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ORIGINAL PAPER

The impact of industrial intelligence on green development: research based on intra- and inter-industry linkage effect

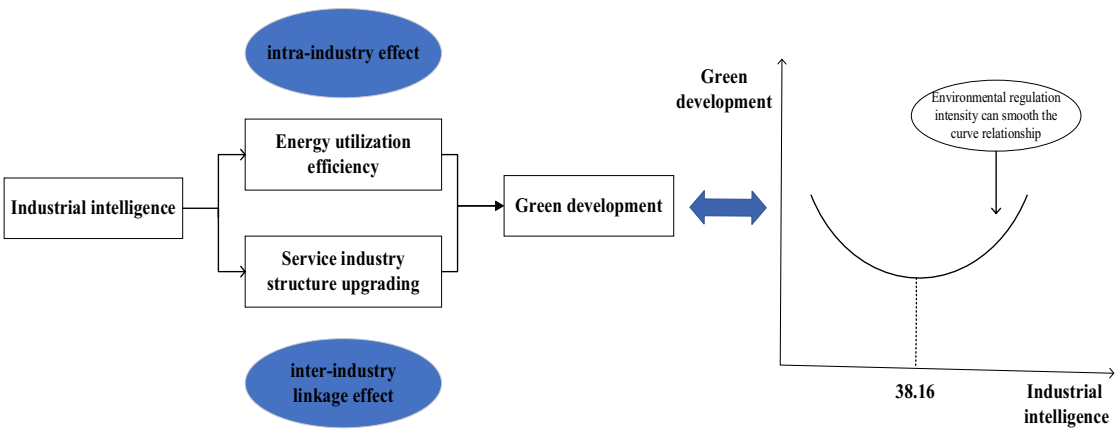
Fengfu Mao[1] · Yuqiao Hou[1] · Xiaorui Xin[1] · Hai Wang[1]

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Abstract

With the rapid advancement of the deep integration of artificial intelligence (AI) and traditional industries, industrial intelligence has a greater influence on the economy and the environment, which is of great significance in promoting green development. However, the impact of industrial intelligence on green development and the mechanism of its impact are not yet clear. In light of this, this paper uses 284 Chinese cities as samples to examine the influence of industrial intelligence on green development, explores the impact path of industrial intelligence on green development through intra- and inter-industry linkage effects, and addresses the moderating role of environmental regulation intensity on the relationship between them. It is discovered that there is a U-shaped feature between industrial intelligence and green development, and environmental regulation intensity can smooth the curve relationship between them. Heterogeneity analysis found that regional characteristics, industry type, and city size will make the U-shaped impact different. Further mechanism testing reveals that the low level of industrial intelligence inhibits energy utilization efficiency and causes a low-end service industry structure, which is not conducive to green development. When the level of industrial intelligence is high, it promotes energy utilization efficiency and a high-end service industry structure, which is conducive to green development.

Graphical Abstract



Keywords Industrial intelligence · Green development · Environmental regulation intensity · Energy utilization efficiency · Service industry structure upgrading

Introduction

Over the past century, global warming has become increasingly serious. Especially in the last 30 years, the pace of global economic development has been accelerating, the

✉ Xiaorui Xin
xinxr1988@163.com

[1] School of Economics, Zhejiang Gongshang University, Hangzhou 310018, Zhejiang, China

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demand for energy from human activities has been increasing (Sun et al. 2021), and anthropogenic emissions have caused huge ecological pressures. Green development has emerged as an inevitable choice to combat global warming (Bina and La Camera 2011). The United Nations Development Programme introduced the notion of green development in 2002, calling for coordinated and win–win progress between global development and ecological environment. The "Rio + 20" Summit in 2012 created the groundwork for global green growth. The notion of green development gained broad worldwide attention and finally became the global mainstream development paradigm (Dolge and Blumberga 2021). China is an advocate and practitioner of the concept of green development. As the world's second-largest economy, it has had the highest total energy consumption for the past ten years. China's energy conservation and emission reduction are not only a commitment to the international community but also inherent requirements of China's economic growth mode transformation.

How to achieve green development is a big challenge for China now (Xu et al. 2019). The original extensive growth mode driven by investment, resource input, and external demand is unsustainable. To achieve green development, we must seek appropriate development methods. The fast advancement of industrial intelligence has paved the way for green development with the emergence of the fourth industrial revolution. Industrial intelligence is the process of penetration and application of AI in the industry (Preuveneers and Llie-Zudor 2017), which has brought about the reshaping of industrial structure and the transformation of corporate production methods. Research shows that industrial intelligence can promote green development by promoting technological innovation (Chen and Liu 2022), improving productivity, and optimizing resource allocation efficiency (Qian et al. 2022). However, some scholars put forward the view that industrial intelligence does not always promote green development and believe that industrial intelligence consumes a lot of electricity and causes a lot of energy loss (Brossog et al. 2015). Low levels of industrial intelligence prevent the industry from improving productivity, which is detrimental to green development (Zhao et al. 2022; Fang et al. 2022).

Although scholars study industrial intelligence and green development, there is still room for further improvement. First, most scholars study how industrial intelligence affects green development based on provincial panel data (Zhao et al. 2022; Fang et al. 2022), ignoring the heterogeneity of different cities, leading to certain limitations in the conclusion. Some scholars measure green development with a single index, namely green total factor productivity (Qian et al. 2022), which is difficult to reflect the overall characteristics of green development. Second, previous research mostly studies the effect path of industrial intelligence on green development from the perspective of intra-industry effect, such as innovation and human capital effects (Chen and Liu 2022), productivity and resource allocation effects (Qian et al. 2022), while ignoring inter-industry linkage effect. In fact, industrial intelligence has distinct technology spillover characteristics, which will not only directly affect the output efficiency of the industry but also influence related industries based on the production network (Autor and Salomons 2018) and then affect green development. Third, existing literature demonstrates that industrial intelligence consumes a large amount of power and energy in the early stages, which is detrimental to green development (Zhao et al. 2022; Fang et al. 2022), but does not explain how to mitigate adverse effects. Environmental regulation, as a non-market intervention tool used by the government to address pollution, plays a role in reducing the negative impact of manufacturing activities on the natural environment. This paper introduces environmental regulation, further discusses the moderating role of environmental regulation intensity in the impact of industrial intelligence on green development, and answers when strengthening environmental regulation is effective.

In view of the above deficiencies, in order to clarify the relationship between industrial intelligence and green development, this paper constructs a multidimensional evaluation system from the city level to measure green development, empirically examines the impact effect of industrial intelligence on green development and its functioning mechanisms, and explores the role of environmental regulation intensity in the relationship between industrial intelligence and green development. The following are this paper's marginal contributions: (1) Regarding research samples, this work is no longer limited to provincial panel data or a single index but expanded to the city level, using comprehensive indicators to measure green development to provide more universal and valuable conclusions for reference. (2) In terms of causality identification, this paper considers the technology spillover of industrial intelligence and puts intra- and inter-industry linkage perspectives in the same framework, providing new empirical evidence for the impact mechanism. (3) Regarding research content, this research measures environmental regulation intensity and answers whether environmental regulation intensity can mitigate industrial intelligence's negative effects on green development. We find that environmental regulation intensity can smooth the U-shaped relationship between industrial intelligence and green development and alleviate the adverse effects of low industrial intelligence on green development.

The rest of the study is structured as follows: Sect. "Literature review and hypotheses development" reviews the relevant literature and provides further theoretical analysis. Section "Methods and data" introduces the research methods and data in detail. Section "Result and discussion" makes an empirical analysis, shows the regression results, and

discusses the research findings. Section "Conclusions and outlook" briefly summarizes and puts forward policy suggestions, research deficiencies, and prospects.

