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Research on the Impact of Industrial Intelligence on Inclusive Green Growth

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Abstract: The fourth generation industrial revolution represented by intelligence, as a new economic form, provides a feasible path for achieving economic growth, optimizing the ecological environment and improving residents' income. The conclusion shows that industrial intelligence promotes inclusive green growth on the whole, and after robustness test, endogeneity test, heterogeneity test and causal regression analysis, the result is still significant, which indicates that the benchmark regression results in this paper have strong robustness. Causal identification shows that the "Made in China 2025" policy has promoted the improvement of industrial intelligence to a certain extent, and the use of differential model research shows that industrial intelligence can promote the improvement of inclusive green growth, and a series of robustness tests are conducted to demonstrate that the conclusion is reasonable and reliable.

1. Introduction

With the rapid development of economy and society, population and policy dividends gradually disappear, production costs continue to increase and the contradiction between labor supply and demand becomes more obvious, and the comprehensive competitiveness of traditional manufacturing industry faces great challenges, and there is a problem of "big but not strong". The fourth technological revolution driven by artificial intelligence marks the continuous expansion of the scale of information technologies such as 5G, artificial intelligence, and big data, and enables the real economy to continuously promote industrial transformation and upgrading. In the face of the fourth scientific and technological revolution, the government has introduced a number of policies to seize the opportunity of informatization development. As early as 2017, The State Council issued the "New Generation of artificial Intelligence Development Plan", and the 2022 "Government Work Report" pointed out that "accelerate industrial digital intelligent transformation, and vigorously develop strategic emerging industries." Industrial robots as an important indicator to measure the level of industrial intelligence, the International Federation of Robots report shows that in 2021, the number of industrial robots installed worldwide continues to increase, 2011-2021, China's industrial robot density climbed year by year, 2021, China's industrial robot density of 322 units / 10,000 people, An increase of 76 units / 10,000 people from 2020, surpassing the United States for the first time, ranking fifth in the global industrial robot density list.

At the same time, while the economic scale continues to expand, environmental pollution and social equity issues are also prominent. At present, China has become the world's largest carbon emission country, and the impact of air pollution represented by PM2.5 on residents' health has also attracted great attention from the government. The Gini coefficient has risen from 0.14 in 1978 to 0.55 in 2020, higher than the warning value of 0.4 for the international Gini coefficient. The report put forward new requirements for high-quality economic development, emphasizing that on the basis of economic growth, green development and social equity should be attached importance, which is consistent with the concept of inclusive green growth, that is, stable economic growth, sustainable green environment and inclusive social development are also important ways to sustainable development. This has pointed out the direction for China's economic and social development in the coming years, and also provided ideas for solving the main contradiction in Chinese society at present, that is, the transition from extensive development to inclusive and green development. However, in the post-pandemic era, how to balance economic growth, ecological environment and social equity has become an important issue for inclusive green growth.

In view of this, this paper brings industrial intelligence, biased technological progress and urban inclusive green growth into the unified analysis category, systematically demonstrates the direct impact of industrial intelligence on urban inclusive green growth and the indirect impact of biased technological progress on the relationship between the two, and tries to answer whether industrial intelligence can directly enable urban inclusive green growth. The answers and discussions on this question will provide reliable empirical evidence and policy implications for China's green economic recovery and inclusive growth in the post-COVID-19 era.

The main innovations of this paper are as follows: (1) In terms of theoretical framework, industrial intelligence and urban inclusive green growth are included in the same analytical framework, and the internal mechanism of industrial intelligence's impact on inclusive green growth is deeply analyzed, which is conducive to deepening and improving the theoretical basis of industrial intelligence and inclusive green growth research. (2) In terms of variable measurement, it enriches the index system of industrial intelligence, refining the inclusive green growth measurement and decomposition, ensuring the comprehensive objectivity of variable measurement, and filling the research gap of variable measurement in existing literature. (3) In terms of empirical analysis, this paper takes 280 cities at the prefecture level and above as research objects to empirically-test the impact of industrial intelligence on inclusive green growth, and examines the direct impact channels from three dimensions of market effect, green effect and equity effect, which is more comprehensive and refined than previous literatures, with a view to identifying the impact direction of industrial intelligence on inclusive green growth. And further enrich the relevant empirical research.

