adjacency weight matrix (0–1), urban cluster adjacency weight matrix (0–1), and provincial adjacency weight matrix (0–1) to reconstruct the spatial econometric model. It could help explain the positive spatial spillover effect of AI development on urban IGG at the spatial distance, city scale, urban cluster scale, and provincial scale.

Table 11 presents the empirical test results of spatial spillover effects based on various spatial weight matrices. The regression results of the SDM model show that the spatial

autoregressive coefficient of IGG level (ρ) is still significantly positive at the 1% level, indicating that it is appropriate to adopt spatial econometric models for empirical tests. After replacing the spatial weight matrix, the coefficient of the spatially weighted term of AI (W × AI) remains significantly positive. This implies that the conclusion that AI development has a positive spillover effect on urban IGG in neighboring regions is robust and reliable. In addition, under the adverse geographical distance weight matrix and city adjacency weight matrix, the coefficients of the spatial weighted term of AI (W × AI) are more significant, indicating that urban contiguity or geographical proximity is more conducive to the spillover effect of AI development. The new generation of digital technologies represented by big data and AI has broken the constraints of space, which not only strengthens the dynamic role of resource elements but also alleviates the barriers to technological exchanges between cities, thus driving urban collaborative development and further promoting the IGG level of neighboring regions. Compared with the provincial linkages, the spillover effect of AI development caused by the linkages between urban clusters is weaker. The possible reason is that China's major urban agglomerations and metropolitan areas are still in the initial stage of construction, and the economic and social ties between urban clusters are not close enough to support the spillover effect of AI development. In the future, the central and local governments should accelerate the construction of urban agglomerations and metropolitan areas and continuously deepen regional cooperation and exchanges.

Table 11. SDM regression results based on various spatial weight matrices.

Variables	(1)	(2)	(3)	(4)
	Distance	**City Adjacency**	**Urban Cluster Adjacency**	**Provincial Adjacency**
AI	0.0153 *** (0.0042)	0.0206 *** (0.0054)	0.0183 *** (0.0035)	0.0190 *** (0.0047)
W × AI	0.0165 *** (0.0053)	0.0259 *** (0.0067)	0.0119 * (0.0104)	0.0160 ** (0.0068)
ρ	0.4021 *** (0.0335)	0.5132 *** (0.0688)	0.3132 *** (0.0301)	0.3589 *** (0.0497)
Control variables	YES	YES	YES	YES
W × Control variables	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	2730	2730	2730	2730
R^2	0.5241	0.6122	0.4837	0.5051

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively. The robust standard error is enclosed in parentheses.

7. Research Conclusions and Implications

7.1. Conclusions

Based on panel data regarding prefectural cities in China from 2010 to 2022, this paper scientifically measures the IGG level and AI development level of Chinese cities. We use the panel econometric model, instrumental variable method, mechanism test model, and spatial econometric model to empirically study the impact, influence mechanism, and spatial spillover effects of AI development on urban IGG. The research conclusions are as follows: (1) AI development significantly promotes urban IGG, and this conclusion still holds after a series of robustness and endogeneity tests. (2) The effect of AI on IGG will exhibit heterogeneity due to differences in urban characteristics such as government financial

support, information infrastructure development, and innovation and entrepreneurship vitality. (3) Mechanism test reveals that AI development fosters urban IGG through digital technology innovation and industrial structure optimization. (4) AI development has a positive spatial spillover effect on IGG in neighboring cities.

7.2. Policy Implications

Based on the research conclusions, the following policy implications are proposed. First, seize the favorable opportunity to promote the development of AI. Given that there is still a certain gap between the development level of AI in China and that in developed countries, local governments should fully recognize the importance of AI development for urban IGG, implement the 14th Five-Year Plan for intelligent manufacturing, and build a well-structured industrial intelligence ecosystem centered around data through technological integration, infrastructure development, and talent cultivation, thereby providing strong support for urban industrial digital transformation, networked collaboration, and intelligent transformation. The government should formulate a long-term and comprehensive AI development plan, clarify the core role of AI in promoting urban IGG, and set up phased goals and evaluation mechanisms. Establish a cross-departmental collaborative working group to coordinate cooperation between different government departments, industry associations, and scientific research institutions in AI applications, ensuring policy consistency and efficient implementation. Formulate and improve laws and regulations related to AI applications, including data protection, privacy security, ethics, and morality, to provide legal protection for the healthy development of AI.