Literature review and hypotheses development

Related literature review

Research status of green development

Green development is a mode of economic and social development that aims for efficiency, harmony, and sustainability. Its concept is mainly put forward by domestic and foreign scholars based on criticizing the traditional development mode. Since the notion of green development was introduced, the connotation (Georgeson et al. 2017), characteristics (Hu and Zhou 2014; Xu et al. 2019), measurement (Xu and Ouyang 2022), and its influencing factors were analyzed from multiple perspectives. Among them, the realization path and influencing factors of green development have been given more and more attention by researchers recently. Existing research discusses the conditions for realizing green development from the perspectives of economic transformation, institutional policy, and environmental factors. First, under the path of economic transformation and upgrading, scholars consider that industrial structure (Lin et al. 2017), industrial agglomeration (Cheng et al. 2018; Yuan et al. 2020), openness (Song et al. 2019), foreign investment (Zhou et al. 2020), and technological progress (Liu and Dong 2021) will promote the transformation and upgrading of regional economic structure, optimize the allocation of regional factors, improve regional economic efficiency, and thus realize green development. Second, some scholars believe that environmental regulation can promote green development (He and An 2019), and an emission rights trading system can improve total factor energy efficiency (Shi and Li 2020). However, some scholars point out that environmental regulation usually increases enterprises' emission reduction costs and system compliance costs. Thus, enterprises' willingness to innovate is reduced and the green performance of innovation activities is ultimately worsened (Wu and You 2019; Wang et al., 2023). Third, from the perspective of environmental protection and pollution reduction, scholars focused on public expenditure (Zhang et al. 2021), energy structure and its efficiency (Wang et al. 2019), low-carbon governance (Lin and Jia 2018), environmental regulation (Yuan and Xiang 2018), natural resources (Lee and He 2022), and other environmental factors on the realization of green development.

The effect of industrial intelligence

Industrial intelligence has profound economic, social, and environmental effects. At the economic level, the influence of industrial intelligence on productivity and economic growth is the main topic of discussion. Some academics believe that industrial intelligence will increase economic growth and productivity. From a macro perspective, some scholars have found that the application of AI technology can increase total factor productivity and promote economic growth (Yang and Tian 2023). From a micro perspective, some scholars have pointed out that industrial intelligence is reflected in the use of robots in the production process, and enterprises adopting robots can obtain more output (Koch et al. 2021). However, some scholars point out that industrial intelligence is not enough to promote high productivity growth, and low growth will continue for a long time (Summers 2014). Brynjolfsson et al. (2018) provided a theoretical explanation for the paradox of the rapid development of industrial intelligence and low productivity growth. They believed that when using AI technology, enterprises need to adjust costs and organizational changes. The lag in implementation and restructuring is the main reason for the lag in productivity. The social level is more concerned with the employment impact effect of industrial intelligence, which is primarily reflected in the following aspects: First, substitution effect and complementary effect. Industrial intelligence will substitute for routine manual tasks and complement non-daily cognitive ones, which encourage the development of human capital (Bravo et al. 2011). Second, employment polarization effect. The substitution of intermediate-skilled personnel for industrial intelligence is the most serious. Simultaneously, the number of jobs in high-skilled industries and low-skilled service industries has increased (Goos et al. 2014). Third, employment creation effect. Although industrial intelligence will replace some of the labor force, it will also create some new tasks and new positions in the development process (Acemoglu and Restrapo 2019). The environmental level is mostly represented by the influence of industrial intelligence on environmental governance and carbon emissions. The use of AI technology may not only improve company production conditions and facilitate the upgrading of sewage treatment facilities (Ye et al. 2020) but also increase the effectiveness of cross-regional government oversight and the degree of pollution control (Zhang and Li 2021). Additionally, the influence of industrial intelligence on carbon emissions is more complex. Industrial intelligence will increase electricity demand, leading to significant carbon emissions, but it can also curb carbon emissions by promoting technological innovation and energy utilization efficiency (Tao et al. 2023; Huang et al. 2023; Mao et al., 2023).

Industrial intelligence and green development

The literature closely related to this paper focuses on the influence of industrial intelligence on green development. The green growth effect brought by industrial intelligence has drawn increasing attention from academics, but empirical research on them is not rich. From the perspective of theoretical research, industrial intelligence can reduce the opposition between economic growth and environmental protection by improving energy utilization efficiency and strengthening environmental fine management (Liang 2019), and can also provide new solutions to solve problems such as dynamic supervision of environmental pollution (Shi 2020). From the perspective of empirical research, some academics believe that industrial intelligence helps with green development. Korinek and Stiglitz (2021 pointed out that there is a complementarity between industrial intelligence and green transformation, and AI technology can release a significant portion of labor forces to support the green transition. Tang and Chi (2022) found that the advancement of green development efficiency is driven by industrial intelligence. Industrial intelligence can also promote green development by promoting technological innovation (Chen and Liu 2022), improving productivity, and optimizing resource allocation efficiency (Qian et al. 2022). A few scholars believe that industrial intelligence has a U-shaped impact on green development. Zhao et al. (2022) and Fang et al. (2022) used China's provincial panel data to find that AI has a significant U-shaped impact on green total factor productivity.

From different perspectives, scholars have studied the important role of technological progress, environmental regulation, and other factors on green development as well as the influence effect brought by industrial intelligence, especially the green growth effect of industrial intelligence, which lays the foundation for this study. However, the existing literature also has some shortcomings: when studying the influence of industrial intelligence on green development, provincial panel data is mostly used, ignoring urban heterogeneity, or a single index is adopted to measure green development, which makes it difficult to measure green development comprehensively; when analyzing the effect mechanism, it only considers it from the perspective of intra-industry, ignoring the technology spillover of industrial intelligence; and little literature considers whether environmental regulation can regulate the influence of industrial intelligence on green development. Therefore, based on urban panel data, this study further discusses how industrial intelligence affects green development, studies the mechanism of action based on intra- and inter-industry linkage effects, and answers how environmental regulation intensity affects the relationship between them.

Theoretical mechanism

So far, few studies have shown the mechanism of industrial intelligence affecting green development based on both intra- and inter-industry linkage effects. Therefore, we attempt to propose a possible explanation for the influence of industrial intelligence on green development.

Intra-industry effect

Based on economic logic and existing literature, this essay claims that intra-industry effect is mostly evident in energy utilization efficiency. The promotion and application of AI technology will affect energy utilization efficiency and have a profound impact on green development.

In the short term, low levels of industrial intelligence lead to low energy consumption efficiency, which is detrimental to green development. The use of industrial robots during the early stages of industrial intelligence may directly result in increased power consumption and energy intensity. The energy required by industrial robots has grown to comprise a significant portion of the total energy consumed by industrial processes. Studies have shown that the power consumed by industrial robot applications accounts for nearly 8% of the total energy consumption of manufacturing enterprises (Brossog et al. 2015). The early development of AI technology depends on data centers and machine learning systems. Training AI language processing systems will consume a lot of energy (Strubell et al. 2019). In the early stage of industrial intelligent development, the increase in energy consumption did not bring about a sharp rise in productivity. Due to the potential "productivity paradox", the full play of technology "dividend" needs the development of related complementary innovation and combined innovation, and the improvement of productivity by AI needs a long cycle (Brynjolfsson et al. 2018). Industrial intelligence cannot have a significant impact on economic growth and production efficiency in the short term as expected. Therefore, in the early stages of industrial intelligent development, the energy utilization efficiency is low, and the increase in output is not enough to offset the energy consumption caused by the increase in electricity demand, thus adversely affecting green development.