2. Literature Review

Inclusive green growth is a concept of both "green" and "inclusive" economic growth, which has rich theoretical connotation. At present, studies on inclusive green growth mainly focus on calculation and analysis and spatio-temporal pattern. Few literatures directly discuss inclusive green growth from the perspective of industrial intelligence. Scholars mostly analyze the correlation between industrial intelligence and total factor productivity.

(1) Based on the improvement of industrial intelligence level, many scholars gradually adjusted the key point to the relationship between intelligence and total factor productivity in the process of exploring the impact of intelligence. Some scholars have proposed that the level of intelligent development has a positive impact on total factor productivity. For example, Graetz and Michaels extracted the basic data of 17 countries in their research, and found that robots can increase labor productivity by 0.36%, resulting in an increase in total factor productivity and a decline in output prices to a certain extent [1]. Acemoglu and Restrepo proposed that the substitution effect of automation is very obvious, as is the effect of total factor productivity. In a lower capital environment, the effect of production efficiency can replace labor force, thus forming higher productivity [2]. In the study, Kromann et al. extracted data from 9 countries starting from the industrial robot index to analyze the manufacturing industry, and found that the industrial robot index has a positive impact on the total factor productivity. If the index density increases by 1 unit standard deviation, the total factor productivity will increase by more than 6%[3].

Some scholars have also proposed that industrial intelligence will act on total factor productivity based on a negative path, that is, there is a "productivity paradox". In his research, Roach focused on American data, combined with the effect of the large-scale application of data analysis computers on total factor productivity from 1977 to 1984, and found no significant correlation between the two [4]. Solow also found a similar situation and proposed the "productivity paradox" [5]. Brynjolfsson found in his research that this situation also exists in the field of information technology [6]. Subsequently, Kettinger et al. explored 30 case companies in their study and demonstrated the "productivity paradox" [7], which was also verified by Carr [8]. In their research, Brynjolfsson and Hitt focused on American data, extracted data information from 1987-1991, analyzed the internal correlation between information system expenditure and productivity, and found that there was a "productivity paradox", but this phenomenon appeared in the middle and late 1990s [9]. Dewan and Kraemer's study started with the data of 36 countries and found that information technology would enable the productivity of developed countries to achieve continuous improvement, while the "productivity paradox" would only appear in developing countries [10]. Lin and Shao's research focuses on American enterprises. Based on the data from 1988-1992, they find that the lack of "productivity paradox" exists in the information technology industry. There is no substitution effect between information technology investment, traditional capital and labor force, and the importance of information technology investment is the same as that of capital, so it is difficult to replace labor force [11]. Chen and Lin extracted data from 15 countries and found that "productivity paradox" exists in all countries regardless of their development level through phased study of data from 1993 to 2003 [12].

Review: The above studies provide rich evidence for the relationship between industrial intelligence and inclusive green growth. However, there are few literatures on the impact of industrial intelligence on inclusive green growth, and there is no comprehensive consideration from the three perspectives of economic growth, energy conservation and emission reduction, and social equity. Therefore, this paper will conduct an in-depth exploration of the above issues from both theoretical and empirical perspectives, in order to provide important references and policy enlightenment for the next stage of industrial intelligence and urban transformation.

3. Theoretical Mechanisms

Inclusive green growth is the key to high-quality development, and its significance is not only related to economic growth, but also related to the balanced allocation of resources, environment, social and people's livelihood interests (Li Hua and Dong Yanling, 2021; Ren et al., 2022[13]). Therefore, when analyzing the impact of industrial intelligence on the inclusive green growth of cities, this study will pay attention to industrial intelligence and carry out analysis in the aspects of economic growth, energy conservation and emission reduction and social equity:

First of all, industrial intelligence can speed up economic development

Combined with the theory of endogenous economic growth, industrial intelligence can effectively promote technological progress, accelerate industrial upgrading, and ensure the all-round allocation of elements (Xie Yanxiang, 2023), which is extremely beneficial to the cultivation of endogenous momentum of economic growth, and can also accelerate inclusive green growth. On the one hand, industrial intelligence has made big data and AI technology widely used, accelerated the technological progress of production and energy-saving industries, and reduced the consumption of various energy sources. On the other hand, industrial intelligence makes the exchange of various information between industries more convenient, has a significant promoting effect on the "integration of the two", and is of great significance to the development of high value-added models in traditional industries (Li Jinlin et al., 2021). At the same time, build economies of scale and advantageous structure, accelerate the development of emerging industries, and achieve the improvement of production efficiency and profits. In addition, intelligence accelerates the development of new business models, such as B2B and O2O (Jing Wenjun, 2019). In addition to enhancing various new demands, these methods also allow various factors such as data, labor, and technology to be better allocated, speeding up the precise allocation of supply and demand factors, and playing a role in promoting high-quality economic development.