Second, promote the application of AI technology and thus empower urban IGG. The government should promote the application of AI in the construction of green infrastructure. Encourage the use of AI technology to optimize building design, operation, and maintenance, improve building energy efficiency, and reduce carbon emissions. For example, AI can be used to achieve intelligent temperature control, energy-saving lighting, and so on. Promote the application of AI in traffic management, such as intelligent traffic signal control, autonomous vehicles, etc., to reduce traffic congestion and emissions and improve travel efficiency. Use AI technology for environmental monitoring, such as air quality prediction, water quality monitoring, etc., to provide a scientific basis for environmental protection. Meanwhile, the application of AI in the development of a green economy should be promoted. Support the application of AI technology in traditional industries and promote the transformation of industries towards green and low-carbon development. For example, using AI to optimize production processes and reduce energy consumption and emissions. Develop AI-based green financial services, such as green credit and green bonds, to provide financial support for green projects. Conduct green employment training for AI technology, improve the quality of the workforce, and promote the sustainable development of the green economy. In addition, it is necessary to enhance the role of AI in promoting social inclusiveness. Use AI technology to improve the level of urban services, such as intelligent medical care, intelligent education, etc., and narrow the service gap between urban and rural areas and regions. Promote the application of AI in community governance, such as intelligent security, intelligent garbage classification, etc., to improve the efficiency of community governance and the quality of life of residents. Pay attention to the impact of AI technology on vulnerable groups and ensure that the dividends brought by technological progress can benefit all people. For example, providing customized intelligent services for the elderly, disabled, and others.

Third, explore models for AI development tailored to enterprise conditions and city-specific strategies. China's AI development holds significant potential, significantly advancing green development and inclusive growth. On the one hand, the development of AI should not solely focus on scale and speed but should proceed gradually and align with market demands. Consequently, the government must prevent short-sighted actions and enhance the top-level planning and overall strategy for AI development. On the other hand, AI development should integrate regional characteristics and application needs, ensuring

that intelligent technology aligns with the city's actual developmental level to prevent efficiency losses due to resource mismatches. Regions should intensify efforts in building a new generation of digital technology platforms centered around AI, to tackle critical core technologies and extend the reach of intelligent manufacturing technologies such as system integration. Enterprises should be positioned as the focal point of digital transformation, leveraging market forces to drive intelligent industry transformations through application scenarios and demand. Furthermore, we should fully utilize AI's empowering role in optimizing industrial structures, deepening its penetration into traditional sectors, and fostering innovations in production methods such as intelligent workshops, factories, and supply chains. Enterprises with extensive management practices should be systematically guided in assessing their intelligent manufacturing capabilities, understanding their current strengths and areas for improvement, and developing tailored intelligent manufacturing strategies.

Finally, emphasize the "spillover effect" of AI on urban IGG. The development of AI not only promotes IGG within the region but also enhances IGG levels in neighboring areas. Consequently, it is essential to adopt a regional coordinated development approach, efficiently dividing tasks and enhancing collaboration based on each region's strengths. On the one hand, leveraging some regions' strong manufacturing base and advanced information technology, along with the national manufacturing innovation center initiative, we aim to establish an open-source community for AI technology innovation. Additionally, we will overcome "information islands," emphasizing the synergistic effects of small steps towards large-scale advancements, to strengthen shared creation and sharing in cutting-edge technology areas, fostering industrial development that is both large-scale and environmentally responsible. On the other hand, by refining the alignment and implementation mechanisms, establishing industrial demonstration sites, enhancing the integration and linkage of the industrial and innovation chains, and perfecting common data circulation support platforms, we can harmoniously integrate technology research and development with industrial development and application deployment, establishing a coordinated and systematic regional layout that effectively leverages the strengths of AI and promotes collaborative progress while adhering to market principles.

7.3. Limitations and Future Directions

Last but not least, some limitations of this work also set paths for future research. First, this paper used the urban industrial employment structure, the number of urban labor forces, and the number of industrial robots at the industry level to construct an AI development indicator at the city level. Due to the rich connotation of AI, with the continuous expansion of data sources, more comprehensive quantitative indicators can be considered constructed from the dimensions of data, technology, and application to reflect the development of AI. Second, while this paper utilizes macrocity level data for its empirical study, empirical evidence at the microfirm level is also worth exploring. This is helpful to provide beneficial enlightenment to promote the development of AI technology at the enterprise level. Finally, as AI technology increases the speed and efficiency of information exchange and knowledge dissemination, it increases spatial connectivity between regions, which can have important implications for IGG. Therefore, further discussion on how the differences in AI development across cities may impact outcomes can enrich the empirical results and enhance the study's practical relevance for concrete policy guidance.

Author Contributions: Writing—original draft preparation, H.F.; Writing—review and editing, H.F.; Methodology, H.F.; Supervision, R.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data are available with reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

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