However, in the medium to long run, with the improvement of industrial intelligence levels and the enrichment of application scenarios, the energy utilization efficiency of various economic sectors has been greatly improved through intelligent upgrading and transformation, which is conducive to green development. As a general technology, AI has the potential to be popularized. It can be improved over time and produce complementary innovation, which greatly improves productivity (Yin and Zeng 2023). The production mode of enterprises has greatly changed as a

result of the advancement of industrial intelligence. Industrial intelligence helps enterprises build a closed-loop network system covering the whole life cycle of products, such as R&D design, equipment production, transmission, and assembly so that enterprises can respond rapidly, perform dynamic optimization, and promote the efficiency of green development (Yang and Shen 2023). Although the use of robots will still increase energy consumption, when industrial intelligence develops to a certain stage, the productivity gains brought about by AI technology will greatly increase total output. In other words, the increased output from industrial intelligence far outweighs the increased energy use. At this time, industrial intelligence improves energy utilization efficiency and is conducive to green development.

In summary, industrial intelligence affects green development by affecting energy utilization efficiency. When industrial intelligence is weak, energy utilization efficiency is diminished, and productivity increases are insufficient to offset energy consumption, which is detrimental to green development. When industrial intelligence is strong, energy utilization efficiency is greatly improved, and productivity far outpaces the additional energy consumption level, which is conducive to green development.

Inter-industry linkage effect

Industrial intelligence enables the industries in the supply chain to realize their green and efficient development by using intelligent technology, but it also affects the development of other industries in the whole supply chain. This part attempts to examine the "squeeze effect" and "dividend effect" brought by industrial intelligence among different industries from the perspective of industrial linkage.

When industrial intelligence is underdeveloped, the "squeeze effect" dominates, resulting in a low-end service industry structure. Industrial intelligence, while accelerating technological progress, will replace the labor force in the secondary industry dominated by manufacturing, resulting in the flow of manufacturing labor to other industries. The use of robots initially replaced low-skilled labor in manufacturing, reducing manufacturing jobs (Dauth et al. 2018). The low-skilled labor force mainly flows to the living service industry with poor productivity performance, that is, retail, wholesale, catering service, and other sectors with slow technological progress, which leads to the low-end structure of the service industry (Rodrik 2018). At this time, even if the manufacturing industry has developed production technology and improved productivity, the relatively rapid growth of the productivity of the intelligent sector will lead to an increase in the relative cost of the non-intelligent sector without the application of AI and other technologies, which may result in Baumol's disease, resulting in a high capital share of the overall economic growth and a relatively low economic growth rate (Aghion et al. 2018). Green development is currently hindered by the low-end structure of the service sector brought on by the "squeezing effect".

With the advancement of industrial intelligence, the "dividend effect" has begun to play a significant role, promoting a high-polarization service industry structure. When industrial intelligence reaches a certain level, manufacturing productivity will increase significantly, driving the development of producer services and high-end services in the same industrial chain as manufacturing (Acemoglu and Restrepo 2018). Producer services and high-end services include communications, computer services, transportation services, business services, and other service industries that provide intermediate service inputs for manufacturing. The improvement of manufacturing efficiency will greatly increase the demand for producer services and high-end services, promote large-scale, specialized production, and technological innovation of producer services and high-end services, so as to advance the growth of producer services and high-end services, and promote the high-end structure of the service industry (Wang et al. 2020). Service industry structure upgrading can improve production efficiency and energy resource utilization, promote the transformation of production factor input to low carbonization, the development of production modes to high precision, and the extension of the industrial chain to high added value (Zhang and Zhong 2022), thus promoting green development.

In summary, industrial intelligence affects green development by affecting service industry structure upgrading. When industrial intelligence is weak, the "squeeze effect" dominates, resulting in a low-end service industry structure that does not support green development; when industrial intelligence is strong, the "dividend effect" dominates, which supports a high-polarization service industry structure and is conducive to green development.

Based on the above analysis, the following theoretical hypothesis is proposed:

H1 Industrial intelligence and green development have a nonlinear U-shaped link.

H2 Industrial intelligence affects green development by affecting energy utilization efficiency.

H3 Industrial intelligence affects green development by influencing service industry structural upgrading.

The regulatory role of environmental regulation

How does environmental regulation affect the relationship between industrial intelligence and green development? From the perspective of industrial intelligence, which itself consumes electricity and energy, stronger environmental

regulations will improve the degree of standardization and operational efficiency of industrial intelligence and reduce energy waste and pollution emissions. As environmental regulations become stronger, the hindering effect of industrial intelligence on green development is mitigated, thus flattening the first half of the U-shaped relationship curve between industrial intelligence and green development. Strict environmental regulations, on the other hand, may inhibit innovation dynamics and cause industry development to weaken. Against this backdrop, the quality enhancement of industrial intelligence may be relatively weak, leading to the flattening of the second half of the U-shaped relationship between industrial intelligence and green development.

From the perspective of green development, the realization of green development requires regulation and guidance from the regulatory authorities. Environmental regulation has become a key policy for realizing green development, which promotes the upgrading of regional industrial structure by forcing a large number of highly polluting enterprises to shut down (Luo and Qi 2021). Environmental regulation promotes the flow of production factors from heavily polluted industrial sectors to clean industrial sectors, accelerates the clean-up of industrial structure, changes the substitution rate of non-energy factors of production for energy factors of production, and thus enhances green development, shifting the inflection point of industrial intelligence for green development to the left. However, strict environmental regulations will hinder the improvement of production efficiency, thus hindering green development. Overall, the shift in the inflection point of the U-shaped curve of the relationship between industrial intelligence and green development is uncertain.

Based on the above analysis, this paper proposes the following hypothesis:

H4 As the intensity of environmental regulation increases, the U-shaped curve of the relationship between industrial intelligence and green development tends to flatten.

H5 As the intensity of environmental regulation increases, the inflection point of the U-shaped curve of the relationship between industrial intelligence and green development moves with uncertainty.

Methods and data

Method

Benchmark regression model setting

Most scholars assume that individual effect exists in the form of a fixed effect when studying how industrial intelligence affects green development (Zhao et al. 2022). From the data structure of this paper, it has the characteristics of wide N and short T. To avoid the omission of individual characteristic variables that do not change over time and the influence of time trends on dependent variables, this paper attempts to establish a two-way fixed effect model. At the same time, the results of the Hausman test and F test also show that the two-way fixed effect method should be used for regression. The model structure is as follows:

$$\mathrm{GRE}_{i,t} = \alpha_0 + \beta_1 \mathrm{INTE}_{i,t} + \beta X_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t} \quad (1)$$

$$\mathrm{GRE}_{i,t} = \alpha_0 + \alpha_1 \mathrm{INTE}_{i,t} + \alpha_2 \mathrm{INTE}_{i,t}^2 + \beta X_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t} \quad (2)$$

In model (1), $\mathrm{GRE}_{i,t}$ represents the green development level of city i in period t, and $\mathrm{INTE}_{i,t}$ represents the degree of industrial intelligence of city i in period t. Coefficient β_1 reflects the influence of industrial intelligence on green development. $X_{i,t}$ represents a series of control variables, μ_i represents the city fixed effects, ν_t represents the year effects, and $\varepsilon_{i,t}$ represents the random disturbance term. In Model (2), to test the nonlinear impact of industrial intelligence on green development, the square term of industrial intelligence ($\mathrm{INTE}_{i,t}^2$) is added as an explanatory variable in Model (1), and the interpretation of other variables is consistent with Model (1).

Firstly, we regress formula (1) and then regress formula (2). If both α_1 and α_2 pass the significance test, and the goodness of fit of formula (2) regression is higher than that of Eq. (1), it indicates that the influence of industrial intelligence on green development is not linear. If α_2 is positive and α_1 is negative, it shows that there is a U-shaped relationship between them.