Secondly, industrial intelligence enables energy conservation and emission reduction

Existing data show that industrial intelligence makes the coupling and collaborative governance of government and enterprises in environmental protection more efficient (Tang Xiaohua, 2022; Hui Shupeng,2021), is the key to energy conservation, emission reduction and green development. At the level of government environmental supervision, industrial intelligence also provides more regulatory technologies, such as the Internet of Things, remote sensing technology, etc. These facilities can dynamically monitor data such as sewage discharge and water quality (Zhang Wei, 2021), so as to give early warning to pollution sources and control carbon emissions. In terms of energy conservation, at present, China's manufacturing industry has problems such as high energy consumption and serious pollution (Li Xin et al., 2022), intelligent manufacturing and green manufacturing projects to promote high-end, intelligent and green manufacturing, so as to make the allocation of energy resources more reasonable and greatly improve the utilization efficiency (Zhang Wanli et al., 2022); In terms of enterprise green governance, the intensive transformation of production mode has become the focus (Li Guanghao and Zhou Xiaoliang, 2021), and smart devices, smart workplaces and other digital tools have gradually adjusted the traditional manual and empirical production mode to the standard and standardized mode of operation. Energy, process and cost data become more efficient in the transmission and fine-tuning process, which means that enterprises are also more efficient in management, which ultimately contributes to increased productivity and scientific environmental control.

Finally, industrial intelligence widens the social gap

In the process of the development of industrial intelligence and related ICT automation, there is not only an overall trend of polarization of labor and employment, but also a great change in the pattern of income distribution. In the last century, the share of capital and labor in national income of all countries was relatively stable, which conforms to the "Kaldor typical fact" (Boran et al., 2020[14]; Goyal et al., 2020[15]). Since the beginning of this century, as the return on labor has continued to decline, the steady state is no longer sustainable; In the period 1947-2000, the proportion of labor remuneration in the national income of the United States was 64.3%. After that, the proportion continued to decline, falling to 57.8% in the third quarter of 2010 (Fleck et al., 2011[16]). Economies outside the United States began to see a decline in the share of labor compensation in the 1980s; In contrast, there is an increase in the return on capital, a concentration of income and wealth in the world, and the problem of unbalanced distribution is intensified (Karabarbounis et al., 2013[17]). Artificial intelligence promotes the improvement of production efficiency, which has a positive impact on the return rate of capital factors, but also makes the return gap between labor and capital factors continue to widen (Autor et al., 2003[18]). At the same time, in the development of artificial intelligence technology, there is also the deepening of capital, which will make the proportion of labor remuneration in national income continue to decline, and the difference between the proportion of capital and labor continues to increase.

4. Empirical Analysis

4.1. Measurement of Variables

(1) Industrial intelligence

① Intelligent conditions. Based on the optical cable density, the number of Internet broadband access users, the number of E-mail boxes and other indicators to characterize the setting of intelligent conditions. ② Intelligent application. Based on the two indicators of robot penetration, big data acquisition and data processing at the city level, it is measured. ③ Intelligent technology. Based on artificial intelligence patent analysis.

The data mainly come from Tianyan enterprise database, China patent database, China City Statistical Yearbook, etc. Tianyan Check enterprise database covers 280 million enterprises, the database covers a variety of enterprise types, including enterprise name, registration type, survival status, etc., and the data comes from the national enterprise credit publicity system, SAIC and intellectual Property Office and other platforms, with a certain authority, this paper through the integration of enterprise data, to obtain the data at the prefecture-level city level. Based on the data collation, this paper obtained the panel data of 280 prefecture-level cities from 2008 to 2020 after eliminating the imperfect and unreasonable values.