Moderating effect model setting

In order to examine the effects of environmental regulation intensity on the relationship between industrial intelligence and green development, we use Model (3) to regress the whole sample, and the regression still uses the two-way fixed effect model. The model is configured as follows, with reference to the study conducted by Haans et al. (2016):

$$\mathrm{GRE}_{i,t} = \alpha_0 + J_1 \mathrm{INTE}_{i,t} + J_2 \mathrm{INTE}_{i,t}^2 + J_3 \mathrm{INTE}_{i,t} \times \mathrm{ENRE}_{i,t} + J_4 \mathrm{INTE}_{i,t}^2 \times \mathrm{ENRE}_{i,t} + J_5 \mathrm{ENRE}_{i,t} + \beta X_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t} \quad (3)$$

In formula (3), $\mathrm{ENRE}_{i,t}$ denotes the environmental regulation intensity of city i in period t, and the other symbolic meanings are the same as above. where J_4 determines the shape change of the curve. When J_4 passes the significance test and is positive, it means that the link between industrial intelligence and green development has a steeper

U-shaped curve the more intense the environmental regulation intensity is; otherwise, the link between them has a smoother U-shaped curve. Curve inflection point INTE $^{*}=-\left(J_1+J_3\mathrm{ENRE}\right)/2\left(J_2+J_4\mathrm{ENRE}\right)$, taking the derivative of ENRE, the first derivative is $(J_1J_4-J_2J_3)/2(J_2+J_4\mathrm{ENRE})^2$, It can be seen that the sign of $J_1J_4-J_2J_3$ determines the direction of the curve inflection point. If J_1, J_2, J_3 and J_4 all pass the significance test, and $J_1J_4-J_2J_3$ is positive, it indicates that the greater the environmental regulation intensity, the more the inflection point of the curve moves to the right, and vice versa.

Mechanism test method

This essay investigates how industrial intelligence affects green development in more detail. Based on theoretical analysis, industrial intelligence may impact green development through energy utilization efficiency (ENEF) and service industry structure upgrading (SEIN). The mediating effect model proposed by Wen et al. in 2004 is more suitable for psychological research, but the mediating effect test in economics is not reliable, and there are problems such as endogenous bias and unclear identification of some channels (Jiang 2022). Therefore, this essay refers to the research ideas of Liu and Mao (2019) and tests the mechanism by observing how core independent variables affect intermediary variables. This paper constructs the following regression model:

$$\mathrm{ENEF}_{i,t}=\alpha_0+\beta_1\mathrm{INTE}_{i,t}+\beta_2\mathrm{INTE}_{i,t}^2+\beta X_{i,t}+\mu_i+\nu_t+\varepsilon_{i,t} \tag{4}$$

$$\mathrm{SEIN}_{i,t}=\alpha_0+\beta_1\mathrm{INTE}_{i,t}+\beta_2\mathrm{INTE}_{i,t}^2+\beta X_{i,t}+\mu_i+\nu_t+\varepsilon_{i,t} \tag{5}$$

Instrumental variable method

To reduce the potential endogenous problems, on the one hand, when designing the model, based on fully referring to the existing research literature, we incorporate the variables affecting green development as control variables into the model as much as possible. On the other hand, based on the benchmark model, the instrumental variable method is used to deal with endogenous problems, and the two-stage least squares (2SLS) method is used for regression. Specifically, we draw on the approach of Acemoglu and Restrepo (2020), using the penetration indicator constructed by US robot data as an instrumental variable. Appropriate instrumental variables should meet the two requirements of relevance and exogeneity. A high proportion of Chinese robots depend on imports, mainly from the USA and other countries (Song and Zuo 2022). Therefore, the export of Chinese robots from the USA and the application of American robots will affect the number of Chinese industrial robots, satisfying the correlation hypothesis of instrumental variables. The exogenous hypothesis of instrumental factors is satisfied by the lack of a relationship between industrial robot use in the USA and China's green development.

Variables selection

(1) Explained variable: green development. There are two main methods to measure green development: one is the comprehensive index system evaluation method, and the other is to measure green development efficiency through input and output. Based on the work of Moussiopoulos et al. (2010), we incorporate economy, society, and environment into the framework, construct a comprehensive index system from the three facets of economic development, social progress, and ecological civilization, and use the entropy method to measure it. Table 1 shows the comprehensive evaluation index system.

The entropy weight method is a commonly used objective weighting method. Its basic idea is to determine the objective weight according to the size of index variability. The calculation formula is:

$$\mathrm{GRE}_{ij}=\sum_{j=1}^{m}w_jX_{ij}^{*}$$

Among them, $X_{i,j}^{*}$ is the proportion of standardized index j in the city i in the comprehensive evaluation index system of green development, w_j is the weight corresponding to the index j. GRE_{ij} is the comprehensive level of green development. The larger the value, the higher the level of green development.

(2) Core explanatory variable: industrial intelligence. Acemoglu and Restrepo (2020) drew on the idea of the "Bartik instrumental variable" to construct indicators of "robot penetration" at the US regional level. This paper follows its method to decompose industrial robots at the industry level into the city level and takes the employment share of each industry in the city as the weight to sum the robot density of all industries, thus obtaining the penetration of robots in each city. This paper matches the industry classification in IFR (International Federation of Robotics) with the industry classification of the national economy to obtain the robot stock data and employment number of corresponding industries. The expression of the penetration of each urban robot can be obtained as follows:

$$\mathrm{INTE}_{it}=\sum_{r\in I}\frac{N_{ir}^{t}}{N_{i}^{t}}\frac{R_{r}^{t}}{N_{r}^{t}}$$

Among them, INTE_{it} represents the degree of robot penetration in city i in period t, that is, the level of industrial

Table 1 Comprehensive evaluation index system

System layer	Criterion layer	Indicator layer	Unit	Index attribute
Economic development	Economies scale	Per capita gross regional product	Million yuan	+
	Economic structure	The proportion of tertiary industry output value in GDP	%	+
	Economic benefit	Local fiscal revenue	Million yuan	+
Social progress	Social security	Number of health institutions	pieces	+
		Share of education expenditure in GDP	%	+
	Social welfare	Internet broadband access users	Million people	+
	Development of science and technology	Expenditure on science and technology	Million yuan	+
Ecological civilization	Pollution emission	Ground average industrial wastewater discharge	10,000t/km^2	−
		Ground average sulfur dioxide emissions	t/km^2	−
	Pollution abatement	Harmless treatment ratio for House refuse	%	+
		The comprehensive utilization rate of industrial solid waste	%	+

intelligence. N_{ir}^t represents the number of employees in industry r of the city i in period t, N_i^t represents the total number of employees in the city i in period t, and N_{ir}^t/N_i^t represents the proportion of employees in industry r of the city i in period t. R_r^t represents the number of industrial robots in industry r during period t, N_r^t represents the total number of employees in industry r during period t, and R_r^t/N_r^t represents the robot density at the national level in industry r during period t. Add up the robot density of all related industries in the city i to get $INTE_{it}$. Thus, the spatial distribution of the industrial intelligence level of each city in China is as follows:

Figure 1a–d shows the spatial distribution of industrial intelligence in 2007, 2011, 2015, and 2019, respectively. The overall level of industrial intelligence in the nation continues to rise over time. In 2007, the highest distribution interval of the robot penetration index was 0.92–1.54, while in 2019, the highest distribution interval of the robot penetration index reached 49.41–112.77. Three stages of development can be distinguished over time. The first stage is the start-up period (2007–2010), during which the robot penetration rate is kept at a low level of development. The second stage is the growth period (2011–2014), during which the robot penetration rate continues to rise and the scale of the intelligent industry has been further expanded. The third stage is the period of rapid development (2015–2019), during which robot applications have surged, and AI and various industries have accelerated integration and penetration.