2) Inclusive green growth

Total factor productivity is the driving force of sustainable economic growth, and its measurement standard is the classic Solow model, which is a theoretical model that quantifies the impact on total factor productivity by measuring the impact of technological progress level. However, the research of this model ignores factors such as energy environment and income inequality, which limits its applicability. However, if factors such as energy environment and income inequality are incorporated into the model framework, the traditional Solow model will be transformed into a more comprehensive green Solow model

$$y^t - b^t = (A^t\theta^t)[(l^t)^\alpha (k^t)^\beta (e^t)^\gamma] \quad \alpha,\beta,\gamma \geq 0, 0 \leq \theta \leq 1, b^t = \sum_{f=1}^{F} mac_f^t n_f^t \quad (1)$$

among, l k e is the input factors (labor, capital, energy), y b is the output variable (GDP, pollutants, income gap) α β γ δ Is the elastic coefficient, A θ is the efficiency factor, mac

f F n is marginal emission reduction cost, pollutant, pollutant type and pollutant emission

Transmutating the above formula, and based on the fact that the growth rate of the variable is equal to the rate of change of its natural logarithm [19], the formula for calculating inclusive green total factor productivity is obtained:

$$TFP = \frac{\Delta A}{A} + \frac{\Delta \theta}{\theta} = \frac{\Delta (y-b)}{(y-b)} - \alpha \frac{\Delta l}{l} - \beta \frac{\Delta k}{k} - \gamma \frac{\Delta e}{e} \tag{2}$$

As can be seen from the above equation, according to the inclusive green total factor productivity formula, input factors such as labor, capital and energy, as well as expected output and non-expected output, will have an impact on inclusive green total factor productivity. From the left side of the formula, the improvement of inclusive green total factor productivity in the process of development can be adjusted based on technological progress, or it can be improved based on the improvement of efficiency. Efficiency optimization and technological progress are mainly manifested in the reduction of energy consumption by low-efficiency enterprises through increasing technological investment, especially various technological investment at the level of energy conservation and emission reduction. Gradually approaching the production possibility boundary; Areas with low efficiency can adjust their industrial structure, increase the proportion of high-tech industries, reduce the proportion of industries with high energy consumption and high emissions, achieve inclusive green total factor productivity growth in the region, and introduce strict environmental supervision and preferential fiscal and tax policies to further strengthen research and development. Technologies related to energy conservation and emission reduction promote technological progress in the whole region through spillover and induced effects, achieve continuous upgrading of industrial structure, win-win situation between economic development and energy conservation and emission reduction, and enhance inclusive green total factor productivity. From the right side of the formula, reducing factor input of labor, capital and energy can also improve inclusive green total factor productivity. At present, there are different degrees of distortion in China's factor market. If the government artificially lowers factor prices, it will bring economic growth in the short term, increase factor use, and may also improve inclusive green total factor productivity. This economic growth model is not sustainable, and the reform of factors is more difficult, which is not conducive to sustainable economic development.

Considering the availability of data, this paper selects 280 cities in China from 2008 to 2020 as research samples, all of which are extracted from China Urban Statistical Yearbook and CEADs carbon emission database. Among them, labor, capital and energy are input indicators, labor indicators mainly refer to the human capital of each city, and the number of employees at the end of each city is a measurement indicator. This paper uses the method of "perpetual inventory" to estimate the capital stock and regards it as the amount of invested capital. The standard coal of the total energy consumption of each city is used as energy input. Because the prefecture-level city does not publish the energy balance table, it is temporarily unable to get the 17 types of energy consumption at the provincial level. In this paper, the energy consumption of natural gas and liquefied petroleum gas, electricity consumption of the whole society, and urban heating (steam heating, thermal power plant heating) published in China City Statistical Yearbook is used for reference, and the total energy consumption is obtained through the conversion coefficient of standard coal. In the determination of output index, the expected output value is represented by GDP. The index of undesirable output mainly includes environmental pollution and social equity. For details, see Table1.