From a regional perspective, the industrial intelligence level is stepped, and the hierarchical effect is significant. In general, the space can be divided into three levels. The eastern region forms the first level, playing the role of "leader goose" in the field of AI. The central region and the northeast region are on the second level, with industrial intelligence in the middle. The western region is at the third level, and industrial intelligence is relatively low. The central region's catch-up momentum is obvious over time. In addition to the coastal areas, the central region is actively accelerating the industrial layout of AI, implementing talent and scientific research incentive policies, and has a development trend of "curve overtaking".

(3) Moderator variable. The moderator variable is environmental regulation intensity (ENRE). According to Dong et al. (2022), this paper selects five indexes, including the removal amount of industrial sulfur dioxide, the removal amount of industrial soot, the treatment rate of domestic sewage, the harmless treatment rate of domestic garbage, and the comprehensive utilization rate of general industrial solid waste, and constructs the comprehensive index of ENRE by the entropy weight method.

(4) Intermediary variables. The intermediary variables are energy utilization efficiency (ENEF) and service industry structure upgrading (SEIN). Among them, for ENEF, we refer to the practice of Lyubich et al. (2018), where the ratio of regional GDP to energy consumption is used as an alternative variable for energy utilization efficiency (ENEF). At the same time, to eliminate the interference of price factors, we take 2007 as the base period and use the provincial GDP deflator to reduce it. For SEIN, we draw on the practice of Wang et al. (2020), which takes the share of the number of employees in the service industry in the total employment of each region as its approximate reflection.

(5) Control variables. Green development is also affected by infrastructure level, financial development level, industrial structure, external development degree, and natural population growth rate. The control variables are as follows: ①Infrastructure level (LNINFR). This paper measures the total amount of urban posts and telecommunications

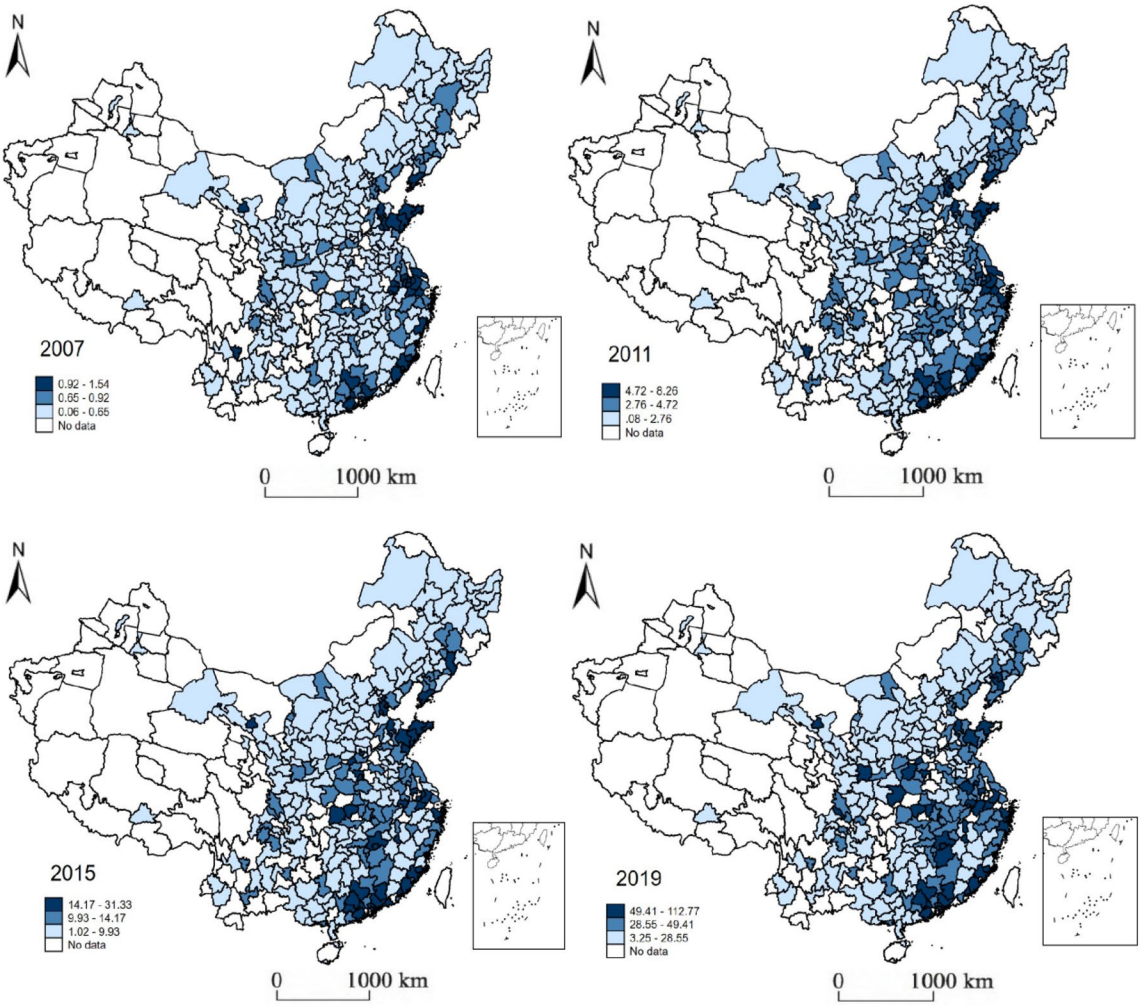


Fig. 1 Spatial distribution of industrial intelligence level

businesses by logarithm. ②Financial development level (FINA). This paper uses the ratio of the year-end loan balance of financial institutions to urban GDP. ③Industrial structure (IS). We use the secondary industry GDP to the tertiary industry GDP proportion to measure. ④External development degree (OPEN). We use the actual use of foreign capital in the city to account for the proportion of regional GDP to measure. ⑤Natural population growth rate (NPGR). This paper is measured by the ratio of the natural increase in population (births minus deaths) to the average population over the same period.

Sample selection and data description

The study period is from 2007 to 2019, including 284 cities in China. Robot data come from IFR, mainly including robot stock data from various industries in China. The data for other variables are derived from "China City Statistical Yearbook", "China Labor Statistical Yearbook", "China Environmental Yearbook", and statistical yearbooks of provinces and cities. Considering the existence of outliers or statistical errors in some data, both GRE and INTE are bilaterally reduced by 1%, and some missing values are interpolated by the interpolation method and mean method. The unbalanced panel data are obtained after preliminary processing. The descriptive statistics of the main research variables are shown in Table 2.

Result and discussion

The impact of industrial intelligence on green development

Table 3 displays the results of the whole-sample regression using formulas (1) and (2). To show the robustness of the results, we also list the regression results with and without control variables.

Table 2 Descriptive statistics

Variable	Obs	Mean	Std	Min	Max
GRE	3555	0.0876	0.0587	0.0241	0.4167
INTE	3556	9.0999	11.6317	0.1035	55.0479
ENRE	3407	0.0828	0.0913	0.0051	0.8923
ENEF	3355	0.2367	0.5697	0	10.4498
SEIN	3556	0.5341	0.1331	0.0991	0.9060
LNINFR	3549	10.3302	1.2291	1.9459	16.4299
FINA	3548	0.9070	0.5817	0.0753	9.6221
IS	3553	1.3540	0.7279	0.1935	10.6026
OPEN	3553	0.0176	0.0187	0	0.1988
NPGR	3550	5.7030	5.4323	−16.6400	40.7800

Table 3 Estimation results of the impact of *INTE* on *GRE*

	(1)	(2)	(3)	(4)
INTE	−0.00033**	−0.00127***	−0.00024*	−0.00116***
	(0.00014)	(0.00041)	(0.00013)	(0.00041)
$INTE^2$		0.0000154**		0.0000152**
		(0.0000063)		(0.0000063)
LNINFR			−0.00435**	−0.00431**
			(0.00172)	(0.00171)
FINA			0.00101	0.000791
			(0.00185)	(0.00185)
IS			−0.000143	−0.000206
			(0.00170)	(0.00174)
OPEN			0.219***	0.218***
			(0.0693)	(0.0694)
NPGR			−0.0000926	−0.0000741
			(0.000166)	(0.000166)
Constant	0.08885***	0.08932***	0.12632***	0.12652***
	(0.00121)	(0.00118)	(0.01628)	(0.01620)
City fixed effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Observations	3555	3555	3542	3542
R^2	0.1460	0.1486	0.1550	0.1575

Note: Values in parentheses are cluster robust standard errors; *, **, and *** denote 10%, 5%, and 1% significance levels, respectively; the same in the following tables unless otherwise noted

In Table 3, column (1) and column (2) are the regression results without control variables. In column (1), when $INTE^2$ is not added, the influence coefficient of INTE on GRE is negative. In column (2), INTE has a significant negative impact on GRE, and $INTE^2$ has a significant positive impact on GRE. Compared with the results of column (1), the goodness of fit of column (2) has increased, indicating that the impact of INTE on GRE is not linear but U-shaped. Column (3) and column (4) are the regression results of adding control variables, respectively. From the regression results in column (4), we can see that the INTE and $INTE^2$ are significant at the levels of 1% and 5%, respectively. The influence coefficient of INTE is negative, and the influence coefficient of $INTE^2$ is positive. It proves again that when INTE advances, the level of GRE is characterized by first decreasing and then increasing.

This paper calculates the inflection point value of INTE to GRE from inhibition to promotion based on the results of column (4). According to the coefficient value, the inflection point value can be calculated to be 38.16, that is, when INTE of the sample is lower than 38.16, it is in the primary stage, which will hurt GRE; when INTE exceeds the critical value, it will promote GRE. The findings are similar to the research conclusions of Zhao et al. (2022) and Fang et al. (2022). These two scholars also believe that INTE and GRE have a U-shaped link. The difference is that Zhao et al. (2022) believe that the inflection point of INTE to promote GRE is between 5.92 and 7.11; Fang et al. (2022) calculated an inflection point of 4.5. The reason for the above phenomenon may be that the sample data they use are provincial panel data, while this paper uses urban panel data, and their measurement of GRE uses a single indicator, while this paper uses a comprehensive indicator.

The moderating effect of environmental regulation intensity

In the early stage of industrial intelligence development, INTE will inhibit GRE. What methods can mitigate industrial intelligence's negative effects on GRE? With Chinese government's increased focus on the environment, environmental regulation intensity (ENRE) may influence how INTE and GRE are related. To study the influence of ENRE on the relationship between INTE and GRE, this paper uses the formula (3) for regression. Table 4 displays the results of the regression.

Table 4 shows the regression result without control variables in column (1) and the regression result with control variables, city fixed effects, and year effects in column (2). According to column (2), we can find that "$INTE^2 \times ENRE$" is significant at the level of 10%, and the coefficient is negative, which proves that as ENRE increases, the U-shaped relationship curve between INTE and GRE is more gentle. After that, calculate $J_1J_4 - J_2J_3$, its value is 0.00000064, greater than 0. Therefore, as *ENRE* increases, the inflection point of the curve shifts to the right, but the movement is not obvious. The above results show that *ENRE* alleviates the inhibitory and promoting effects of INTE on GRE, but it has no discernible impact on the turning point of INTE from inhibition to support of GRE. Although from the second half of the U-shaped curve, the mitigation of the promotion effect is not conducive to INTE to promote GRE, on the whole, it

Table 4 Moderating effect test of *ENRE*

	(1)	(2)
INTE	−0.00210***	−0.00199***
	(0.00056)	(0.00057)
$INTE^2$	0.0000478***	0.0000475***
	(0.000018)	(0.000018)
INTE × ENRE	0.0310**	0.0308**
	(0.0142)	(0.0144)
$INTE^2$ × ENRE	−0.00107*	−0.00106*
	(0.000570)	(0.000573)
ENRE	0.0131	0.0139
	(0.0163)	(0.0159)
Constant	0.08591***	0.12852***
	(0.00267)	(0.01609)
Control variables	No	Yes
City fixed effects	Yes	Yes
Year effects	Yes	Yes
Observations	3406	3393
R^2	0.1820	0.1916

can delay the reduction of GRE under the influence of INTE, which is critical for stabilizing GRE.

Robustness test and endogenous test

The benchmark regression results show that INTE first inhibits GRE and then promotes it. The regression findings are next submitted to a robustness test to strengthen the trustworthiness of the preceding conclusions.

Replace core explanatory variables

According to the IFR report, the most important use sector of industrial robots in the world is manufacturing, which shows that the density of manufacturing robots accounts for the largest proportion of all industries. Therefore, we take the density of manufacturing robots as the core explanatory variable and conduct regression on the benchmark model again. Table 5 shows the results in column (1). The results demonstrate that the coefficients of INTE and $INTE^2$ remain significantly significant even if the explanatory variables are replaced, demonstrating the robustness of the benchmark regression results.

Controlling province and time joint fixed effect

Both the city fixed effects and the year effects are taken into account in the benchmark regression model, but there are still some unobserved factors that change with time at the provincial level. For instance, the influence of year-on-year changes in the investment of polluting enterprises at the provincial level on *GRE*. The advantage of controlling such a set of fixed effects is that the variables used to identify the coefficient β_1 of the key explanatory variable which from different prefecture-level cities within the same province in the same year, so that the identified β_1 is more accurate than not controlling this set of fixed effects. This approach draws on Wang (2013). After further controlling the joint fixed effect of provinces and years, the results are shown in Table 5 column (2). When we add the cross-term of the product of province and year, the U-shaped effect of INTE on GRE still exists significantly.

Table 5 Robustness test estimation results

	Replace core explanatory variables	Controlling province and time joint fixed effect	Subsample regression	Adding control variables	Instrumental variable method
	(1)	(2)	(3)	(4)	(5)
INTE	−0.00115***	−0.00089*	−0.00102**	−0.00115***	−0.00110***
	(0.00036)	(0.00049)	(0.00042)	(0.00043)	(0.00041)
$INTE^2$	0.0000152***	0.0000129*	0.0000132**	0.0000154**	0.0000144**
	(0.0000054)	(0.0000073)	(0.0000065)	(0.0000064)	(0.0000066)
Constant	0.12315***	0.19802***	0.09633***	0.13124***	
	(0.01586)	(0.01405)	(0.01670)	(0.01625)	
Control variables	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes
Province × Year	No	Yes	No	No	No
Observations	3713	3542	3297	3378	3539
R^2	0.1655	0.4545	0.1429	0.1575	0.1580

Subsample regression

As cities located in the administrative center have political, economic, and resource advantages nationwide, they tend to have stronger comprehensive economic strength and pay more attention to GRE. Moreover, they tend to have greater environmental regulation, have higher entry thresholds for polluting enterprises, and tend to transfer high-polluting enterprises within the city to other places. Cities located in the administrative center may be systematically related to GRE. Therefore, according to the urban classification criteria, we eliminate the municipalities and sub-provincial cities and then return the remaining samples. Table 5 column (3) displays the regression findings. The results reveal that the coefficient of each explanatory variable, its positive and negative, and its significance are consistent with the previously estimated results.