Table 1. Statistics of input-output indicators

Regional	labor (10,000)	Capital (ten thousand yuan)	Energy (10,000 tons of standard coal)	GDP (100 million yuan)	Environmental pollution	Social equity
The whole country	50.0508	32217.7509	11630.2187	10909.1413	32720.3051	0.4323
The east	85.7373	46882.7037	15228.8873	17150.3777	41433.1630	0.4284
Middle part	43.3891	30328.9358	11400.3012	9762.4905	34033.6485	0.4336
west	35.7364	18926.4818	8198.7627	5501.8198	23052.2883	0.4352

4.2 Model Construction

This paper mainly studies the impact of industrial intelligence on inclusive green growth. We initially fit the relationship between the two, and the results show that the two are linearly positively correlated. Therefore, the following linear econometric model is established in this paper:

$$igg_{it} = \beta_0 + \beta_1 ini_{it} + \sum Controls_{it} + \gamma_t + \theta_i + \varepsilon_{it} \tag{3}$$

In the model, i represents the city, t represents the year,the explained variable igg_{it} epresents the inclusive green growth, the main explanatory variable ini_{it} represents the level of industrial intelligence, $\sum Controls_{it}$ represents the collection of various control variables, γ_t represents the time fixed effect, θ_i represents the fixed effect of the city that does not change with time, ε_{it} is the random disturbance term, β_0 β_1 is the coefficient estimate After conducting F test and Hausman test, according to the test results, urban fixed effects that control both time fixed effects and do not change with time are selected, and the panel bidirectional fixed effects model is used for regression.

4.3 Data Sources

The data sources involved in this paper are as follows: First, the original data of the industrial intelligence level measured in this paper comes from the Tianyan enterprise database, China patent database, International Federation of Robotics, China Statistical Yearbook and China City Statistical Yearbook. Secondly, the inclusive green growth calculated in this paper, in which the social and economic data required for accounting, such as GDP, labor, capital, etc., are from China Urban Statistical Yearbook, China Economic Network database and EPS database and relevant local government reports, and the energy data used is from China Energy Statistical Yearbook and China Urban Statistical Yearbook. And finally, The control variable data used in this paper came from China Statistical Yearbook, China Economic Census Yearbook, China Electronic Information Industry Statistical Yearbook, China Science and Technology Statistical Yearbook, China Energy Statistical Yearbook, China Environmental Statistical Yearbook, China Population and Employment

Statistical Yearbook, China Labor Statistical Yearbook, China Economic Net database and EPS data Library, etc.

4.4 Control variable selection

Considering that the influencing factors of inclusive green growth involve economic, social and other aspects within the region, this paper comprehensively considers these factors and sets the following control variables:

Table 2. Qualitative description of each variable

Variable class	symbol	Metrics and descriptions	unit
Inclusive green growth	*igg*	Directional distance function and green Luneberg productivity measurement	/
Industrial intelligence	*ini*	From the intelligent condition, intelligent application, intelligent technology and other three aspects of 10 indicators using the entropy weight method	/
Industrial structure	*struc*	Value added of tertiary industry as a proportion of GDP	/
Economic growth	*pgdp*	Natural logarithm of GDP per capita (2000 constant price)	Ten thousand yuan/person
Environmental regulation	*er*	Proportion of investment in environmental governance in GDP	/
Educational input	*edu*	Use of education as a share of GDP	/
infrastructure	*inv*	Per capita road construction area	m^2
Government expenditure	*fin*	Government spending as a share of GDP	/
Human capital level	*scale*	The ratio of undergraduate and junior college students to the total population at the end of the year	/
R&d personnel input	*scient*	R&d investment as a percentage of GDP	/

4.2 Benchmark Regression Analysis

This section uses a fixed effects model to estimate equation (4.1) and reports the direct effects of industrial intelligence on inclusive green growth. The baseline regression results are shown in Table 3.

As shown in Table 4-3, it can be found that in column (1), no control variables are added, only industrial intelligence and inclusive green growth are regression, and the time fixed effect and city fixed effect of the model are not controlled. The estimated coefficient of ini is 0.1547, which is significantly positive at the 1% level. In column (2), adding industrial structure *stru*, economic growth *pgdp*, environmental regulation *er*, educational input *edu*, infrastructure *inv*, government expenditure *fin*, human capital level *scale* and R&D *scie* input on the basis of column (1), without controlling the time fixed effect and city fixed effect of the model, the coefficient of *ini* is estimated to be 0.0827, which is significantly positive at the 1% level; In column (3), no control variables are added, only industrial intelligence and inclusive green growth are regressed, and the estimated coefficient of the model is 0.3222, which is significantly positive at the 1% level. In column (4), based on column (3), the estimated coefficient of industrial structure *stru*, economic growth *pgdp*, environmental regulation *er*, educational input *edu*, infrastructure *inv*, government expenditure *fin*, human capital level *scale* and R&D *scie* input, and controlling for time fixed effects and urban fixed effects of the model, *ini* is 0.2477, which is significantly positive at the 1% level. It can be seen that proposition 1 of this paper has been verified, that is, industrial intelligence directly enhances inclusive green growth. The symbols and directions of the other control variables are generally in line with the expectations of the existing literature and will not be discussed here. It is worth noting that in China, the largest developing country, industrial intelligence has a positive effect on inclusive green growth, which can provide an important reference for other developing countries and less developed countries to make policies.