Adding control variables

To further alleviate the problem of omitted variables, this paper adds a green technology innovation indicator for robustness testing. We use green patent applications as a proxy variable for green technology innovation. The test results are reported in Column (4) of Table 5. The significance and sign direction of the core explanatory variables are consistent with the benchmark regression results, thus verifying the robustness of the previous conclusions.

Instrumental variable method

This work employs the instrumental variable approach to do two-stage least squares regression to take into account the endogenous issue of the model and further validate the robustness of the results. The test results are reported in Column (5) of Table 5, which leads to a conclusion that is consistent with the preceding text and proves the validity of both the benchmark model and the conclusion. According to the results of the Stock–Yogo weak instrumental variable analysis, the *F* value of the Cragg–Donald test between weak instrumental variables and endogenous explanatory factors is 1808.19, which is higher than the threshold of 7.03 under the 10% error level. As can be seen, the instrumental variable chosen is suitable, and the weak instrumental variable is not an issue.

Heterogeneity analysis

Distinguishing regional characteristics

Because of the disparities in economic growth across China's regions, there is often a large digital divide, with the eastern region having much greater levels of INTE than the other regions. So, does the effect of INTE on GRE vary by region? To answer this question, we divide the overall sample into four regions: eastern, central, western, and northeast, and studies the regional heterogeneity. Table 6 displays the model's regression findings. We find that the U-shaped influence of INTE on GRE is more prominent in the eastern, central, and northeastern regions and has not yet appeared in the western region.

Specifically, the results of columns (1), (2), and (4) in Table 6 demonstrate that in the eastern, central, and northeastern regions, the relationship between INTE and GRE is U-shaped, with differences only in the size and significance of the influence coefficient. Among them, in the eastern region, the influence coefficients of the primary and quadratic terms of INTE on GRE are −0.00367 and 0.0000473, respectively, and have passed the significance test at the 5% level; in the central region, the influence coefficients of the primary and quadratic terms of INTE on GRE are −0.00246 and 0.0000360, respectively, and have passed the significance test at the 1% level. In the northeast region, the influence coefficients of the primary and quadratic terms of

Table 6 Regional heterogeneity regression results

	Eastern region (1)	Central region (2)	West regional (3)	Northeast region (4)
INTE	−0.00367**	−0.00246***	0.00024	−0.00251***
	(0.0018)	(0.00073)	(0.0011)	(0.00080)
$INTE^2$	0.0000473**	0.0000360***	−0.0000075	0.0000384**
	(0.000023)	(0.000011)	(0.000018)	(0.000014)
Constant	0.22944***	0.08765***	0.07848***	0.10813***
	(0.03422)	(0.03348)	(0.02271)	(0.02634)
Control variables	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Observations	1011	1002	1093	436
R^2	0.1381	0.2585	0.1937	0.5023

INTE on GRE are −0.00251 and 0.0000384, respectively, and pass the significance test at the levels of 1% and 5%, respectively. The results of column (3) show that in the western region, the influence coefficients of INTE on GRE have not passed the significance test. This is mainly because the level of INTE in the eastern, central, and northeast regions is significantly higher than that in the western region, and the level of INTE in some cities has crossed the inflection point in the later period, which will have a significant U-shaped impact on GRE. For the western region, there is still a huge room for improvement in the level of INTE, and it has not yet reflected the driving effect on GRE. The result verifies the conclusion of Fang et al. (2022). The slight difference is that they divide the sample into three regions: eastern, central, and western regions, while we split the overall sample into four areas. It is considered that the U-shaped impact of INTE on GRE is more prominent in the eastern and central regions, while the effect has not yet appeared in the western region.

Distinguish industry types

Next, this paper divides the robot density of different industries and discusses how the influence of INTE on GRE changes with the density of industrial robots. Specifically, the primary industry refers to agriculture, forestry, animal husbandry, and fishery (excluding agriculture, forestry, animal husbandry, and fishery services); the second industry refers to the extractive industry (excluding mining auxiliary activities), manufacturing (excluding metal products, machinery, and equipment repair industry), electricity, heat, gas and water production and supply industry, and construction industry; the tertiary industry, namely the service industry, refers to other industries except for the primary industry and the secondary industry.

From the regression results of columns (1)—(3) in Table 7, we can see that the effect of INTE on GRE is more prominent in the secondary industry. Specifically, in the primary industry, the influence coefficient of INTE on GRE fails to pass the significance test. The reason is that, from the perspective of the whole country, AI is still in the early stages of development. Compared with the input of production factors in traditional agriculture, the cost of using intelligent machines is higher, so the influence coefficient in the primary industry is not significant. In the secondary industry, the primary term coefficient of INTE on GRE is negative, the quadratic term coefficient is positive, and the significance test is passed at levels of 1% and 5%, respectively. This shows that in the secondary industry, INTE first inhibits GRE and then promotes it. The reason is that the use of industrial robots will increase power and energy consumption. Therefore, when INTE is inadequate, the productivity effect brought by industrial robots is not enough to offset the energy consumption intensity generated, which will harm GRE. When INTE is strong, the productivity effect far offsets the energy consumption intensity generated, which is advantageous for GRE. In the tertiary industry, the primary term coefficient of INTE to GRE is significantly positive, and the quadratic term coefficient is not significant, indicating that there is no nonlinear relationship between INTE and GRE in the tertiary industry. The further linear test shows that INTE in the tertiary industry has a significant positive impact on GRE at the level of 1%, and the influence coefficient is 0.047. This demonstrates that the wide application of AI in the tertiary industry not only encourages the transformation and upgrading of the traditional service industry into the intelligent industry but also greatly improves the productivity of the service industry by optimizing the quality of service, expanding the scope of service, and improving the technological progress of the service industry. It helps to solve Baumol's disease and also provides an important guarantee for GRE.

Table 7 Industrial heterogeneity regression results

	Primary industry (1)	Secondary industry (2)	Tertiary industry (3)
INTE	0.00044	−0.00081***	0.08630*
	(0.00958)	(0.000284)	(0.0479)
$INTE^2$	0.0008830	0.0000088**	−0.0446000
	(0.00297)	(0.00000344)	(0.0526)
Constant	0.12782***	0.12753***	0.12612***
	(0.01613)	(0.01619)	(0.01563)
Control variables	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Observations	3542	3542	3542
R^2	0.1571	0.1606	0.162

Distinguish city size

This paper further analyzes the heterogeneity of city samples by scale classification. In 2014, the "Notice on Adjusting the Criteria for the Size of Cities" promulgated by the relevant departments of the Chinese government divided Chinese cities into five categories according to the number of permanent residents in urban areas, namely megacities, supercities, large cities, medium cities, and small cities. Based on the above conditions, this paper sorts out the population size of China's prefecture-level cities according to the population data of the seventh national census. Given the few amount of megacities and supercities and to simplify the analysis, this paper classifies megacities, supercities, and large cities as large cities and divides the city size into three categories: small cities, medium cities, and large cities.

Table 8 displays the regression results. Regression findings for small, medium and big cities are shown in columns (1), (2), and (3), respectively. We can find that in small cities, INTE has a U-shaped impact on GRE and passes the significance test at the 5% level; in big cities, the coefficient of INTE on GRE is negative, the coefficient of $INTE^2$ on GRE is positive, and it passes the significance test at 1% and 5%, respectively. In medium cities, the influence coefficient fails the significance test. It could be due to China's "pollution haven" phenomenon, as heavily polluting enterprises face increasingly stringent environmental regulation constraints, they have no more than two options: in situ transformation or outward transfer. Because the transformation faces the problems of large investment scale and high risk, heavily polluting enterprises are more inclined to shift the pollution production part to low-regulation areas (Wang and He 2021). The environmental regulation intensity of medium and small cities is more relaxed than that of large cities, and the resource endowment and labor force of medium cities are more sufficient than those of small cities. Therefore, medium cities have become the first choice for the transfer of polluting enterprises, resulting in the inability of *INTE* to achieve the *GRE* promotion effect of medium cities at this stage.

Mechanism analysis

The empirical findings above indicate a U-shaped relationship between INTE and GRE. So what is the mechanism by which INTE impacts GRE? Through the above theoretical analysis, the development of the digital economy can affect GRE by affecting energy utilization efficiency and service industry structure upgrading. Next, we conduct an analysis based on intra- and inter-industry linkage effect.

Firstly, INTE affects GRE by affecting energy utilization efficiency (ENEF). Column (1) in Table 8 is the intermediary test result of INTE affecting ENEF. The primary term coefficient of INTE is significantly negative at the level of 5%, and the quadratic term coefficient is significantly positive at the level of 5%, indicating that there is a significant U-shaped relationship between INTE and ENEF. When INTE is low, it is unable to improve ENEF, which is detrimental to GRE; when INTE reaches a certain level, it can promote ENEF and contribute to GRE.

Secondly, INTE affects GRE by affecting service industry structure upgrading (SEIN). Based on theoretical analysis, AI technological changes represented by industrial robots will create a large number of new jobs closely related to the service industry, promote the expansion of employment in the service industry, and promote SEIN. Column (2) in Table 9 is the intermediary test result of INTE affecting SEIN. The primary term coefficient of INTE is significantly negative at the level of 1%, and the quadratic term coefficient of INTE is significantly positive at the level of 1%. This demonstrates that, at low levels, INTE inhibits SEIN, which

Table 8 City heterogeneity regression results

	Small city (1)	Medium city (2)	Metropolis (3)
INTE	−0.00124**	−0.00041	−0.00173***
	(0.00056)	(0.00081)	(0.00066)
$INTE^2$	0.0000191**	0.0000059	0.0000244**
	(0.0000071)	(0.000013)	(0.0000094)
Constant	0.00800***	0.07262***	0.15150***
	(0.03253)	(0.02336)	(0.01978)
Control variables	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Observations	349	1192	2001
R^2	0.5309	0.1467	0.1814

Table 9 Mechanism test results

	ENEF (1)	SEIN (2)
INTE	−0.01266**	−0.00672***
	(0.00516)	(0.00107)
$INTE^2$	0.000151**	0.000074***
	(0.000072)	(0.000014)
Constant	0.25242**	0.52336***
	(0.11755)	(0.05851)
Control variables	Yes	Yes
City fixed effects	Yes	Yes
Year effects	Yes	Yes
Observations	3344	3542
R^2	0.0322	0.2689

is detrimental to GRE; at higher levels, it can promote SEIN and have a positive impact on GRE.

Conclusions and outlook

Conclusions

Based on the data of industrial robots published by IFR and taking 284 cities in China from 2007 to 2019 as research samples, this paper empirically tests how *INTE* affects green development and discusses the influence channels from the perspectives of intra-industry and industrial linkage. The conclusions of this paper are as follows: (1) Industrial intelligence has a U-shaped impact on green development. Green development decreases initially and then increases as industrial intelligence advances. After a series of robustness tests, this conclusion is still valid. (2) Environmental regulation intensity moderates the inhibiting and promoting effects of industrial intelligence on green development but has no discernible impact on the inflection point movement of industrial intelligence from inhibiting to promoting green development. (3) In the eastern, central, and northeastern regions, industrial intelligence has a more pronounced U-shaped impact on green development than in the western region, where it has not yet been fully demonstrated; the nonlinear relationship between industrial intelligence and green development is more inclined to the secondary industry, which is not shown in the primary industry, but shows a linear relationship in the tertiary industry. (4) Further mechanism test shows that a low level of industrial intelligence inhibits energy utilization efficiency, resulting in a low-end service industry structure that is not supportive of green development; a high level of industrial intelligence promotes energy utilization efficiency and a high-end service industry structure that is beneficial to green development.

Policy proposal

On the basis of the aforementioned study findings, this report suggests three policy implications:

First, strengthen the innovation of AI theory and practice and improve the level of industrial intelligence. When industrial intelligence reaches a certain level, green development can be realized. For areas that have not yet crossed the inflection point, we should guide public opinion on intelligent transformation and integration, strengthen the research and development of key AI technologies, and promote the embedding of AI technologies in enterprise production. For regions that have crossed the inflection point, we should take the opportunity of the fourth industrial revolution to further support enterprises in promoting smart transformation and integration through independent innovation and other means, so as to give full play to the "dividends" of smart development. In addition, realizing the value of environmental regulation and alleviating the adverse effects brought by the early stage of industrial intelligence development are also essential. Promote the differentiation mechanism of environmental policies, formulate regional development strategies and environmental protection policies, and promote the formation of a balanced state of green development among regions.

Second, actively adjust the energy structure and improve energy utilization efficiency. Industrial intelligence affects green development by affecting energy utilization efficiency. To improve energy utilization efficiency, the focus needs to be on improving energy consumption structure and efficiency. From the point of view of enterprise production, we should phase out enterprises with high energy consumption and low output as well as backward technology and equipment, adopt intelligent means to achieve advanced technology, and improve the economic output rate of resources. At the same time, we'd better lessen our reliance on traditional energy sources, encourage the usage of clean and renewable energy, and promote further low-carbon, clean, and smart energy consumption. From the perspective of social consumption, we should improve the level of resource recycling and advocate reasonable consumption patterns. Guide the whole society to establish a correct concept of resource consumption, avoid extravagance and excessive consumption, and promote civilized consumption and green consumption.

Third, promote service industry structure upgrading and help green development. The service sector's structure influences industrial intelligence's impact on green development. Service industry structure upgrading is an important part of industrial intelligence to enhance green development. First of all, we should promote the benign transfer and undertaking of human capital and resources, promote the integration of human capital with producer services and high-end services, provide innovative talent support, and promote the interactive development of producer services and high-end services from the perspective of collaborative positioning and industrial interaction with manufacturing. Secondly, build an interconnection platform between manufacturing and producer services and high-end services and improve the undertaking and integration of manufacturing, producer services, and high-end services. Finally, promote the intelligent development of the life service industry, encourage the life service industry to innovate technology and business models, and accelerate the realization of green development.

Deficiency and outlook

Although this paper provides further empirical evidence for analyzing the influence of industrial intelligence on green development and analyzes the impact mechanism from the

perspective of intra-industry and industrial linkage, there are still some shortcomings. When examining the industrial linkage effect, we mainly examine the linkage effect of the second industrial intelligence, especially the manufacturing intelligence, on the service industry from the industrial perspective and do not directly examine the influence of industrial intelligence on its upstream and downstream industries from the perspective of the input–output relationship, namely the forward correlation effect and the backward correlation effect. In future research, we can use micro-enterprise data to further analyze the impact mechanism of industrial intelligence on green development from the perspective of input–output and more carefully study the forward linkage effect and backward linkage effect.

Author contribution FM contributed to the conceptualization, resources, writing—reviewing, and funding acquisition. YH contributed to the software, data curation, formal analysis, and writing—original draft. XX (corresponding author) was involved in the investigation, methodology, supervision, visualization, review and editing. HW assisted in the validation, and writing—reviewing.

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Data availability The data and materials are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest This manuscript has not been published or presented elsewhere in part or in entirety and is not under consideration by another journal. We have read and understood your journal's policies, and we believe that neither the manuscript nor the study violates any of these. The authors declare that they have no conflict of interest.

Ethical approval Not applicable.

Consent to participate Not applicable.

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