Table 3. Benchmark regression results

	(1)	(2)	(3)	(4)
	igg	*igg*	*igg*	*igg*
ini	0.1547***	0.0827*	0.3222***	0.2477***
	(5.5330)	(1.7957)	(5.0161)	(3.1193)
stru		0.0007***		0.0009***
		(3.7671)		(2.6230)
pgdp		-0.0064		0.0698***
		(-1.5505)		(3.9678)
er		-0.0008***		0.0030**
		(-3.0184)		(2.5231)
edu		-0.3411**		-1.2888***
		(-2.1480)		(-3.7382)
inv		-0.0107**		-0.0343***
		(-1.9970)		(-3.4851)
fin		0.0081		0.0811*
		(0.2968)		(1.7660)
scale		-0.0013		-0.0379***
		(-0.5136)		(-4.1066)
scie		-0.1144		-1.4552***
		(-0.1921)		(-2.8629)
cons	0.0071***	0.0730*	-0.0005	-0.5251***
	(3.8173)	(1.7707)	(-0.1738)	(-3.1491)
Fixed time	no	no	Yes	Yes
Regional fixation	no	no	Yes	Yes
R^2	0.0109	0.0238	0.1496	0.1900
N	3640	3640	3640	3640

In addition, in order to enhance the robustness of the conclusion, this paper also introduced three subdivision variables of industrial intelligence, namely intelligent condition $ini1$, intelligent application $ini2$ and intelligent technology $ini3$, and substituted them into equation (3) to perform panel bidirectional fixed effect model regression, as shown in Table 4.

Table 4. Benchmark regression results: subdivided independent variables

	(1)	(2)	(3)
	igg	*igg*	*igg*
*ini*1	0.4412^{***}		
	(3.4262)		
*ini*2		2.0664^{***}	
		(5.9687)	
*ini*3			0.4287^{***}
			(2.8859)
stru	0.0013^{***}	0.0010^{***}	0.0012^{***}
	(3.7853)	(3.1794)	(3.6234)
pgdp	0.0714^{***}	0.0790^{***}	0.0733^{***}
	(5.5526)	(6.2846)	(5.8101)
er	0.0030^{***}	0.0026^{***}	0.0030^{***}
	(3.8990)	(3.3169)	(3.8987)
edu	-1.2687^{***}	-1.2648^{***}	-1.2684^{***}
	(-4.1257)	(-4.1380)	(-4.1292)
inv	-0.0352^{***}	-0.0362^{***}	-0.0341^{***}
	(-3.8264)	(-3.9581)	(-3.7090)
fin	0.0802^{**}	0.0900^{**}	0.0789^{**}
	(2.0660)	(2.3285)	(2.0342)
scale	-0.0344^{***}	-0.0363^{***}	-0.0372^{***}
	(-4.1817)	(-4.4403)	(-4.3936)
scie	-1.2138	-1.4111^{*}	-1.2877
	(-1.5433)	(-1.8101)	(-1.6327)
cons	-0.5602^{***}	-0.6171^{***}	-0.5635^{***}
	(-4.5612)	(-5.1802)	(-4.6653)
Fixed time	Yes	Yes	Yes
Regional fixation	Yes	Yes	Yes
N	3640	3640	3640
R^2	0.0528	0.0620	0.0533

As shown in Table 4, industrial intelligence is specifically subdivided into intelligent conditions, intelligent applications, and intelligent technologies. Among them, $ini1$ indicates industrial intelligent conditions, $ini2$ indicates industrial intelligent applications, and $ini3$ indicates industrial intelligent technology. It can be found that in column (1), after controlling control variables such as industrial structure $stru$, economic growth $pgdp$, environmental regulation er, educational input edu, infrastructure inv, government expenditure fin, human capital level $scale$ and R&D $scie$ input, and controlling time fixed effect and city fixed effect of the model, the estimated coefficient of $ini1$ is 0.4412, which is significantly positive at 1% level. This may be because, the implementation of industrial intelligence, can help enterprises to achieve high-end industrial development, traditional intelligence and digitalization is not enough to support the rapid development of enterprises, and the implementation of industrial intelligence can encourage enterprises in the digital, networking and intelligent aspects of the necessary improvements, so that product quality continues to rise, so as to promote enterprises to achieve high-end industrial development. Therefore, the positive impact on inclusive green growth is more significant. In column (2), after controlling for control variables such as industrial structure $stru$, economic growth $pgdp$, environmental regulation er, educational input edu, infrastructure inv, government expenditure fin, human capital level $scale$ and R&D $scie$ input, and controlling for time fixed effects and city fixed effects of the model, the estimated coefficient of $ini2$ is 2.0664, which is significantly positive at the 1% level. This may be because industrial intelligence can realize the full chain connection of production processes such as design or production and circulation, so as to realize the transformation from digitalization to networking and then to intelligence, and then help enterprises reduce the cost of production factors, reduce data statistics personnel, save labor costs, and ensure the immediacy of data. Schedulers can check the production situation at any time through computers and mobile phone apps, control the production from every tiny link of production, accurate scheduling, and ensure timely delivery of products. Cloud platform monitoring can ensure the accuracy of data, improve the comprehensive utilization rate of equipment, and formulate timely strategies according to the production situation. Compared with $ini1$, they pay more attention to inclusive green growth factors. Therefore, the positive impact on inclusive green growth is significant. In column (3), after controlling for control variables such as industrial structure $stru$, economic growth $pgdp$, environmental regulation er, educational input edu, infrastructure inv, government expenditure fin, human capital level $scale$ and R&D $scie$ input, and controlling for time fixed effects and city fixed effects of the model, the estimated coefficient of $ini3$ is 0.4287, which is significantly positive at 1% level. This may be because industrial intelligent technology is a typical interdisciplinary subject, involving mechanical engineering, control engineering, electronic technology, computer network, embedded technology and artificial intelligence technology, is composed of identification analysis, industrial wireless, special line and other network services, as well as by optical access equipment, switches, Internet of things modules, industrial communication gateways and other network equipment. The network infrastructure that promotes the comprehensive interconnection of people, machines and things in the industrial environment is an important part of the industrial Internet, which plays an important role in the penetration of other industries, and therefore has a significant positive impact on inclusive green growth. The symbols and directions of the other control variables are generally in line with the expectations of the existing literature and will not be discussed here.

5. Conclusions

Based on the typical facts of industrial intelligence and inclusive green growth, this chapter constructs an econometric model to empirically analyze the impact of industrial intelligence on inclusive green growth, and conducts robustness, heterogeneity test and endogeneity test, using the exogenous event of "Made in China 2025" to carry out causal identification. The main conclusions are as follows:

(1) In the main effect analysis: the coefficient of industrial intelligence on inclusive green growth is significantly positive, which means that industrial intelligence can promote inclusive green growth, and the sub-indicators of industrial intelligence, industrial intelligence conditions, intelligent applications and intelligent technologies can also improve the level of inclusive green growth.

(2) In the analysis of robustness, heterogeneity test and endogeneity test, whether it is changing

independent variables and dependent variables, adding control variables, lagging control variables, eliminating special time periods, special cities and special policies, the results all show that industrial intelligence can significantly improve the level of inclusive green growth in China, and the results are relatively stable. In different regions, different digital development levels, and different fairness and efficiency, industrial intelligence shows different characteristics for inclusive green growth. And whether it is regression of instrumental variables or lagging dependent variables, the conclusion is still robust, indicating that industrial intelligence can positively affect inclusive green growth.

(3) In cause-and-effect identification analysis, the "Made in China 2025" policy has promoted the improvement of industrial intelligence to a certain extent. The use of differential model research shows that industrial intelligence can promote the improvement of inclusive green growth, and a series of robustness tests are conducted to show that the conclusion is reasonable and reliable.

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If any, should be placed before the references section without numbering.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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